Title: Spatial Awareness: Good Practices and Pragmatic Recommendations for Developing Spatially Structured Stock Assessments

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Abstract

Spatial population structure is a fundamental aspect of marine populations, yet it is rarely incorporated in stock assessment models. The unit stock assumption, a common feature of many assessments, is an axiom of the single-species modeling convention, which developed in the mid-20th century when the spatial resolution of fishery data was coarse and uncertain, computing power limited, and the impact of biocomplexity on sustainable harvest levels not well understood. Despite rapid advances along all of these research fronts in the 21st century, spatial assessments remain rarely utilized as the basis of management decision-making. A potential hindrance to broader utilization of spatial stock assessments is the lack of guidance on how to choose an appropriate spatial modeling framework for a given application. Thus, we review the types of spatial assessment models available, summarize options to parameterize population structure, offer guidance to promote the development of candidate spatial assessment models for application in management procedures, and provide a pragmatic guide for choosing a spatial assessment model given observed spatial structure, data limitations, and management concerns. A spatial assessment should match the assessment unit(s) to interdisciplinary stock identification of unit populations, adequately represent the spatial structure within an assessment unit, simultaneously model multiple interacting population units, when appropriate, and provide outputs for managers that can be used to prevent local depletion of spawning populations. As data permits, higher resolution intra-population spatial structure can be addressed to increase homogeneity within the modeled unit, while connectivity among population units may also be explicitly incorporated. Small sample sizes can limit spatial assessment applications, but incorporating novel data sources and parameterizing models efficiently (e.g., sharing parameters among spatial units, implementing habitat preference functions to improve movement dynamics, and including spatial autocorrelation) can resolve some practical constraints. Management strategy evaluation should be more widely utilized to identify minimally complex management procedures that provide robust advice, while imprecision of spatial models should be weighed against the inherent bias of spatially aggregated assessments.

Highlights

- Assessment units should match stock identification of unit populations and sub-structure.
- Reproducible, fluid data workflows that enable multiple spatial aggregations are required.
- In principle, panmictic assessments should only be applied to unit populations.
- Pragmatic spatial approaches can adequately emulate biological complexity.
- Aggregated and spatial assessments should be evaluated through spatial simulation testing.

Keywords

Stock Assessment; Spatial Ecology; Fisheries Management; Animal Movement; Tag-Recovery

1. Introduction

The implementation of quantitative, science-based management advice for marine resources is often touted as a critical element for maintaining, developing, or rebuilding towards sustainable fisheries (Quinn, 2003; Hilborn, 2012). The current basis for quantitative fisheries management is typically an integrated stock assessment, which models the population dynamics of the species to estimate stock status and sustainable catch limits by minimizing differences between predicted and observed values of fishery-dependent catch, age or length compositions, and auxiliary data sources (e.g., fishery-independent estimates of abundance, tagging data, or omics information; Maunder and Punt, 2013). As with any model attempting to emulate the complexities of coupled human-natural systems, stock assessments make simplifying assumptions to ensure tractability given data availability and knowledge gaps (Punt, 2023). The primary simplification in assessment models is the unit stock assumption, wherein the modeled stock is a single, well-mixed, panmictic population that is closed to immigration or emigration, is reproductively isolated, consists of a dynamic pool of individuals with identical vital rates, and that fishing effort is homogeneously distributed (Beverton and Holt, 1957; Cadrin, 2020). Since the early 2000s, confronting spatial structure has been highlighted as a primary concern for the assessment science discipline (Quinn, 2003; Hilborn, 2012; Cadrin, 2020; Punt et al., 2020), yet many assessment units still do not match the biological boundaries of a unit population due to jurisdictional or management constraints, thereby violating the implicit assumption of a unit population (Kerr et al., 2017).

The structure and productivity of marine resources is determined by numerous interacting processes, including biophysical conditions, habitat type and availability, movement and individual behavior, and spatiotemporal patterns in harvest (Lowerre-Barbieri et al., 2017). Spatial structure can manifest as high biocomplexity (i.e., complex population or genetic structure within a species), non-homogenous patterns in distribution and abundance within a population, or spatial heterogeneity in demographics (e.g., phenotypic variation; Ciannelli et al., 2013). Maintaining rich biocomplexity is important for ensuring population resilience and stability when a species is confronted with environmental and anthropogenic perturbations, but assessing and managing every spawning contingent within a population may not be pragmatic or necessary (e.g., when a contingent is a population sink or a high degree of reproductive mixing occurs; Kerr et al., 2017). Thus, defining an appropriate spatial resolution for monitoring, assessing, and managing marine resources depends on the spatial population structure present, yet must also make pragmatic simplifications as to the degree of intra-population structure to address.

Despite the limited number of spatial assessment models that are applied in fishery management, simulations have demonstrated that accounting for spatial population structure within assessment frameworks improves model robustness and the likelihood of successful and sustainable fisheries management advice (e.g., Ying et al., 2011; McGilliard et al., 2015; Bosley et al., 2022). Moreover, ignorance of spatial population structure in assessments has been identified as a major factor in the erosion of biocomplexity, stock collapses, and inhibition of subsequent rebuilding for many species (e.g., northern cod populations in the Atlantic; Smedbol and Stephenson, 2001). However, research is needed to identify minimally complex spatiotemporal assessment models that can provide adequate management advice to monitor and avoid local depletion or erosion of population components, given the need to balance parsimony and complexity when confronted with limited data, especially as sample sizes diminish with increasing model resolution (Cope and Punt, 2011;

Berger et al., 2017b; Bosley et al., 2022). Punt et al. (2020) concluded that moving beyond the unit stock assumption represents the primary challenge for the next generation of stock assessment platforms, and that the adequate incorporation of population structure and spatial dynamics needs to be at the forefront of future model development.

Building on the guidance provided by Punt (2019a,b) and the discussions during the 2022 Center for the Advancement of Population Assessment Methodology's (CAPAM) 'Good Practices in Stock Assessment Modeling' workshop, we summarize 'good practices' for developing spatial assessment models. The variety of potential population structures and model archetypes that can be implemented are discussed, then we highlight the decisions and assumptions that must be addressed at each stage of model development. Finally, recommendations for initial good practices are provided, which conclude with pragmatic recommendations for developing spatial assessments that fulfill the needs of management given real world data limitations. Although good practices start with stock identification and data collation and are closely intertwined with the related field of spatiotemporal modeling, good practices for these disciplines are covered by similar publications (respectively: Cadrin et al., 2023; Thorson, 2019a), and we focus solely on the application of spatially explicit stock assessment models for provision of fisheries management advice. Moreover, given that spatial stock assessments have only recently entered the operational 'application' phase (Goethel and Cadrin, 2021), the rate of novel developments in this field often outpace the ability to gather 'lessons learned' regarding implementation. Therefore, the recommendations provided are based on current knowledge and are expected to improve and advance in the coming years as spatial models are increasingly utilized within management frameworks.

2. The Continuum of Biological Spatial Population Structure

2.1. Spatial Nomenclature

For any interdisciplinary scientific field, developing a consistent nomenclature is necessary to ensure common understanding and congruous methodology. As Cadrin (2020) highlights, the stock assessment discipline is plagued with inconsistent terminology because a 'stock' is a loose concept that can encompass a species, a population, or a component of a population. As assessments attempt to more realistically emulate biological systems and terms are adapted from the biological sciences to fit subsequent simplified mathematical constructs (e.g., the metapopulation concept; Kritzer and Sale, 2004), it is imperative that more consistent nomenclature be utilized. For spatial models, maintaining common definitions of spatial units is needed to allow communication across disciplines (e.g., data collectors, modelers, managers, and stakeholders), while ensuring commonality within and across spatial model archetypes to avoid conflating population structure definitions. We adopt the terminology of Goethel and Berger (2017, Table 1 therein; effectively consistent with Marr, 1957; Cadrin et al., 2014; Cadrin, 2020) for defining spatial units. However, it must be acknowledged that these terms will evolve with advancements in the biological and genetic sciences.

2.2. Types of Population Structure

Although a population is a biological unit, fishery 'stocks' have often been defined geographically. Thus, from a modeling perspective, the stock assessment unit should reflect the biological population unit (as defined through stock identification methods), but 'areas' may also need to be modeled to account for intra-population structure (i.e., spatial heterogeneity) or spatiotemporal population overlap (i.e., sympatry). For example, a population can be contained within a single area or span multiple areas (with larval dispersal or post-settlement movement across areas), and may exhibit spatiotemporal overlap with other population units across or within areas (Punt, 2019b).

There are three basic types of population structure (with multiple sub-variants) to be considered within a marine species (Figure 1), which are primarily defined by the scale of density dependence in productivity, the degree of reproductive mixing, and connectivity (Goethel et al., 2011): a panmictic population (with or without intra-population spatial heterogeneity), metapopulation structure with multiple sub-populations, or multiple unit populations with natal homing (i.e., no reproductive connectivity, but possible spatiotemporal overlap among sympatric populations). For panmictic populations, density-dependence in recruitment is assumed to occur at the population scale, while connectivity among areas within the population can occur through larval or post-settlement movement. When multiple, demographically independent population components interact through reproductive mixing (i.e., dispersal or permanent migration), such that limited genetic structure persists, they are sub-populations in a metapopulation. In a metapopulation, the scale of density dependence in recruitment is driven by the nature of pre-recruit dispersal. If larvae are primarily maintained within the sub-population and limited dispersal to other sub-populations exists, then local density dependence is maintained. Conversely, if extensive larval drift occurs with mixing of pre-recruits across sub-populations, then density-dependence is based on abundance of the entire metapopulation. An array of complex post-settlement movement patterns may exist. Biological traits are specific to the current sub-population or area (as opposed to being linked solely to the natal population), which assumes a strong phenotypic response in demographics (i.e., individual demographic rates are likely to adapt to local conditions).

Rich biocomplexity often results from sympatric population structure and spatiotemporal overlap of multiple populations with limited reproductive mixing (e.g., many herring and cod species; Smedbol and Stephenson, 2001). The reproductive isolation assumption implies that individuals only interbreed within their 'home' or 'natal' spawning population, despite potentially overlapping with individuals of multiple populations throughout the year and across areas (e.g., during feeding). Individuals will often perform a spawning migration to a spawning area occupied primarily by members from their natal population. Temporal isolation mechanisms may also occur so that natal populations show fidelity to unique spawning seasons. Thus, spatial structure due to reproductive isolation is variously termed 'home fidelity', 'overlap', or 'natal homing', though herein the latter is utilized as it best represents the dynamic nature of sympatric populations with natal fidelity. Because there is no interbreeding, natal homing implies local density dependence in recruitment dynamics, where only individuals within the natal population that are present at the time of spawning add to the spawning stock for that population. A complicating dynamic of natal homing structure is whether demographic rates (e.g., growth, maturity, and natural mortality) are based on natal population (i.e., genetic), environment (i.e., phenotypic, determined by area-specific characteristics), or a mixture of both.

3. Decision Points in Development of Spatial Stock Assessments

Developing a spatially explicit stock assessment requires many of the same data and model decisions as a typical integrated assessment, but it also needs to address implicit assumptions in spatially-aggregated approaches (e.g., homogeneity in distribution, demographics, and fishing intensity across the spatial domain). For most spatial modeling initiatives, it is recommended to begin with a conceptual model that is as complex as possible, then simplify the complexity based on stock identification, ecological knowledge, data availability, and management goals (see Section 4). Conceptual models should integrate primary hypotheses and ecological knowledge regarding population structure, recruitment dynamics, and connectivity. Decisions during conceptual model development can then help narrow down model options, determine the primary axes of model evaluation and uncertainty, and be subsequently used to identify whether estimates from exploratory models align with expectations and expert opinion. As part of the initial conceptual model development process, high resolution data analysis can help identify spatial patterns, population structure, and feasible modeling options. Although pragmatic approaches to spatial model development are recommended (see Section 5), maintaining flexibility to explore multiple spatial structures throughout the model development process can be valuable for understanding sensitivity to model assumptions and associated uncertainty in management advice. Moreover, results from more complex models, which are not necessarily being pursued as the basis of management advice, can be used to condition operating models that test the performance of simpler models (Goethel et al., 2016).

The full suite of spatial population structures can be represented by a single, generalized population dynamics model, which tracks each natal population along with current area while also accounting for either global or local density dependence (e.g., Goethel et al., 2011 with a further generalized version provided by Punt, 2019b). Aside from whether a natal population is tracked and the scale and functional form of recruitment (Punt, 2019a), the main differences among model types will be the movement dynamics (Punt, 2019b). Similarly, assumptions regarding how demographics vary across populations and areas can lead to further complexity and model variations. Punt (2019b) details the primary decisions at each stage of spatial model development, while providing recommendations on how to choose among options. Here, we review the main overarching decisions in the model development process related to determining spatiotemporal structure, fishery characteristics, recruitment dynamics, spatial abundance scaling, connectivity, demographic variation, data integration, and model diagnostics, but we recommend consulting Punt (2019b) for a full review. Table 1 outlines the decision points and the majority of potential parametrization options that need to be addressed during the development of a spatial stock assessment and is meant as a strategic guide to aid model building (both for conceptual and applied assessment models).

3.1. Spatiotemporal Structure

The critical decision for spatial models is how to define an appropriate spatial and temporal structure to allow adequate representation of population structure, while balancing parsimony, model stability, and tractability (i.e., ability to estimate parameters and associated tradeoffs in computing time). There are essentially three overarching model structures currently available for spatial assessment models: broad-scale spatially stratified, high resolution spatially stratified, and spatiotemporal (though a variety of spatially implicit approaches also exist, see Section 5). The majority of spatially explicit assessments utilize the spatially stratified framework, wherein the model domain is parsed into broad-scale strata (i.e., areas) and movement is explicitly modeled (Goethel and Cadrin, 2021). Spatially stratified models are able to balance the spatial resolution of historical fishery data with fine-scale spatial dynamics, while maintaining tractability (Goethel et al., 2011). However, there is a loss of information from high resolution data sources due to aggregation from precise fishing or sampling (e.g., haul) locations to areas, while spatial correlation in processes across areas are often ignored, which limits the number of areas that can be effectively modeled (Cao et al., 2020). High resolution spatial models have been developed (e.g., the Spatial Population Model, SPM, and SEAPODYM; Dunn et al., 2020; Lehodey et al., 2008) that can include hundreds of spatial strata using various functional forms to reduce effective parameters (e.g., habitat preference functions for movement), but these are based on quasi-estimation frameworks used primarily for conditioning simulation scenarios (e.g., Mormede et al., 2017; Senina et al., 2020). Spatiotemporal assessment models, which allow for continuous space and time dynamics (though, these are typically implemented using high resolution discretization of the spatiotemporal domain) have been developed in recent years, and demonstrate promise because of the ability to fit data at the scale it is collected (i.e., haul locations) and reduce effective parameters by incorporating random effects and spatial autocorrelation (Cao et al., 2020). However, spatiotemporal assessment models are data intensive and have yet to be demonstrated with complex spatial population structure (e.g., natal homing or metapopulation dynamics). We focus the remaining sections primarily on the decisions associated with spatially stratified frameworks, given that these are currently the most frequently implemented and have the longest history of application, but many of these decision points are common across model frameworks.

3.1.1. Temporal Structure

Although the yearly time step will be adequate for most spatial assessments, there may be certain spatial dynamics that warrant finer temporal resolution. For example, when seasonal movement patterns exist, particularly for natal homing models that include feeding and spawning migrations, it may be necessary to implement quarterly time steps (e.g., Taylor et al., 2011). However, simplifying assumptions, such as instantaneous spawning migrations (Goethel and Berger, 2017), may be sufficient. Other processes including year-round recruitment, seasonal spawning, dynamic growth (e.g., fast growth during the first year of life), or seasonal fishing may also warrant further refinements to the temporal structure (e.g., as is done in many tuna models). For example, seasonal time steps may be needed for metapopulation models that have subpopulations spawning in different seasons. As with any additional model partition, increasing the number of time steps must be weighed against the additional parameters to be estimated.

3.1.2. Population Structure

The ultimate goal of incorporating spatial dynamics is to more thoroughly represent biocomplexity and enable improved estimation of local and global productivity. Thus, based on stock identification and ecological knowledge, the assessment unit should match the observed biological delineations of unit populations or sub-populations, thereby encompassing essentially self-sustaining units (Cadrin et al., 2019). For modeling population structure, the population dynamics should reflect one of the three main structures outlined in Section 2, with associated stock-recruit functions matching the scale of density dependence (see Section 3.2) and movement dynamics that can adequately emulate the observed connectivity patterns (see Section 3.4).

Depending on the population structure and complexity, it may be necessary to model both populations and areas, particularly with sympatric populations and natal homing where multiple populations overlap across space and through time. When intra-population spatial heterogeneity is present, a single population can be modeled with multiple areas and potential interactions (i.e., movement) among areas. For metapopulation models, each sub-population should be simultaneously modeled and treated as a unique population component with explicit interactions. For natal homing models, if no overlap of populations occurs, then reproductively isolated populations can be modeled separately (i.e., with individual panmictic assessments). Conversely, when complex movement patterns exist, overlap in an area should be explicitly modeled to account for mixed population catches.

When reproductive mixing occurs, either in a panmictic population with spatial heterogeneity or among sub-populations in a metapopulation, individuals are often assumed to adopt the biological characteristics of the area currently occupied or sub-population most recently joined (i.e., phenotypic variation is assumed to control demographics and natal population does not need to be tracked). However, dynamic pool models may apply empirical mixture samples (e.g., weight-at-age) without assuming the adoption of local vital rates (e.g., Goethel et al., 2015a,b). Most natal homing models assume genetic-based traits (e.g., the morph option in Stock Synthesis 3, though the platform only allows for one population with genetic variants within it), which implies that demographics are controlled by the natal population (and do not differ if a fish moves across areas; e.g., Taylor et al., 2011). Developing, parametrizing, and applying assessment models that account for natal homing also often require some data sources to be collected while fish are spatially segregated (e.g., fishery or survey data collected during spawning times) to develop baselines for each population, which can be fit directly in the model or used to inform population composition information (e.g., based on genetics, otolith microchemistry, parasite infestation, or population-specific movement from tagging data) to proportionally assign data (e.g., total catch) to population of origin (Li et al., 2015, 2018; Vincent et al., 2017).

Even when no interactions (i.e., connectivity) occur among population units, there is likely a benefit to simultaneously modeling multiple units, as it may be appropriate to share parameters (e.g., selectivity) or demographics (e.g., growth or maturity) among population units when data is limited (Thorson and Wetzel, 2015; Johnson and Cox, 2019; Punt, 2019b). Simplifications to the assumed population structure (e.g., using the spatially-implicit fleets-as-areas approach or a population of origin assessment to replace a full natal homing model when connectivity is inestimable) may be adequate to account for spatial heterogeneity, in certain circumstances (see Section 5). Similarly, when there is uncertainty in biocomplexity (i.e., the exact number of population units), overestimating (or being optimistic regarding) the number of population units will provide information to protect all spawning components, though with decreased precision (Punt et al., 2018; Punt, 2019b).

3.1.3. Spatial Resolution

The number of population units and areas to be modeled should be primarily identified through stock identification approaches. Input from managers can further help identify the spatial resolution needed to adequately reflect and inform spatial management (e.g., areas closed to fishing). At a minimum, the assessment unit should match the biological population unit, and all populations in a region should be modeled simultaneously. It may then be necessary to model additional areas within a population or metapopulation. In some instances, the number of areas will match the number of population units, but it may also be necessary to model spatial heterogeneity within a population or allow movement of multiple populations across multiple mixing areas (i.e., with natal homing models). In particular, the number of areas should reflect differences in fishery characteristics, demography (e.g., strong phenotypic gradients), or recruitment across a population, thereby ensuring that dynamics within an area are as homogenous as possible (Punt, 2019b). Identifying spatial patterns in age and length composition data through regression tree analysis (e.g., Lennert-Cody et al., 2013) may provide a useful approach for identifying areal boundaries and demarcating differences in fleet or biological (e.g., growth) characteristics (Punt, 2019b). Similarly, any obvious ecological boundaries or management actions that may impact spatial dynamics (e.g., areas closed to fishing) should be accounted for by area delineations (e.g., McGilliard et al., 2015). Increasing model resolution enables improved monitoring of local depletion, but will reduce sample sizes and increase model imprecision (Cope and Punt, 2011). However, given the importance of monitoring for potential spatial depletion, when feasible, spatial resolution should attempt to explicitly address intra-population dynamics.

3.1.4. Fleet Structure

Spatial areas should also reflect spatial heterogeneity in fishing characteristics, with emphasis on adequately accounting for the footprint of historical fleets, given that initial spatial coverage and levels of fishing are critical for informing population scale and regional depletion. Because historical data is often coarse, a given fleet should be able to occur across multiple areas with temporal variability (i.e., to better account for changing fishery dynamics as well as the resolution of fishery data). Similarly, fleets should be allowed to have variable characteristics (i.e., fishing mortality and selectivity) across areas. The number of fleets in a given area should reflect the primary fishing sectors that operate in the area. To enable tractability and reduce the number of parameters, it may be appropriate to assume that selectivity, availability, or catchability across population units within an area is constant for a given gear type or that these parameters are the same across multiple areas for a given fleet (Punt, 2019b).

Domed selectivity patterns often result from relative availability of fish to a fleet (O'Boyle et al., 2016). Therefore, explicitly accounting for spatial structure and connectivity may theoretically imply that all fish of a given age or length class are equally available to a gear within an area (i.e., no cryptic biomass exists). However, given that no spatial model can effectively account for all factors impacting availability (i.e., untrawlable or otherwise inaccessible habitat), domed selectivity functions will still be warranted, though these should be carefully implemented (Methot, 2023).

3.2. Recruitment Dynamics

The scale of density-dependence in the stock-recruit relationship is effectively determined by the assumed population structure, as detailed in Section 2.2, and should match the population unit. For example, for natal homing population structures, only fish that are within the delineated spawning area during the spawning season are assumed to add to the spawning biomass. When intra-population spatial structure is modeled and multiple areas are present, global density-dependence is assumed for the panmictic population and area-specific recruitment can be estimated through an apportionment factor multiplied by the total population-wide recruitment. For a metapopulation, if larval dispersal is limited, then local density dependence is assumed and each sub-population maintains a unique stock-recruit relationship. Moreover, when a subpopulation spans multiple areas, global density dependence may be assumed across the sub-population with areal apportionment of total recruitment from that sub-population. Conversely, if larval dispersal distances are large and extensive pre-settlement mixing occurs across sub-populations, then global density-dependence is assumed and a single stock-recruit function is applied for the entire metapopulation with apportionment to each sub-population. For natal homing models with no reproductive mixing, local density dependence is assumed and each population maintains a unique stock-recruit relationship.

Random deviations can be applied temporally to the population, metapopulation, or sub-population recruitment estimate and to the areal apportionment estimate (if utilized), while area-specific deviations can also be applied (see Punt, 2019a for a generalized spatial stock-recruit function). Both temporal and areal deviations could be calculated as random effects to reduce the effective parameters, while parameter sharing across populations (e.g., common steepness or virgin recruitment parameters) could help improve estimation performance (Punt, 2019b). Simulations suggest that when uncertainty exists in the spatial scale of density-dependence (i.e., the assumed population structure), then it is better to assume local density-dependence in recruitment, because assuming global and using apportionment can lead to large bias in recruitment estimates and associated reference points when local dynamics do exist (Punt, 2019a; Kapur et al., 2021). It is also important to simultaneously consider parametrization of recruitment and movement dynamics to ensure plausible model outcomes (Cadrin et al., 2019), because recruitment and movement are highly correlated in spatial models (i.e., due to both processes being able to 'create' individuals to match observed abundance indices and compositional data). Ignoring movement or assuming naïve movement parametrizations can lead to highly biased and potentially implausible productivity and spatial recruitment estimates (Goethel et al., 2015a,b). Therefore, spatial recruitment estimation and associated correlation analysis can be a potential diagnostic tool for identifying misspecification, while priors based on expert judgment are often needed to keep recruitment parameters from entering implausible solution spaces (Goethel et al., 2021). Comparing estimated recruitment dynamics with expectations from the conceptual model can help ensure that outputs are plausible.

3.3. Initial Spatial Distribution and Regional Abundance Scaling

As spatial complexity increases, estimation of initial abundance and general scaling of relative abundance among areas within a population or across multiple populations can be difficult. For instance, when local abundance diverges, data signals informing estimates for smaller population units or areas are often inundated by those from larger population units causing model instability (Vincent et al., 2017; Goethel et al., 2019a). Similarly, for widely distributed species that require many areas to be modeled (e.g., tuna species), maintaining plausible and stable abundance estimates is not always feasible with the available data. For some coastal species, fishery-independent survey data is available to provide information on scaling across population units or areas assuming that catchability is spatially-invariant. Incorporating tagging data to help stabilize movement parameters can also stabilize spatial abundance estimates, albeit requiring additional assumptions (e.g., estimation of reporting rate, tag loss, tag mixing, etc.; see Section 6). However, when synoptic surveys are not available and tagging data assumptions may not be met (i.e., for highly migratory species), then externally estimated relative abundance scaling factors may be needed as priors on proportional distribution of abundance across areas. For instance, Hoyle and Langley (2020) describe a technique for estimating regional scaling factors based on a standardized area-specific catch-per-unit effort (CPUE) abundance index from a widely distributed fleet assuming constant catchability (or selectivity) across model areas, which is widely utilized in spatially explicit tuna assessments.

3.4. Movement

Implementing connectivity that is plausible, estimable, and adequate may be the most difficult aspect of implementing a spatial assessment. When spatial dynamics are driven primarily by pre-recruit dispersal, movement can be implicitly subsumed in the recruit apportionment term to reduce parametrization, a common approach for the current iteration of spatial assessments (e.g., Gulf of Mexico red snapper; SEDAR, 2018). Conversely, when post-settlement movement cannot be ignored, the first step is to develop a conceptual understanding of how fish move scaled to the population level based on current ecological knowledge and population dynamics first principles (e.g., Minte-Vera et al., 2023). Exploratory analysis outside of the modeling framework can be extremely helpful to develop hypotheses of general migration patterns (e.g., timing, extent, frequency, and ontogenetic linkages). Electronic tagging data and observations from integrated tracking networks analyzed in conjunction with ecologists and including input from local or traditional ecological knowledge (LEK or TEK, respectively) sources can provide a detailed understanding of movement patterns within a species, among populations, and across areas (e.g., Lowerre-Barbieri et al., 2021). Identifying whether dispersal (i.e., permanent migration) among population units occurs is an important component of these explorations (i.e., differentiating between a metapopulation and natal homing population structures).

Most spatially-stratified modeling approaches assume box-transfer movement (Beverton and Holt, 1957) where a proportion of one population partition (e.g., age class in a given population, area, and year) is assumed to move into a new partition with instantaneous velocity at the beginning of each time step. In the most unconstrained form, the off-diagonals of the movement matrix would be estimated assuming a multinomial logit-transform to ensure that the sum of movement and residency for a given partition sums to one. In a simple metapopulation model, for example where movement exists only among sub-population partitions, P, and is invariant across all other model partitions (i.e., age, maturity stage, and year), then the number of estimated parameters would be $P*(P\text{-}1)$, while the number of estimated movement parameters increases as a factor of the number of units in each partition (e.g., when age-based movement is estimated, then the number of movement parameters is multiplied by the number of ages; Goethel et al., 2011). The random diffusion-based box-transfer assumption is equivalent to a random walk, but simple alterations are possible to account for advection (e.g., using a biased random walk) or more complicated behavior (e.g., using a correlated random walk; Goethel and Cadrin, 2021).

Parameterizing the movement matrix involves identifying (and more importantly eliminating infeasible) connectivity linkages by and among model partitions (e.g., population, area, age, maturity stage, and year), and requires efforts to make the movement matrix sparser (Punt, 2019b). Identifying the primary axes of movement (e.g., yearly variation or ontogenetic variability) can help remove movement partitions, while parameter blocking (e.g., by age or year) can similarly reduce the number of estimated parameters while maintaining flexibility (Goethel et al., 2021). Functional forms are also commonly used to reduce the effective movement parameters (e.g., the gravity model or linear ramps to define ontogenetic movement; Carruthers et al., 2015). Similarly, habitat preference functions can also be used (e.g., Marsh et al., 2015), but require developing habitat suitability models and consistently updating the environmental layers with operational oceanographic data (i.e., the approach utilized in SPM; Dunn et al., 2020). Though not commonly implemented, treating temporal variation in movement rates as a random effect could help improve parametrization and model stability in spatial models. At the other extreme, when information on movement is extremely limited and effectively self-sustaining populations can be identified, movement among populations or areas can be ignored until more information can be gathered (Cadrin et al., 2019), though some bias would be expected to result (e.g., Goethel et al., 2015b). Movement dynamics should be continually refined as new information is collected.

3.5. Demographic Variation

Understanding how demographic structure (i.e., growth, maturity, fecundity, and natural mortality rates) varies across the spatial domain must be considered within the context of the population structure and carefully implemented in conjunction with the assumed movement dynamics. Punt (2023) notes that adequately describing spatial variation in demographics, particularly growth, is important because it influences interpretation of depletion levels from observed length composition data. The primary decision to consider is whether demographic variation is driven by genetics (i.e., natal population), environment (i.e., current sub-population or area), or influenced by a combination of factors (Punt et al., 2020). Assuming genetically defined demographics is common in natal homing models and is typically implemented by assigning rates based on natal population. Conversely, environmentally driven demographics can be modeled by having phenotypic traits be based on current sub-population or area and having individuals instantaneously adopt these rates when they enter a new biological regime. Implementing more complex, mixed approaches might be feasible by assigning demographics based on natal population and assuming area-based deviations as fish move across areas. A primary complication of modeling spatial variability in demographics is ensuring that fish do not ‘shrink’ or ‘unmature’ as they move among areas with different prevailing biological characteristics (Goethel and Berger, 2017). Using length-based models with size-transition matrices can avoid issues with growth, while modeling mature and immature partitions can achieve the same for maturity (Punt, 2019b). Similarly, tracking previous and current sub-population or area and implementing relative bounds (i.e., no change in a parameter if an individual moves into a sub-population or area where infeasible biology would result) or basing growth increment on the difference between current size and the new sub-population’s or area’s asymptotic size (e.g., Kapur et al., in review) may be feasible. Tag-integrated models can be utilized to help directly estimate natural mortality and growth parameters

(Vincent et al., 2017), while sharing priors across areas or populations for estimated demographic parameters may help improve estimation and avoid extreme variability in biological regimes (Punt, 2019b).

3.6. Data Integration

Integrated spatial models can account for the spatiotemporal scale of data collection, which enables maximizing the data content by assuming that the data only applies to local scale dynamics (instead of the entire species range; Goethel et al., 2021). Thus, the integrated assessment framework (Maunder and Punt, 2013), which can incorporate almost any data source and model associated observation or sampling error, has improved the amount and information content of data and led to the inclusion of additional data types (e.g., citizen science, LEK or TEK, and genetics information; Sun et al., 2019; Goethel et al., 2022a). As part of the stock identification process (Cadrin et al., 2023), a thorough data inventory should be undertaken to determine the types of data available, the spatiotemporal scale of collection, and their representativeness of population-level processes (Punt, 2023).

However, spatial models inherently require increased data, given the need to incorporate more complex processes at higher resolutions compared to broad-scale spatially-aggregated assessments. Therefore, it is imperative that new data sources become more widely incorporated into integrated spatial assessments. Table 2 outlines the full array of data sources along with the scale of collection, all of which could be considered for integration into a spatial assessment. Goethel et al. (2022a) thoroughly summarizes many of the new data sources that are only beginning to enter into stock assessment data streams. For instance, electronic monitoring data and vessel monitoring system (VMS) information can improve spatiotemporal estimates of catch rates, removals, and fishery distribution. Similarly, self-reported electronic logbooks, LEK or TEK, citizen science data, and app-based digital fisheries data can all provide insight on resource and fishery distributions or ecological processes, while increasing sample sizes from sectors and areas that are typically hard to sample (e.g., recreational fisheries). Integrated ocean monitoring systems can collect operational oceanography and habitat data, which can be used to develop habitat preference functions to guide movement dynamics. Moreover, biophysical individual-based models can inform larval dispersal, enabling implementation of spatially explicit full life cycle models. Implementing tag-integrated models fit to biologging and tagging data can be extremely useful for informing connectivity and estimating movement parameters along with natural mortality and potentially growth (see Section 6 for a discussion of the benefits and caveats of tag-integrated models). Similarly, natural markers (e.g., otoliths and parasite infestation) can be used to identify population composition of catch or survey data, while also aiding estimation of movement, analogous to tagging data. However, recent advances in the omics sciences demonstrate perhaps the most promise for informing spatial dynamics and population structure. With the development of high throughput genetic sequencing, it is now relatively straightforward to process genetic information for operational use. For instance, genetic samples can be easily gathered from existing surveys or sampled from catch, often non-lethally. Those samples can then be quickly processed to identify and assign fish to genetic populations (i.e., to determine population composition of catch or survey data) as well as to determine distributional patterns (Papa et al., 2021). Moreover, close-kin mark-recapture and gene-tagging information can provide direct estimates (or informative priors) of population-specific abundance and movement (or dispersal; Bravington et al., 2016; Trenkel et al., 2022).

Although many of these data types can be incorporated into common assessment platforms after a degree of processing or through developmental versions of the assessment package, aside from mark-recapture data, few platforms are currently able to integrate minimally processed forms of these data streams, which is needed to enable maximizing spatial information content. Moreover, the incorporation of new data sources will require careful consideration of data observation models and data weighting approaches. There is rarely formal guidance on how to weight data within spatially explicit integrated models, given the increasing diversity of data sources being incorporated, but methods for data weighting in spatially aggregated tag-integrated models can be easily adapted for spatially explicit approaches (e.g., Punt et al., 2017a; see Section 6). Similarly, new approaches are being developed to statistically address suboptimal sampling designs and account for observation error in novel data sources (e.g., citizen science data) when directly incorporated within integrated assessment models (Fairclough et al., 2014; Sun et al., 2019). Similarly, the increasing number of self-weighting likelihoods (e.g., the multivariate-Tweedie) being applied to fisheries data may help reduce data weighting concerns (Thorson et al., 2022).

3.7. Model Validation, Diagnostics, Uncertainty, and Sensitivity

Model adequacy is increasingly difficult to validate as spatial complexity increases. Given the relative increase in complexity and processes to be modeled along with the unique data sets incorporated for spatial models, the number of sensitivity runs and model formulations to be explored typically increases rapidly. Thus, developing a thorough understanding of the influences of each model assumption and data input on model results can be more difficult, whereas performing model selection routines can be similarly problematic. Multiple model parameterizations should be considered throughout the model development process, so that sensitivity to primary assumptions can be assessed. Adequately and realistically estimating and conveying uncertainty from spatial models is also not straightforward. However, these are challenges faced by all complex assessment models and can be overcome with careful model development and open communication across disciplines and with stakeholders, but increased time is needed to fully implement and vet spatial models compared to non-spatial counterparts.

Similarly, the dimensionality of spatial models can also make assessing goodness of fit to data and visualizing residual patterns extremely challenging, while limited guidance exists on appropriate diagnostic tools to identify model mis-specification for spatial models (Punt, 2019b). However, typical good practices for implementing diagnostics for integrated assessments [e.g., using residual analysis, model stability metrics, convergence criteria, trends in recruitment deviations, hindcasting, Markov Chain Monte Carlo (MCMC), and retrospective performance] to validate model performance and identify process error are still relevant for spatial assessments (e.g., Carvalho et al., 2021; Kell et al., 2021; Merino et al., 2022). Moreover, it is recommended that single area, aggregated assessments be applied as a diagnostic tool to identify potential spatial structure or dynamics that need to be addressed. Careful analysis of spatial residuals and retrospective patterns from spatially aggregated and spatially explicit assessments can highlight model misspecification. For example, strong patterns in length or age composition or tagging data, when integrated, can be indicative that important movement or spatial recruitment dynamics are being ignored. Moreover, given the potential for high correlation in spatial models, particularly among recruitment and movement parameters, simple plausibility metrics should be explored to ensure that results are generally consistent with expert judgement and expectations. For instance, when models estimate that recruitment occurs primarily in one area with concomitant extreme levels of emigration from that area, then the parametrization may need to be refined to constrain recruitment or movement to better reflect information from LEK, tag recoveries, or prevailing expert knowledge of the species. Perhaps most importantly, simulation testing and MSE, especially where the operating model utilizes a higher spatial resolution than the estimation model, should be routinely implemented to help understand the robustness and limits of applicability for spatial assessments.

4. Recommended Good Practices for Spatial Stock Assessment Modeling

The process of developing contemporary stock assessment models, and subsequent management advice, must include a confrontation of spatial stock structure. However, there is a paucity of guidance available on how best to evaluate spatial modeling options and make parsimonious data and analytical decisions on timeframes conducive to stock assessment schedules. We develop nine good practice recommendations that can help move an assessment process beyond the unit population assumption. Table 3 provides a template that assessment scientists can use when pursuing a spatial assessment that align with current good practices. The steps include: engaging managers and stakeholders, developing flexible data workflows, identifying the need for a spatial assessment, narrowing model options, exploring spatial and non-spatial model diagnostics, simulation testing model performance, selecting a model for management use, and establishing an iterative process to enable stepwise improvements.

4.1. Engaging Managers and Stakeholders

The development of new management procedures in fisheries systems can be a source of apprehension and angst for some fishery stakeholders, creating initial reluctance to accept proposed changes (Young, 2010; Rosenschöld et al., 2014; Berger et al., 2017b). In particular, new modeling approaches, such as those that include spatial structure, can be especially difficult to institute. This is, in part, due to the added dimensionality and associated complexities with spatial models that leads to distrust from a heightened 'black box' perception of the stock assessment model(s) to non-specialists. Therefore, it is necessary to engage managers and stakeholders early and often during spatial model development, including soliciting input and feedback on proposed spatial population structure, management, and policy templates to garner new ideas, revise expectations, develop buy-in, and counter the tendency for institutional inertia that leads to a general lack of support.

Communication among scientists, managers, and stakeholders should, at a minimum, occur to identify population units and structure (i.e., within the stock identification process; Cadrin et al., 2023), refine hypothesis-driven spatial structure ideas, and define templates to facilitate participatory co-management (Smith et al., 1999; Noble, 2000; Linke et al., 2015). In many cases, interactions with fisheries stakeholders who have LEK or TEK offer an additional setting to identify, vet, and 'ground truth' hypotheses (Duplisea et al., 2018; Bergström et al., 2019). Developing spatial models within the co-management paradigm can soften institutional inertia, a noted hurdle to operationalizing spatial models (Berger et al., 2017b), while clear and continued communication can be a primary conduit for effecting change (Goethel et al., 2019b; Miller et al., 2019).

4.2. Develop Flexible Data Workflows

The next step is to perform a full data inventory (as part of the stock identification process) and develop flexible and fluid data workflows to allow exploring data at multiple spatial resolutions. In particular, emphasis should be placed on including novel data sources that can provide high resolution insight into spatial structure (Table 2). As part of the initial data collation process, quality control of each data source should be undertaken at the finest resolution possible, because fine-scale data analysis can often identify sampling bias or data input errors not recognizable after the data are aggregated. Moreover, high resolution analysis of available data will help identify potential spatial structure, population drivers, and inherent data limitations that may prevent implementation of certain model complexities.

Once potential data sources have been identified, development of transparent, reproducible, and fully flexible data workflows are imperative to enable implementation of models with different spatial resolution. In practice, workflows (e.g., computer code) should be developed to easily extract, compile, and evaluate all data types (catch, survey, composition, distribution, and other information) at spatiotemporal scales that match candidate assessment templates. By utilizing a transparent assessment framework (TAF; e.g., https://www.ices.dk/data/assessment-tools/Pages/transparent-assessment-framework.aspx), it will encourage and enable future collaborations and synergistic advancements at later stages in the model development process. However, care must be taken to ensure that sharing high resolution spatial fishery data does not breach data confidentiality agreements. Developing streamlined data sharing protocols across research institutions worldwide needs to be made a priority in the near future to support spatial modeling initiatives.

4.3. Identify Need

It is important to understand and identify the myriad ways that spatial population structure can arise, and the relative challenge each presents for detecting spatial heterogeneity. The most common needs for spatial assessments include:

- Implementation of spatiotemporal management regulations (e.g., political boundaries or spatial management measures such as areas closed to fishing)
- Heterogeneous fishing effort, patterns, and gear
- Genetic differentiation (evolutionary significant units)
- Heterogeneous vital rates (phenotypic variation due to local adaptation) or reproductive dynamics (i.e., productivity)
- Connectivity or heterogeneous availability through movement, recruitment or spawning locations, or other conspecific behaviors

Additionally, non-mechanistic reasons to explore spatial structure in assessments include observations of area-specific trends in abundance, concerns over local depletion, and community-based socioeconomics (Punt, 2019b). Table 4 provides a guide to determine potential drivers of spatial structure, and which can help identify the need for a spatial assessment.

Once the drivers of spatial structure have been identified based on Table 4, a conceptual, hypothesis-driven model should be developed that incorporates the primary spatial complexities. Analysts should start by developing conceptual population models starting with the most complex framework needed to match the scale of unit populations and primary spatial structures determined using interdisciplinary stock identification techniques (Cadrin et al., 2023; Minte-Vera et al., 2023). Conceptual spatial model templates must be predicated on a basic understanding of ecological, genetic, fleet, and management (i.e., social, economic, and political facets) imposed spatial structures. The conceptual model represents a starting point for spatial analyses.

4.4. Narrow Model Options

Spatial assessment model development should then begin with modeling of unit stocks, with complexity added as warranted and feasible (i.e., incorporating spatial structure within a unit population or interactions among unit populations; Cadrin et al., 2023). When the dynamic pool assumption of homogeneity within defined spatial units is clearly violated, then units should be refined to better reflect the true biological structure (Cadrin, 2020). Analytical frameworks can then be developed based on hypothesis-driven spatial templates and analyst decision points (Section 3). Simplification of the analytical approach should occur as needed based on data availability and knowledge gaps in population processes (Figure 2; Kerr et al., 2017; Punt, 2019b). The quantity of modeling choices confronted by analysts increases considerably when developing a spatial model, so narrowing model options will help keep choices tractable and reduce exploratory workloads. At a minimum, spatial models should track the key dynamics of self-sustaining unit populations (Cadrin et al., 2019). Analysts should strive to include movement dynamics, because ignoring movement essentially disperses mortality, confounding areal recruitment and other estimates (Fu and Fanning, 2004; Goethel and Berger, 2017; Cadrin et al., 2019). Maintaining multiple candidate models, especially when there is high uncertainty or broad assumptions, is typically warranted to mitigate unforeseen risk and bound structural uncertainty. The degree of data support for known and hypothesized population dynamics combined with model diagnostics should be used to reduce candidate model options (Carvalho et al., 2021; Kell et al., 2021).

Stock assessment modeling platforms need to be nimble enough to readily develop and parameterize alternative spatial and non-spatial model configurations and model types (Figure 2; see Punt, 2019b for further details). When considering model complexity, parsimony in model structural considerations and parameterization options is the initial guiding principle, followed by model diagnostics (Section 4.5). Options that should be considered to improve parsimony include sharing parameters among fleets, spatial population units, or time periods when commonalities are plausible. Random effects or state-space configurations can also reduce the number of effective parameters, objectively estimate variances (Thorson, 2019b), capture unobserved states (Stock and Miller, 2021), and incorporate spatial (and serial) autocorrelation where appropriate to reduce effective parameters (Cao et al., 2020). Increased flexibility in model objective functions, such as allowing for multi-scalar data fitting procedures (i.e., fit at the highest resolution possible given model resolution and the scale of data collection), can be advantageous as combined, multi-scale approaches become more common (e.g., Thorson et al., 2021).

4.5. Explore Spatial and Non-Spatial Model Diagnostics

Diagnostics from alternative spatial and non-spatial model configurations should be compared to elicit unsatisfactory model behavior and patterns to further refine viable model options. Exploring single-area, panmictic model diagnostics can confirm the presence of spatial structure in the data and highlight scales at which the spatial processes occur. Thus, panmictic models can help identify whether the spatial model is addressing major sources of uncertainty, providing more reliable and stable estimates, and residual analysis can indicate primary sources of spatial structure causing misspecification (e.g., Latour et al., 2001). Diagnostic indicators to watch for include spatial trends in abundance, catch rates, or biological compositions that cannot be explained solely by selectivity across areas, as well as retrospective patterns and autocorrelation in residuals.

When tagging data are integrated into the model, careful consideration of tagging assumptions, such as tag mixing is warranted (Kolody and Hoyle, 2015). Stock assessment tools should continue to be developed that automatically produce diagnostic summaries and statistics (Punt et al., 2020) related to model convergence, goodness of fit, model consistency, and prediction skill (Carvalho et al., 2021). Such diagnostic tools, as well as information from other sources (e.g., LEK, TEK), can be used to refine and further narrow model options.

4.6. Simulation Test Model Performance

The most scientifically defensible way to evaluate whether new or different management procedures (e.g., spatial stock assessment models) are likely to meet management objectives is through simulation testing (Punt et al., 2016; Cadrin, 2020). Good practices must include developing tailored, and conditioned, closed-loop simulations (e.g., management strategy evaluation) that are based on candidate spatial templates, available data, alternative modeling options, and prevailing harvest policies (Kerr and Goethel, 2014; Goethel et al., 2016). Operating models should be implemented at the same or higher resolutions than the candidate spatial assessment models being evaluated to ensure results are robust to a wide range of system uncertainty (Sharma et al., 2020). Fine-scale agent-based models or spatially-resolved ecosystem models (e.g., SPM or SEAPODYM; Kaplan et al., 2021) can be particularly useful, but such tools have been developed for particular situations and are not yet widespread.

Simulations help to identify minimally complex models that form the basis of robust management procedures, and can identify the assessment method that matches management needs (Punt et al., 2017b). Other benefits include understanding the tradeoffs among alternative spatial modeling approaches as they relate to achieving management goals, which can help overcome institutional inertia by directly demonstrating benefits of moving to spatial management procedures. Simulations are a critical decision-support tool for specifying harvest control rules and associated reference points in both spatial and non-spatial contexts.

4.7. Select Models for Management Advice

Analysts often strive for a single best model for inference, when feasible, but multiple models should be retained when uncertainty in assumptions is high, there are competing population dynamic hypotheses, or population parameters are confounded or not adequately resolved.

However, models that result in inconsistencies with the conceptual understanding of the system should be removed from consideration (Punt, 2019b). As model complexity increases, the chance that multiple competing models will be plausible also increases. Therefore, ensemble approaches may be warranted to account for multiple plausible spatial dynamics (e.g., Thompson et al., 2020).

Estimates of stock size, fishing mortality, and stock status are of primary concern for fishery management. The basis for defining reference points may vary depending on the spatial structure of the population and the associated assessment model(s), the estimability of key parameters (e.g., steepness), and management objectives. Careful consideration is often required, because spatial reference points can be particularly sensitive in sensitive in most cases to the assumed spatial structure and dynamics (Goethel and Berger, 2017). Even when data are inconclusive on how best to represent spatial structure adequately, there are approaches that can be used to specify reference points under the auspices of spatial management (e.g., through the use of empirical density-based reference points; Reuchlin-Hugenholtz et al., 2015, 2016).

Maximum sustainable yield (MSY) and stock status-related reference points (e.g., B_0) should consider population structure, in addition to temporal considerations (e.g., incorporating non-stationary, dynamic calculations). Approaches for specifying reference points when there is population structure have shown utility through simulation tests, though differences among assumed spatial structure (e.g., spatial heterogeneity compared with metapopulation dynamics) may be limited unless biological characteristics differ widely across areas or population units (Kapur et al., 2021; Bosley et al., 2022). In some cases, spatially-aggregated, or system-level, benchmarks can be appropriate when a single, homogeneously distributed population unit is assessed or to identify overall population status and the potential for overfishing (Goethel and Berger, 2017). However, the need to adequately address movement patterns when identifying spatially explicit reference points is exacerbated when connectivity is skewed, such as with areal spawning contingents and source-sink movement dynamics. Simulation analysis should be utilized to identify appropriate spatially-referenced fishing mortality-based reference points as part of a well-defined harvest control rule that prevents local depletion, which may indicate that alternates to MSY-based reference points are more appropriate for complex population structures, such as metapopulations (e.g., metrics based on probability of extirpation of contingents or habitat-occupied).

4.8. Iterate to Enable Stepwise Improvements

All participants in the assessment development process, including stakeholders, managers, and assessment analysts, must maintain a realistic outlook on development timelines for spatial models. Undertaking the development of a spatially explicit stock assessment model is a research intensive effort, which requires increased resources and expanded time lines over existing unit population models. It is recommended that iterative and stepwise modeling improvements be undertaken, recognizing that implementing a spatial assessment model is not an all or nothing process. Implementing a stepwise approach, where incremental improvements are made during each iteration of the assessment process (e.g., one step of Table 3 taken each year or iteration of the assessment), can be a pragmatic approach to fully develop spatial assessments. For instance, developing a fully flexible data workflow might occur during one iteration, conceptual models might be outlined during the next, and building of a basic spatial assessment might occur in the following time step. Thereby, improvements to the assessment can be made without placing too much demand on assessment analysts, while incremental steps can be achieved without disrupting the development of yearly operational management advice. Moreover, emphasis on development of thorough conceptual models, which can highlight key uncertainties in understanding of spatial processes or the data needed to inform them, can help highlight priority research foci and data collection needs that may be required before a spatial assessment can be implemented for operational management use.

Moreover, incorporating a TAF concept for assessment development can help build synergistic advancements by encouraging collaboration and code sharing. Thus, by sharing the burden for development of a complex spatial model with a group of analysts or even a cross-institute research team, the time lines required to develop spatial models can be greatly reduced. Moreover, it will become easier to share and communicate model development tips and pitfalls encountered (e.g., computer code), which facilitates a collaborative dissemination of lessons learned and best practices.

Workflow considerations identified in this section (Table 3) must be adaptable as scientific understanding advances (e.g., based on results of management procedure simulations), prevailing environmental conditions change (e.g., productivity regime shifts), or stocks redistribute (e.g., due to climate change) through a systematic iterative process. Periodicity should consider management system and species-dependent information, such as single versus multiple species (complex) management procedures, species generation times, and broad-scale oceanography trends. During each iteration, effort should be dedicated to ensure selected management procedures continue to fit management needs (Goethel et al. 2019b; Edmundson and Fanning 2022). This can be done prospectively through a management strategy evaluation or through real-time monitoring of performance.

As georeferenced data become more available, models become more complex and onerous, and initiatives to support ecosystem-based fisheries management (EBFM; or, similarly, the ecosystem approach to fisheries management, EAFM) become more operational, we anticipate increased demand on the stock assessment workforce. Similar calls to bolster education and training of new assessment scientists that occurred at the turn of the 21st century (NRC, 1998; NRC, 2000), the need for highly skilled stock assessors continues, yet with increasing demands on the required skillset. Therefore, improved training and professional development opportunities focused on integrated assessment models are needed globally (Goethel et al., 2022a), but these opportunities should explicitly highlight spatial model development, given the increased need for and associated complexity of spatial models. Existing limitations on analyst time and capacity will likely remain a major impediment to broadly operationalizing spatial stock assessments. Institutions should periodically revisit institutional norms and intentionally link initiatives (e.g., spatial management measures in response to climate change or in support of EBFM) with capacity. One approach being used to help alleviate capacity shortfalls is less frequent research track stock assessments that explore more complex dynamics, which are coupled with interim operational stock assessments that are considerably less arduous (Lynch et al., 2018). However, regional fisheries management organizations are increasingly asking more of science providers (Ballesteros et al., 2018).

5. Pragmatic Model Development

One of the most difficult aspects of implementing a spatial stock assessment is determining the minimally complex model that can provide adequate advice at scales relevant to management decision-making. The degree to which spatial processes can be ignored or effectively aggregated without reducing robustness of management advice depends on the species, spatial structure, and management goals. Although model resolution that perfectly matches biological reality is not achievable in practice, simplified processes or imperfect assumptions must be weighed against the alternative of using an aggregated model that ignores spatial processes and may violate the underlying stock identification results. Thus, the 'right' model will always be context dependent and should be carefully evaluated by implementing a holistic approach to model selection (as outlined in section 4).

Once the need for a spatial assessment has been identified, the primary decision is selecting a model framework and parametrization that can address the primary drivers of spatial structure within the species or population, given practical constraints to implementing high resolution, high complexity population models with the available data (Figure 2). Although all models are simplifications of reality and practical limitations are inherent in any assessment application, model complexity can be effectively reduced while incorporating important spatial dynamics that impact sustainable harvest strategies. We outline key considerations and model alternatives that form the basis of a pragmatic approach to implementing spatial models that accounts for primary biological and fishery drivers of spatial dynamics, while simultaneously addressing data limitations. Table 4 provides questions that can be used to determine the primary spatial dynamics that should be addressed along with potential data limitations that may warrant model simplification. Table 5 then provides guidelines for making pragmatic choices among the spectrum of spatial assessment frameworks, while emphasizing the minimal data requirements and model limitations associated with each model type. Model frameworks are discussed in order of increasing spatial complexity and, typically, data needs.

5.1. Spatially Aggregated, Panmictic Models

Although most stock assessments currently assume a panmictic population, ignoring underlying spatial dynamics is not expected to perform well for meeting management objectives. However, panmictic assessments are able to provide reliable estimates of population or species-wide abundance, in some cases (Bosley et al., 2022). Thus, spatially aggregated models can be an adequate tool when the assessment unit encompasses a unit population and local depletion is not a management concern, but representative sampling across the entire assessment unit is imperative to ensure model results reflect the dynamics of the entire population. Moreover, when a panmictic assessment is implemented across a broad management area (e.g., Alaska sablefish; Goethel et al. 2022b), methods for apportioning removals to finer spatial scales may be adequate without pursuing more complex spatial assessment frameworks (e.g., Bosley et al., 2019). However, strong spatial patterns in removals are ideally addressed through more explicit considerations of spatial dynamics (e.g., fleets-as-areas or spatial heterogeneity models) when data allow application, given the importance of preventing localized depletion. Conversely, when limited knowledge of underlying spatial structure or connectivity exists, data are of low resolution, and localized depletion is of limited concern, then panmictic models remain a pragmatic alternative that can provide an initial first estimate of the abundance in the monitored unit or across the entire species range. In particular, when stock identification approaches demonstrate limited agreement and the underlying population structure is highly uncertain, it may be useful to implement a spatially aggregated assessment to develop an estimate of abundance across the species distribution or management jurisdiction to identify immediate management concerns or primary data needs (i.e., to assess species status and determine whether immediate action is required).

5.2. Spatially Implicit Models

5.2.1. Incorporating Spatial Information

Despite the assumption of a panmictic stock structure, spatial information can be incorporated into the model framework through the pre-processing of assessment model inputs. The raising (or expansion) of catch (and composition data) from sampling units to the assessment scale is commonly used to account for spatial heterogeneity in catch monitoring and sampling of biological compositions (e.g., age or length). The pre-processing of life history information such as length, weight, and maturity information often includes using a weighted average of available samples across strata of importance (including three-dimensional space). For example, stratified sampling of size and age data by season and area can account for spatiotemporal variation in growth or size-at-age with samples weighted by expanding to catch in each season and area. More formal spatiotemporal analyses of catch (Thorson and Haltuch, 2018) or survey index data (Thorson et al., 2015) that use geostatistical tools to implicitly account for spatial structure by integrating multi-dimensional data relationships and interdependence are becoming standard practice (Thorson et al., 2020). In particular, spatiotemporal index standardization models based on either CPUE or survey data can be applied to account for area effects while still pursuing an overall, spatially-integrated population index of abundance. The development of geo-referenced spatiotemporal models can elicit insight into local patterns even in the absence of a spatially-explicit assessment. Collectively, these approaches can incorporate fine-scale patterns into aggregated catch, composition, life history, or abundance indices that represent spatially-implicit information for informing a panmictic stock assessment. However, spatiotemporal model-based indices are often highly sensitive to data availability and modeling decisions, potentially resulting in changes in the index as new data are integrated (Commander et al., 2022). Therefore, careful simulation testing of spatiotemporal approaches is warranted before use within an assessment or, especially, as the basis of an empirical HCR. Furthermore, a spatially explicit assessment model is recommended when multiple population units are present (i.e., the unit population assumption is violated).

5.2.2. Spatially Defined Fleets

Fleets-as-areas (or areas-as-fleets) is an approach to spatially stratify fishery or survey interactions with the vulnerable biomass of a population in a panmictic stock assessment (Berger et al., 2012; Waterhouse et al., 2014). A fleet-structured model is most commonly used to account for differences in the availability of fish (presence) to a particular gear type by allowing selectivity (identified here as the conditional process of capturing fish of a certain size or age given they are present), and hence fishing mortality, to be different by area. For example, dome-shaped selectivity often results when fishing is spatially heterogeneous or spatial structure exists among sub-populations with low rates of mixing (Sampson and Scott, 2011; Sampson, 2014). Spatial differences in availability can then be implicitly modeled via areal selectivity to address spatial structure (e.g., resulting from life stage-specific distributions) to better match spatial variation in observed composition data. The application of hierarchical binary decision rules (e.g., regression tree algorithms; Lennert-Cody et al., 2010) is one method that shows promise for quantitatively defining fleet structure to capture spatial heterogeneity in observed data and ensure selectivity is relatively constant across selected fleet domains (H. Xu, Inter-American Tropical Tuna Commission, pers. comm., October 24, 2022).

The fleets-as-areas modeling approach can be a sufficient minimally complex model for management use when there is limited understanding of the mechanisms underpinning population structure, little demographic variation, no concern of local depletion, and the model is tested to ensure it informs management needs (Berger et al., 2012; Lee et al., 2017; Punt et al., 2017b). Using simulations, Punt et al. (2017b) showed that a fleets-as-areas model can achieve desired management goals, in some instances, when it is appropriately matched with companion harvest control rules. However, the performance of fleet-structured models is generally poorer, and often considerably biased, relative to spatially-explicit models when complex spatial population dynamics are present and are correctly specified in the spatially explicit assessment model (Hurtado-Ferro et al., 2014; Punt et al., 2017b; Bosley et al., 2022). Fleets-as-areas models are likely to be most applicable when stock identification validates using a single population unit and a portion of the population is unavailable to harvest, or when there are life cycle migrations (e.g., seasonal or ontogenetic) that temporarily reduce availability of population components within a population (Lee et al., 2017). When there is intra-population heterogeneity, it can be helpful to pre-process spatial information (e.g., spatiotemporal survey index models) to integrate key sources of geographic variability before applying a fleet-structured model.

5.3. Spatially Disaggregated Assessment Without Spatial Interactions

When spatial structure is observed and data can be adequately parsed to a population unit or spatial area (i.e., with sample sizes that allow assessment at the finer resolution), then spatially disaggregated models can be applied. Perhaps the most common and simplest form of spatial assessment is the simultaneous modeling of multiple population units within a species or geographic region, but without explicitly modeling interactions (i.e., connectivity) among units (Cadrin et al., 2019). Spatially disaggregated approaches allow delineating unit populations, demographically independent sub-populations, or areas within a population that exhibit strong spatial heterogeneity, thereby better representing the underlying spatial processes than spatially implicit approaches (Cope and Punt, 2011). Delineating and modeling multiple spatial units allows matching primary stock identification results when little further information exists to inform spatial dynamics and connectivity. Simultaneously modeling multiple, independent population units may be adequate even when movement occurs, if movement rates are low or essentially random (i.e., demonstrate limited time or ontogenetic trends; Goethel et al., 2015a,b). In data-limited situations, parameters can be shared among population units (e.g., selectivity or recruitment parameters) to reduce the number of estimated parameters and to help confront potential reductions in data sample sizes at increased model resolutions.

When sympatric, overlapping populations exist due to natal homing and genetic population divergence, it is possible to utilize genetic or natal origin data to determine the population mixture of survey and catch data (i.e., through a variety of population composition techniques; Kerr et al., 2020). Although sampling and operational analysis (i.e., for use in stock assessment on a year-to-year basis) of population composition data can be resource-intensive, the availability of such data allows implementation of population of origin assessments by assigning mixed population catch data to the appropriate natal population (e.g., Cadrin et al., 2019). Each population can then be simultaneously, but independently assessed, assuming that limited straying occurs among populations. Although explicitly modeling movement dynamics (e.g., spawning and feeding migrations) should provide more realistic representations of complex natal homing dynamics, population of origin assessments provide a simplified assessment approach that may be appropriate when movement dynamics are not well understood.

5.4. Spatially Explicit Assessments with Spatial Interactions

When spatial structure exists and connectivity is a primary driver of spatial dynamics, then a spatially explicit assessment should be undertaken with explicit modeling of connectivity. Spatially stratified assessments can be utilized to effectively model complex broad-scale population structure (e.g., metapopulation and natal homing dynamics) when data resolution is relatively coarse (e.g., for historical catch data; Goethel et al., 2011). Connectivity should then be parametrized to effectively represent the primary drivers of movement (i.e., time or age trends), while considering incorporation of novel data sources and unique parametrizations of movement (e.g., based on habitat preference functions; e.g., Marsh et al., 2015) to improve estimation.

When high-resolution data exist and fine-scale population structure is observed, then full spatiotemporal models can be implemented. Although spatiotemporal approaches better utilize the information content of spatial data and can effectively reduce the number of estimated parameters compared to spatially stratified approaches (i.e., by explicitly accounting for spatial autocorrelation), they can only be implemented when data sources include fine-scale spatial coordinates (i.e., exact haul locations or high-resolution grid coordinates; Cao et al., 2020). Increased implementation of hybrid spatial frameworks, which link spatially stratified assessments with high resolution spatiotemporal sub-models, can better incorporate multi-scalar data sources (e.g., coarse resolution historical catch data with high resolution survey and electronic tagging data) while accounting for complex population structure (e.g., Thorson et al., 2021).

6. Primary Directions for Advancement in Spatial Stock Assessment

As a comparatively new sub-discipline within stock assessment, spatial modeling approaches are evolving quickly, and good practices are attempting to keep pace. Modeling conventions and active research are still exploring good practices for how to: adequately incorporate the various types of animal marking data (i.e., mark-recapture, electronic tags, and gene-tagging), handle data weighting in a spatial context, and calculate appropriate spatial reference points.

Tracking individuals, groups, or populations of fish can provide insights into a species demography and ethology (e.g., movement, connectivity, survival, abundance, habitat use, behavior, population structure, and stock composition; Table 2). Although conventional tagging data can provide information to estimate spatial population parameters, there is typically a need to account for nuisance parameters (e.g., tag loss, tagging mortality, and tag reporting rates; Hoyle et al., 2015;

Vincent et al., 2017) and adhere to tag model assumptions (e.g., complete tag mixing with the untagged population; Kolody and Hoyle, 2015) in order for inference to be valid and results to remain unbiased. Electronic tagging can be scaled to the population and provide highly informative movement and mortality patterns (Galuardi et al., 2010; Vincent et al., 2017). Gene tagging and close-kin mark-recapture methods can be used to directly estimate movement and potentially abundance (or a prior distribution on abundance and areal scaling), but do not require estimation of additional nuisance parameters, such as tag loss and reporting rates (Pine et al., 2013; Bravington et al., 2016). The field of omics (i.e., natural markers) can also provide data on population composition, movement, and stock identification without having to worry about mixing assumptions, because the chemical, genetic, or parasitic mark is intrinsic to all individuals in the population (Elsdon et al., 2008; Kerr and Campana, 2014). Environmental DNA (eDNA) can be used to identify occupancy (distribution) and perhaps density (relative abundance), including spatial patterns, which was shown for Pacific hake (*Merluccius productus*) where eDNA estimates mirrored estimates from the traditional acoustic-trawl survey (Shelton et al., 2022). Information from animal marking experiments and genetic signatures or marks should be fully explored, and vetted, when crafting spatial stock assessments. Integrating multidisciplinary sources of data together, including pairing physical and genetic marking techniques, across multiple scales can extend applicability and enhance robustness of results. For example, Taylor et al. (2011) used a combination of conventional and electronic tags along with otolith microchemistry in a spatially-explicit model for Atlantic bluefin tuna (*Thunnus thynnus*) to estimate movement, mixing, and stock composition, leading to an assessment that identified population specific trends and rebuilding times within an inter-connected natal homing population structure. Thorson et al. (2021) developed a hybrid species distribution model to estimate fine-scale seasonal movement rates of Pacific Cod (*Gadus macrocephalus*) by integrating climate and habitat information with conventional tagging, fishery, and survey operations data. Additional advancements could come from improving tag study designs and analysis (Goethel et al., 2019a), including understanding when release versus recapture conditioned approaches are more robust and the associated tradeoffs in each method (McGarvey et al., 2010, Vincent et al., 2020). Improving the use of ocean tracking networks (e.g., biologging data; Lowerre-Barbieri et al., 2019) and dynamic ocean management principles (Maxwell et al., 2015; Hidalgo et al., 2016) will provide synergistic fine-scale multidisciplinary information to support population structure hypotheses, spatial model development, and parameter estimation. Increasing collaborations between data collectors, tag modelers, geneticists, and population modelers should offer further synergies towards integrating tagging approaches into management procedures, which itself will benefit from continued development of best practices (Sippel et al., 2015; Goethel et al., 2022a; Bravington, 2023).

However, methods to to fully utilize and maximize the information content from existing data will also be necessary to advance the development and reliability of spatial stock assessments. For instance, methods to resolve historical data that is often self-reported at coarse scales (i.e., large-scale management units) will need to be developed. Flexible likelihood functions could be implemented that allow spatial aggregation in model predictions to fit the scale of observed historical data, while allowing for more fine scale population dynamics to fit the scale of the higher resolution recent data (e.g., fishery-independent survey data). Ensuring that data remain representative, such as when scaling from tagged individuals to the population or when there are non-random sampling schemes, is also a heightened concern as the number of spatial units increase. Moreover, methods to deal with boundary issues in data collection protocols are needed, such as addressing edge effects when limited data are collected at range extremes (Cressie, 2015).

As a wider variety of data sources (Table 2) are incorporated into integrated spatial assessments, developing methods to appropriately weight across both the data sources and spatial areas will be imperative. The first step to incorporating new data in integrated assessments is to develop appropriate observation models and statistical likelihood functions. For instance, Taylor et al. (2011) demonstrated how to incorporate electronic tagging and otolith microchemistry data into a spatial assessment of Atlantic bluefin tuna. Similar approaches are being developed for citizen science data (e.g., Sun et al., 2019), oceanography data, genetics, and electronic monitoring (see Goethel et al., 2022a for a synthesis), and spatial modeling frameworks are well suited to address the spatial structure associated with most of these new data types. Once appropriate likelihood functions are developed, careful consideration must be given to how each data source is weighted, which should adequately reflect the relative uncertainty across all data sources. Methods for weighting tagging data along with typical fishery-dependent and fishery-independent data in spatially-aggregated models exist (e.g., Punt et al., 2017a) and can be easily extended to spatial frameworks. However, data weighting is a complex topic, and the addition of new data and spatial complexities is likely to require further exploration to provide robust guidance for spatial models.

How to adequately incorporate spatial information into the development of robust harvest advice and associated biological reference points also remains an open-ended research topic, especially given the multidimensional nature of spatial processes, incomplete understanding of how movement and connectivity might influence these calculations, and undefined policy decisions (Goethel and Berger, 2017). However, methods for calculating spatial reference points have been developed over the last decade (e.g., Ying et al., 2011; Bosley et al., 2019; Kapur et al., 2021), and further explorations with spatially explicit MSE tools is likely to enhance understanding of robust management procedures (e.g., Punt et al., 2017b). Additionally, approaches for addressing transitions across biological regimes in spatial models (i.e., how to deal with 'shrinking' fish) are currently being developed (e.g., Kapur et al., In Review), which should improve the ability to calculate dynamic spatial reference points. Empirical spatial reference points based on area occupied or density have also gained traction (e.g., Reuchlin-Hugenholtz et al. 2015, 2016), which provide a more intuitive approach that is less reliant on equilibrium assumptions (i.e., which are clearly violated by spatial dynamics) and could be easily melded with spatiotemporal assessments.

7. Conclusions

The first step in assessment model development should be to match assessment boundaries to unit populations as determined through multidisciplinary stock identification methods, which is undertaken with stakeholders in a participatory framework. As part of the stock identification process, a thorough data inventory should be performed to determine all potential data sources available for use in a spatial model (Cadrin et al., 2023), emphasizing novel data types that might inform spatial dynamics and population structure (Table 2). Next, emphasis should be placed on developing an iterative, reproducible, and flexible data workflow, which allows extracting and collating all data sources at a variety of spatial aggregations. Fluidity in data extraction and aggregation will enable rapid data manipulation to support multiple model structures (e.g., simultaneous development of spatially explicit and spatially aggregated models). Model design and resolution should then be determined by the biological reality, data availability, model parsimony, and the needs and goals of management. Our good practices guide for the process of implementing spatial structure in a stock assessment process (Table 3) can be utilized to identify when a spatial model is necessary (Table 4) and to guide model development (Table 1) of an appropriate and pragmatic spatial model structure given associated data limitations (Table 5). The model development process should follow the participatory modeling paradigm, such that stakeholder engagement enables incorporation of LEK, modeling assumptions are carefully vetted, the model building process is fully transparent, and the model meets the needs of fishery management. Candidate models should be thoroughly tested via simulation analysis or management strategy evaluation (MSE) for robustness to data limitations, primary assumptions, and simplifications of spatial processes. Implementing high resolution (e.g., individual- or agent-based), data-conditioned, spatially explicit operating models will help identify the minimally complex spatial assessment model structure and overarching management procedure that can provide robust and sustainable management advice. Our good practices guide is dynamic and subject to rapid adaptation as the field of spatial stock assessment evolves over the coming years, especially as the amount and types of spatially resolved data continues to proliferate. Punt (2023) notes that analyst decisions are often influential to model outcomes. Therefore, understanding how and why decisions are made throughout the model development process can help guide good practices. Moreover, good practices are often influenced by operational implementation of a given assessment (and associated successes and failures with a given model framework). Thus, it is expected that much is yet to be learned about spatial model applications as they become more widely implemented for operational management advice.

Striving for more realistic spatial structures in assessment frameworks is not an all or nothing endeavor. Stepwise improvements can and should be undertaken within the confines of capacity-constricted assessment timelines. Each assessment iteration can aim to undertake a step towards a more spatially explicit assessment (e.g., based on the steps in Table 3). However, developing flexible data extraction and aggregation tools should be a primary consideration, given that these are paramount for testing multiple model structures. Similarly, implementing transparent assessment frameworks (i.e., the TAF approach) where code is shared, multiple researchers can synergistically build spatial assessments, and lessons learned are widely communicated, will help overcome the institutional inertia currently impeding spatial model applications.

Adequately addressing species interactions as well as environmental drivers requires incorporating spatiotemporal dynamics in model frameworks, because ecosystem processes are inherently spatial (Plaganyi et al., 2014). Thus, as single species spatial models mature and understanding of mechanistic relationships between distribution, connectivity, and habitat usage improves, spatial habitat preference functions represent a natural segue for incorporating ecosystem components into tactical single species management advice. Eventually, the increasing trend towards spatially explicit assessment approaches should lessen the gap between single species assessments and models of intermediate complexity for ecosystem assessment (MICE), while providing a natural link (i.e., spatial structure) where the two approaches can be used synergistically to aid model development and advance ecological knowledge across disciplines. We envision that accounting explicitly for spatial dynamics and habitat preference in spatial assessments represents one of the most logical frameworks for linking operational assessments with ecosystem models to directly mesh quantitative single species fisheries management advice and EBFM.

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10. Tables

Table 1. A strategic guide for developing spatial stock assessments based on analyst decision points along with example parameterization options to choose amongst. Provided parameterization options are presented from least to most complex.

Decision Point	Parameterization Options
Biological Population Structure	Panmictic?
	Spatial heterogeneity?
	Natal homing?
	Metapopulation?
Temporal Structure	Yearly?
	Seasonal?
Spatial Resolution	Non-spatial (i.e., spatially aggregated or single population)?
	Spatially implicit (e.g., fleets-as-areas)?
	Spatially stratified?
	Spatiotemporal?
Fleet Structure	Use spatial fleets as proxy for availability?
	Combine fleets with similar characteristics?
	Share parameters for a given fleet across areas?
	Incorporate all fleets in all areas?
Recruitment Dynamics	Global density-dependence with apportionment (i.e., single stock-recruit function)?
	Local density-dependence (i.e., single stock-recruit function per population unit)?
Initial Distribution and Scaling	Use external data (e.g., CPUE indices) to scale abundance by region?
	Estimate initial abundance in all areas from all population units?
Dispersal	No interactions among populations?
	Larval dispersal only?
	Full reproductive mixing among sub-populations (i.e., metapopulations)?
	No dispersal, but overlap of populations (i.e., natal homing)?
Movement	No movement?
	Time- and/or age-invariant movement?
	Gravity-based movement (i.e., estimate residency and make simplifying assumptions regarding emigration)?
	Random walk?
	Time periods or age-blocks?
	Functional forms?
	Spatial autocorrelation and movement by distance?
	Habitat preference functions?
	Seasonal migrations (i.e., feeding and spawning migrations)?
	Fine-scale advection, diffusion, and taxis models?
Demographic Variation	Constant across the model domain?
	Vary by area using empirically derived values?
	Vary by population unit (i.e., genetic-based demographics)?
	Vary by area with current-area traits only (i.e., phenotypic-based demographics)?
	Vary by area with source-area and current-area traits (i.e., to avoid infeasible transitions)?
	Vary by area and by population unit?

Table 2. Data sources that can inform spatial population structure decisions, stock assessment configuration options, or be directly incorporated into a spatial stock assessment model. Most generalized assessment platforms are not currently able to integrate minimally processed versions of these data streams.

Data Source	Type	Spatial Resolution	Common Information Content
Genetics	Nucleotide polymorphisms	Population	Stock identification, boundaries, and evolutionary significant units
	eDNA	Population	Species distribution, habitat occupancy, and index of abundance
	Gene tagging	Population	Abundance, survival, movement, stock structure, habitat utilization, and vital rates
Fisheries	Logbooks	Fishing grounds	Fine-scale (discrete) fleet dynamics, harvest locations, and abundance patterns
	Electronic monitoring	Lat/Long	Fine-scale (near continuous) fleet dynamics, harvest locations, and abundance patterns
	Digital reporting	Lat/Long	Near real-time fleet dynamics, harvest locations, and abundance patterns
	Age/length composition	Haul	Ontogeny, recruitment/cohort strength, and selectivity
	Life history and biology	Haul	Phenotypic heterogeneity (e.g., maturity, growth, biomarkers) of the fished population
Population surveys	Index of abundance	Lat/Long	High resolution population unit trends, recruitment, habitat utilization
	Age/length composition	Haul	Ontogeny, recruitment/cohort strength, and selectivity
	Life history and biology	Haul	Phenotypic heterogeneity (e.g., maturity, growth, biomarkers) of the population
Animal Marking	Tag-recovery	Population	Movement, connectivity, survival, habitat, behavior, and population structure
	Telemetry	Lat/Long	Fine scale movement, survival, habitat, behavior, and population structure
	Ocean tracking	Lat/Long	Broad scale movement, survival, habitat, behavior, and population structure
	Natural markers	Population	Population composition and movement (e.g., from otoliths or parasites)
Dynamic Ocean Monitoring	Remote sensing	Lat/Long	Large-scale ecosystem patterns, physical habitat, and oceanography
	Autonomous vehicles	Lat/Long	Directed insights into ecosystem patterns, oceanography, and ecology
	Real-time in situ data logging	Lat/Long	Site-specific network of ecosystem patterns, oceanography, and ecology
Management History	Regulations and measures	Regulatory areas	Changes in fishing patterns, gear types, and harvest specifications
Community Engagement	Traditional ecological knowledge (TEK)	Fishing grounds	Ecological insights through cultural transmission; historical perspective
	Local ecological knowledge (LEK)	Fishing grounds	Ecological insights through observation and interactions with local ecosystems
	Citizen Science	Fishing grounds	Data collection, reporting, and analysis through public engagement

Table 3. Good practice guidelines and workflow elements that facilitate the process of developing spatial stock assessments.

Element	Description
Engage Stakeholders	Iteratively communicate key development steps throughout the workflow and incorporate stakeholder to develop participatory co-management.
Fluidity in Data Preparation	Develop computer code that readily extracts and processes input data and can collate data at multiple spatial scales in a fluid and easily adaptable way, which is amenable to developing alternative spatial population hypotheses and subsequent models.
Formulate Spatial Templates	Develop a hypothesis-driven conceptual model that reflects ecological, genetic, fleet, and management (social, economic, political) imposed spatial structures.
Develop Modeling Options	Develop and parameterize alternative spatial and non-spatial models based on conceptual models, but starting with minimal complexity. Narrow options based on data availability and knowledge gaps in population processes.
Model Selection	Compare and contrast spatial and non-spatial models using quantitative (e.g., residual patterns) and qualitative (e.g., LEK, TEK) diagnostics to further narrow model choices.
Scope of Inference	Maintain multiple models when uncertainty in assumptions is high, there is multiple competing and plausible population dynamic hypotheses, or critical population dynamics parameters are confounded or not adequately resolved.
Reference Points	MSY and stock status related reference points (e.g., B_0) should consider spatial areas, in addition to temporal considerations (e.g., equilibrium assumption or non-stationary, dynamic calculations), when making determinations relative to benchmarks.
Iterate and share procedures	Development should be stepwise, where individual steps can be taken to accommodate resource constraints encountered in an operational assessment timeframe. Model development should be iterative and investing in workflow components that emphasize reproducibility, transparency, and fluidity will be beneficial (e.g., TAF).
Revisit procedures	Workflows must be adaptable as scientific understanding advances, prevailing environmental conditions change, or stocks redistribute through a systematic iterative process.

Table 4. Questions to help identify drivers of spatial structure and determine the need for a spatially explicit stock assessment model.

Primary Issue to Consider	**Guiding Questions to Answer**
What are the needs of management from a spatial perspective?	What is the conservation unit of concern? Has extirpation of spawning contingents occurred or is it eminently possible? Does local depletion within a population unit need to be monitored? Is there spatial structure in fishery removals? Are area-based management tools (e.g., MPAs) a primary component of management? Is the biological population a trans-boundary or trans-jurisdictional resource?
What data are available and what is the spatial resolution of each data set?	What information is available to guide stock identification and which of these data sources can be utilized directly in a spatial assessment model? Do sample sizes support increased model resolution? Does resolution of historical and recent data differ and can it be addressed with flexible observation models? Can novel data sources be directly incorporated to better inform spatial processes? Is there tagging or genetic data to inform natal population of origin or movement?
What is the population structure?	What is the generic population structure (Figure 1)? Is there high biocomplexity within the species? What are the population units that require monitoring? Is there spatiotemporal overlap of spawning contingents and natal homing? Is there reproductive mixing after movement and metapopulation structure? Is the resource patchily distributed and exhibiting intra-population structure?
Does the species move and what type of movement dynamics are observed?	Is there larval dispersal among subpopulations or management areas? Is there post-settlement movement among subpopulations or management areas? Is advective or diffusive movement predominant? Are there strong ontogenetic movement patterns? Do seasonal migrations occur (e.g., feeding, spawning)? Is movement linked to environmental or habitat characteristics? Is there strong interannual variation in movement? Do common movement patterns occur or is movement effectively random? Are source-sink dynamics present?
What biological processes vary spatially?	Do demographic rates vary across the domain? Is recruitment spatially heterogeneous? Does survival vary across the spatial domain? How does movement interact with biological processes? Are demographics primarily influenced by the environment (i.e., phenotypic) or genetics?
What are the potential impacts of climate change on the species or population?	Is species redistribution (i.e., expansion, contraction, or directional shifts) expected? Is there potential for spatially explicit changes in demographics across the species range? Does the model need to incorporate a range-wide resolution to account for climate impacts?

	Is adequate data being collected to detect changes at distributional fringes?
What is the minimally complex management procedure that can provide robust advice at the spatial scale necessary?	Is a spatial model required or can simpler (i.e., panmictic models or empirical harvest control rules) perform adequately for the desired management goals? Can empirical reference points be used in place of model-based reference points?

Table 5. Types of stock assessment models that can be implemented to handle spatial structure (in order of increasing model and spatial complexity), including spatially implicit options that provide pragmatic approaches to dealing with complex biological structure given data limitations.

Model Framework	Model Structure	Primary Source of Spatial Structure	Data Need	Model Limitation	Example Citation
Spatially Aggregated	Panmictic	Single population	Broad-scale	Does not provide information on localized depletion and ignores spatial structure if it exists	Bosley et al., 2022
Spatially Implicit	Spatiotemporal Nested in Panmictic	Single population with biological or fishery spatial structure	High resolution survey or fishery data	High resolution data required and ignores complex population structure if it exists	Cao et al., 2017
	Fleets-as-Areas	Single population with spatial structure in fishery dynamics	Fleet specific	Implicitly treats spatial structure and ignores complex population structure if it exists	Berger et al., 2012
Spatially Disaggregated, No Interactions	Multiple Independent Assessments	Multiple populations with limited or no movement	Population specific	Ignores interactions among population units	Johnson and Cox, 2019
	Population of Origin	Multiple populations with natal homing	Population specific	Ignores interactions among population units and requires genetic or natal origin data to determine stock of origin	Massiot-Granier et al., 2014.
Spatially Explicit with Interactions	Spatial Heterogeneity (Multiple Areas)	Single population with biological or fishery spatial structure	Area specific	Rapid reduction in sample sizes as number of areas increases and difficulty estimating connectivity among areas	NEFSC, 2017
	Metapopulation	Sub-populations	Sub-population specific	Difficult to estimate connectivity among populations	Goethel et al., 2015
	Integrated Assessment o Multiple Populations	Multiple populations with natal homing	Population specific	Requires genetic or natal origin data to determine population of origin and knowledge of spawning migrations (i.e., degree of homing)	Taylor et al., 2011
	Hybrid Spatiotemporal	Single or multiple populations with spatial structure	Population specific, high resolution survey or fishery data	High resolution survey, fishery, tagging, and/or presence/absence data; limited examples of application for complex population structure	Thorson et al., 2021
	Full Spatiotemporal	Single or multiple populations with spatial structure	Population specific, high resolution survey or fishery data	High resolution survey, fishery, tagging, and/or presence/absence data; limited examples of application for complex population structure	Cao et al., 2020

11. Figures

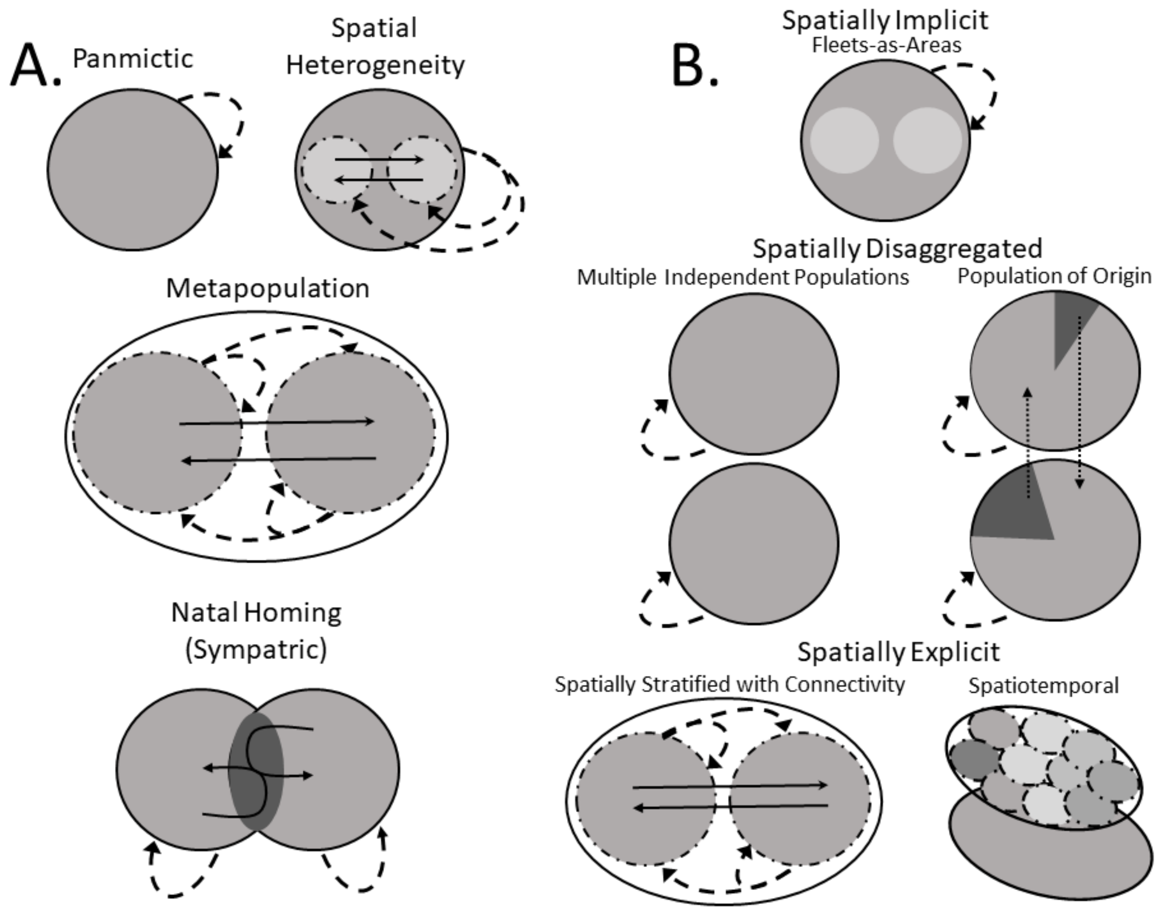

Figure 1. The primary population structures that are typically modeled in stock assessments (A) and the continuum of spatial model structures that can be used within a stock assessment model (B). Solid lines represent population boundaries, dashed lines are intrapopulation units, borderless circles represent fleets, solid arrows represent movement, dashed arrows indicate the scale of larval dispersal, and dotted arrows demonstrate data exchange (i.e., placing data in the population of origin).

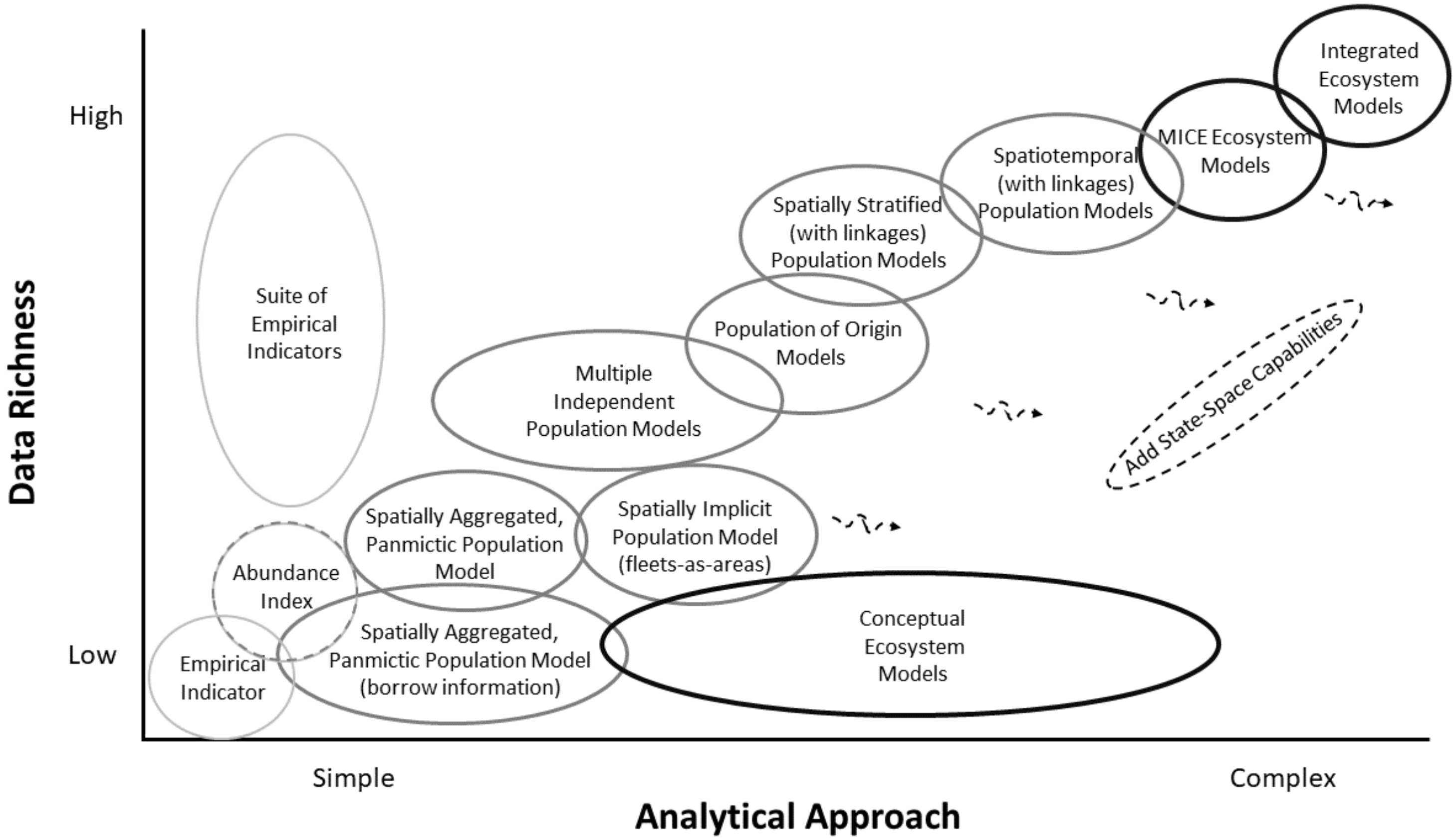

Figure 2. A generalized representation of approaches (empirical, light circles; stock assessment model, intermediate-tone circles; ecosystem model, bold circles) that can be used to directly or indirectly incorporate spatial structure into procedural management frameworks depending on relative data availability, statistical techniques (e.g., addition of state-space capabilities), and management objectives.