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**Introduction to 'Space Oddity: Recent Advances
Incorporating Spatial Processes in the Fishery Stock
Assessment and Management Interface'**

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Title: Introduction to ‘Space Oddity: Recent Advances Incorporating Spatial Processes in the Fishery Stock Assessment and Management Interface’

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Introduction

The field of fisheries science, and, in particular, fish population dynamics and stock assessment modeling has rapidly progressed over the last decade, largely due to advances in computing power, statistical theory, and data collection technology (Maunder and Punt 2013). Higher resolution data (e.g., catch locations or animal tracks collected via global positioning systems) along with continually improving computational ability have enabled new explorations into how best to model the complex biological and anthropological processes driving fish populations. The result has been a reemergence of modeling tools previously deemed too complex or data intensive, as well as the development of new methods to handle multi-dimensional, spatiotemporal parameter estimation in statistically rigorous ways.

Spatial analyses now represent a cornerstone in contemporary fisheries modeling and are becoming routinely explored in stock assessment, largely due to the growing quantity of spatially-explicit data being gathered, advances in statistical modeling techniques, and computing power. The importance of incorporating spatial structure into population dynamics models and resultant management decisions for many aquatic species has been widely recognized for more than half a century (e.g., see the spatial models proposed by Beverton and Holt 1957); however, there has historically been a lack of empirical data to adequately support these types of analyses (Goethel et al. 2011). Particularly over the last two decades, the expanding field of spatial ecology has demonstrated the importance of spatial population structure for its role in regulating population productivity, which has led to a growing awareness of the need to incorporate spatial processes into the stock assessment-management interface (i.e., the interaction between scientific advice and resulting management actions; see Figure 1 in

Berger et al. 2017, this issue). Acknowledgement of the need to match scientific outputs to the spatiotemporal scale of fisheries management decisions has led to a rapid proliferation of spatial modeling techniques, advances in stock assessment methodology, and analyses that suggest improved policy performance (Kerr et al. 2016).

Several scientific conferences and symposia have been dedicated to spatial modeling techniques in fisheries science and ecology since 2010, which have resulted in special journal issues including: “Reconciling Spatial Scales and Stock Structure” in the journal *Fisheries Research* (La Valley and Feeney 2013); the spatial subsection of the “World Conference on Stock Assessment Methods” in the *ICES Journal of Marine Science* (Cadrin and Dickey-Collas 2015); “Spatial Analysis, Mapping, and Management of Marine Fisheries” in the journal *Marine and Coastal Fisheries* (Rubec 2016); “Advances in Fish Stock Delineation” also in *Fisheries Research* (Pita et al. 2016); “Spatial Ecology” in the *International Journal of Geo-Information* (2017); and “Beyond Ocean Connectivity” in the *ICES Journal of Marine Science* (2017). Recognizing that modeling of spatial processes and distributional patterns was rapidly expanding in fisheries science, a theme session titled “Space Oddity: Recent Advances Incorporating Spatial Processes in the Fishery Stock Assessment and Management Interface” was convened at the 145th American Fisheries Society Annual Meeting in Portland, Oregon (2015). The symposium provided a forum to discuss recent advances in spatial modeling, while also highlighting how the results of these approaches could be utilized in current fisheries management paradigms. The symposium was well-attended and contained 24 presentations on various spatial modeling applications. The current special issue includes a selection of papers stemming from the “Space Oddity” symposium (or related to the symposium theme; Table 1), which collectively represent

significant advancements in accounting for spatial processes in fisheries science. Here, we provide a brief treatment of the main research themes arising in the special issue. A comprehensive review of recent advances in spatial modeling, including further discussion of symposium themes and research presented in the special issue, can be found in Berger et al. (2017, this issue).

Symposium Themes

Modeling Classifications

Spatial fisheries models presented at the symposium tended to take either an implicit (empirical) or explicit (first principles) approach to modeling spatial processes and could be broken down into several classifications based on the modeling approach and goals of the analysis (Table 1, Figure 1). Empirical approaches tended to focus on analyzing spatial distributions without explicitly attempting to model the factors responsible for these observed patterns of catch or abundance. Analyses ranged from spatiotemporal valuation mapping (Miller et al. 2017, this issue), which evaluates how species distributions and resulting economic value have changed over time, to geostatistical distributional modeling. The latter approach has been a rapidly emerging subdiscipline that allows researchers to infer how species distributions may change over time based on spatial autocorrelation among catch rates and various biotic and abiotic environmental factors (Thorson et al. 2017, this issue). Distributional modeling can be utilized to improve survey design (Cao et al. 2017, this issue), predict and reduce potential bycatch (Kai et al. 2017, this issue), and explore hypotheses leading to evolving fleet dynamics (Ducharme-Barth and Ahrens 2017, this issue). Additionally, accounting for the distribution of catch (and resultant fishery catch rates) can be incorporated into spatiotemporal depletion estimators to

87 better account for density-dependence and improve estimates of abundance (Cadigan et al. 2017,
88 this issue).

89
90 Explicitly modeling the movement and migration of individuals to account for the emergent
91 distributional patterns caused by connectivity among population units has led to a different,
92 demographically-structured, approach to spatial modeling (Figure 1). Tagging models are often
93 needed to estimate movement with complex spatiotemporal population structures and fishery
94 dynamics (e.g., Laretta and Goethel 2017, this issue) and to highlight connectivity pathways
95 and movement tracks of individual animals using geolocation (Liu et al. 2017, this issue).

96 Although traditional tagging data, such as identifiable physical implants or marks, can be directly
97 utilized within assessment models to help estimate movement and other biological parameters,
98 biological tags (e.g., parasite infestation rates, otolith microchemistry) can also be informative of
99 population interactions across space and time (Gao et al. 2010; de Moor et al. 2017, this issue),
100 and may be less costly than traditional tagging methods.

101
102 New insights into best practices for parametrizing spatial models are accumulating, and these can
103 be particularly useful for developing and configuring a new spatial model and for determining
104 whether a spatial or non-spatial assessment model is most appropriate for a given scenario
105 (Langseth and Schueller 2017, this issue). Further development of best practices in spatial
106 modeling will continue, relying heavily on simulation testing, which is a powerful tool for
107 exploring the performance of new state-of-the-art spatial frameworks. Simulation testing has
108 seen broad application for addressing the robustness of spatial stock assessments to connectivity
109 assumptions, particularly in comparison to spatially-implicit (e.g., separating estimates of fishing

mortality and selectivity by area) or spatially-aggregated models that are unable to directly confront spatial processes. Assessment performance has been examined using simulations across a variety of spatial and non-spatial modeling assumptions, including homogenously distributed fishing effort (Truesdell et al. 2017, this issue), environmentally-driven recruitment (Denson et al. 2017, this issue), un-modeled processes [e.g., age-based movement (Lee et al. 2017, this issue) or larval dispersal (Little et al., this issue)], and complex population structures (e.g., natal homing; Vincent et al. 2017, this issue).

The process of developing a spatial simulation model often generates new insights or hypotheses about the mechanisms that drive spatial population structure. Alternative hypotheses about spatiotemporal fleet dynamics, connectivity, or biological processes can be built into the simulation framework, which can inform management decision-making (e.g., Kerr et al. 2017, this issue). Similarly, simulations exploring alternate states of nature (e.g., potential species interactions) can be utilized to demonstrate responses to environmental variation (e.g., climate change) through projections and forecasts (e.g., Kapur and Franklin 2017, this issue).

Bridging the assessment-management interface requires understanding how connectivity and population structure influence sustainable harvest levels through the development of biological reference point models that can incorporate spatial processes (Goethel and Berger 2017, this issue). Tools are now available to account for spatial structure and spatial dynamics throughout the fishery management process (i.e., data collection, population modeling and stock assessment, calculation of biological reference points, provision of management advice, and establishment of sustainable harvest policies). Accounting for spatial processes is not necessary in all managed

fisheries, thus decisions to employ these techniques may be guided by numerous factors including the availability of spatial information, the scale at which spatial processes operate relative to management decisions, and bias or risk associated with applying non-spatial assessments or management strategies. Fortunately, closed-loop feedback simulation models, which form the basis of management strategy evaluation, can help identify the robustness of the entire assessment-management system to spatial structure and connectivity among population components (Punt et al. 2017, this issue).

Synergistic Approaches

Although implicit (e.g., geostatistical distribution models) and explicit (e.g., demographically structured models) methods to modeling spatial processes appear to be diametrically opposed approaches, discussion at the symposium revealed that they could, in fact, be used synergistically. Each approach represents a standalone tool that, when applied in conjunction with alternate spatially-explicit methods, can provide extended benefits. For instance, species distribution models can be utilized to refine stock abundance indices, which can then be integrated into a spatially-explicit stock assessment model. Improved abundance indices, which better account for spatial attributes and autocorrelation across the spatial domain, will directly translate to more accurate (and precise) assessment outputs and resulting spatial management advice. Post-assessment, geostatistical methods can then be utilized to also improve real-time adaptive spatial management (e.g., bycatch avoidance; see Figure 3 in Berger et al. 2017, this issue). By combining spatial methods, the entire assessment-management framework can be continually refined and improved to account for spatial patterns at each step of the management process.

Integrating Spatial Models into Management Advice

One of the most prominent themes encountered throughout the symposium was the need for a wider application of spatial analyses, particularly spatial stock assessments. Also, there is a clear need for improving the perception and acceptance of spatial analyses so that they are more widely utilized as the basis of management advice. Although spatially-explicit assessment models have been evaluated for determining stock status for a handful of species (e.g., Hampton and Fournier 2001; Thorson and Wetzel 2015), many applications [of which the authors are aware] have either been relegated to further development and peer review or have been used as operating models for examining the robustness of non-spatial assessments and the resulting management advice.

Several common difficulties for implementing spatial analyses as the basis of management advice were identified by Berger et al. (2017, this issue). The main barriers include: a lack of information on spatial structure or limited spatially-explicit data sets; an inability to develop operational spatial models in the limited time provided during typical stock assessment cycles; a history of institutional inertia such that there is hesitancy to alter the status quo stock assessment approach; and limited understanding of spatial assessment models by decision-makers and stakeholders. Issues related to data limitations and characterizing population structure are systemic problems for many species. In some cases, management advice based on the results from a spatially-explicit model has not been accepted due to discomfort of managers to integrate new and, oftentimes, technically complex modeling frameworks instead of actual issues with the spatial analysis itself. Ultimately, analysts play an important role vetting, debugging, and

validating new modeling techniques that better utilize available data, but when the use of new techniques represents a paradigm shift in the assessment-management framework, the transition to new approaches may be slow and faced with skepticism. Thus, analysts should be well-prepared to address this skepticism, because spatially-explicit modeling techniques often can provide management quantities that more realistically match real-world processes, and should be readily utilized when appropriate data are available and models are thoroughly validated.

Conclusions

As data collection and analytical techniques become more sophisticated, the quality and quantity of readily available spatial information will inevitably increase, thereby fostering the growth and development of spatially-explicit models for use in fisheries management. Spatial stock assessment models do not always provide the most robust results, but in many simulated cases, their application has been shown to provide more reliable results than assessments that assume spatial homogeneity (e.g., Goethel et al. 2015; Punt et al. 2015). As such, spatial models should be more routinely tested and applied simultaneously with spatially-aggregated counterparts. Simulation analyses, particularly through management strategy evaluation, will continue to be at the forefront of these advancements by providing appraisals of alternative spatial models through estimation of robustness, bias, management risk, and other associated metrics. Additionally, spatial analyses can be used to inform hypotheses about spatial variation in biological parameters along with levels of connectivity, which can provide a realistic basis for developing alternative spatially-explicit operating models used within management strategy evaluation (Goethel et al. 2016).

A critical, but certainly not insurmountable hurdle, will be gaining stakeholder acceptance of contemporary spatial models as adequate (and in many cases improved) tools for providing management advice. Improved communication among scientists, managers, and stakeholders about spatial model structure, limitations, available data, and future needs should prove beneficial for bridging the gap from exploratory to operational spatial models (see Figure 1 and Table 1 in Berger et al. 2017, this issue).

We believe that applied spatial modeling techniques will soon be widespread within fisheries science. Although spatial analyses appear more complex and data intensive than nonspatial counterparts, they allow analysts (and managers) to directly confront many assumptions that are implicit, and thus ignored, in nonspatial models (e.g., parameter homogeneity and closed populations). For many species, spatial analyses can be conducted using existing data sets, and by being more formal about the treatment of assumptions, these analyses provide a higher informational content compared to nonspatial models. In addition, there is an expanding baseline on spatial attributes associated with chemical, physical, and biological variables that can be used by analysts to explicitly address spatial assumptions. The growing evidence from both simulation studies and real-world applications suggest that conservation of spatial population structure plays as an important a role as maintaining target population abundance when attempting to sustainably manage an aquatic resource (Hilborn et al. 2003; Berkeley et al. 2004; Kerr et al. 2016). While accounting for spatial processes is the exception (an oddity) in fishery stock assessment and management to date, we predict that the future of fisheries science will include continued research and advancements in spatial modeling to capture and account for the

224 “*Space Oddity*”. As stated by the musician David Bowie, we “don’t know where [we are] going
225 from here but [we] promise it won’t be boring.”

226

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288 **Table 1.** Summary of articles (listed alphabetically) found in the special issue “Space oddity: recent advances incorporating spatial
289 processes in the stock assessment and fishery management interface”.

Author	Primary Spatial Processes Investigated	Approach	Page Numbers
Berger et al.	Contemporary approaches in spatial modeling	Overview/review	xx-xx
Cadigan et al.	Density-dependent fishery CPUE	Depletion Estimator	xx-xx
Cao et al.	Survey CPUE and habitat covariates	Geostatistical distribution model	xx-xx
de Moor et al.	Connectivity from parasite bio-tagging	Assessment model	xx-xx
Denson et al.	Environmentally driven recruitment	Simulation testing stock assessment robustness	xx-xx
Ducharme-Barth and Ahrens	Fleet distribution and fishing location uncertainty	Geostatistical distribution model	xx-xx
Goethel and Berger	Connectivity and reference points	Reference point simulator	xx-xx
Kai et al.	Fishery CPUE and length composition data	Geostatistical distribution model	xx-xx
Kapur and Franklin	Multispecies interactions with climate change and MPAs	Simulation model	xx-xx
Kerr et al.	Connectivity, recruitment, and demographic rates	Simulation model	xx-xx
Langseth and Schueller	Aggregated versus spatially-explicit fishing mortality estimates	Simulation model	xx-xx
Lauretta and Goethel	Connectivity and mortality	Tagging model	xx-xx
Lee et al.	Age-based connectivity	Simulation testing stock assessment robustness	xx-xx
Little et al.	Connectivity and fishing mortality (MPA)	Simulation testing stock assessment robustness	xx-xx
Liu et al.	Connectivity and environmental attributes	Tagging model	xx-xx
Miller et al.	Valuation of ecosystem services	Valuation Mapping	xx-xx
Punt et al.	Recruitment and fishing mortality	Simulation testing stock assessment robustness (MSE)	xx-xx
Thorson et al.	Fishery CPUE and multispecies interactions	Geostatistical distribution model	xx-xx
Truesdell et al.	Fishing mortality	Simulation testing stock assessment robustness	xx-xx
Turner et al.	Species distributions and ocean forecasting	Geostatistical distribution model	xx-xx
Vincent et al.	Population structure, connectivity, and productivity	Simulation testing stock assessment robustness	xx-xx

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Figure 1. Schematic highlighting the range of approaches presented in this special issue on spatial modeling. The y-axis differentiates overarching model type (i.e., modeling population dynamics first principles versus empirical techniques), and the x-axis differentiates model input needs (i.e., requiring a high number of assumptions to explain population dynamics or large amounts of data). Each of the major spatial modeling methods are graphed with horizontal bars indicating the level of each of the x-axis input requirements. Examples of each technique from papers in the special issue are provided in parentheses.