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Using delta generalized additive models to produce distribution maps for spatially explicit ecosystem models☆

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ABSTRACT

Spatial ecosystem models, such as OSMOSE, have become integral tools in achieving ecosystem-based management for their ability to thoroughly describe predator–prey dynamics in a spatially explicit context. Distribution maps, which define the initial spatial allocation of functional groups abundance, can have a large effect on the predator–prey dynamics that spatially explicit ecosystem models simulate. Here, we introduce the delta GAM approach we developed to be able to produce distribution maps for an OSMOSE model of the West Florida Shelf (Gulf of Mexico), OSMOSE-WFS. This delta GAM approach predicts the spatial distribution of different life stages of the multiple functional groups represented in OSMOSE-WFS ('life-stage groups') at different seasons, over the entire Gulf of Mexico (GOM) shelf including areas where abundance estimates do not exist, using different research survey datasets and regional environmental and habitat features. Our delta GAM approach consists of fitting two independent models, a binomial GAM and a quasi-Poisson GAM, whose predictions are then combined using the delta method to yield spatial abundance estimates. To validate delta GAMs, bootstraps are used and Spearman's correlation coefficients (Spearman's ρ's) between predicted and observed abundance values are estimated and tested to be significantly different from zero. We use pink shrimp (*Farfantepenaeus duorarum*) to demonstrate our delta GAM approach by predicting the summer distribution of this species over the GOM shelf and the West Florida Shelf. Predictions of the delta GAM reflect existing empirical research related to pink shrimp habitat preferences and predictions of a negative binomial GAM previously designed for the GOM. We find that using a delta rather than a negative binomial GAM saves significant computation time at the expense of a slight reduction in GAM performance. A positive and highly significant Spearman's ρ between observed and predicted abundance values indicates that our delta GAM can reliably be used to predict pink shrimp spatial distribution. Spearman's ρ was also positive and highly significant in every life-stage group represented in OSMOSE-WFS and season, though often low. Therefore, delta GAMs fitted for the different life-stage groups and seasons correctly predict qualitative differences between low- and high-abundance areas and are deemed appropriate for generating distribution maps for OSMOSE-WFS. The delta GAM approach we developed is a simple, convenient method to create distribution maps to be fed into spatially explicit ecosystem models, where wide spatial and taxonomic coverage is desired while benefits of high precision estimates are lost at run-time.

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1. Introduction

Ecosystem-based management (EBM) of marine systems has become a central paradigm throughout the world (Pikitch et al., 2004; Garcia and Cochrane, 2005; McLeod and Leslie, 2009). Spatial ecosystem models, such as Ecospace (Christensen and Walters, 2004; Walters et al., 2010), Atlantis (Fulton et al., 2004, 2007) and OSMOSE (Shin and Cury, 2001, 2004), have become integral tools in achieving EBM for their ability to thoroughly describe predator–prey dynamics in a spatially explicit context. Within a spatially explicit context, the predation mortality of functional groups (i.e., groups of species sharing similar ecological niches and life-history traits) becomes influenced by their degree of spatial overlap with potential predators. Therefore, distribution maps, which define the spatial allocation of functional groups abundance or biomass at the start of simulations or at the beginning of each time step, can have a large effect on the predator–prey dynamics that spatially explicit ecosystem models simulate.

Fisheries management in the Gulf of Mexico (GOM) has recently begun to embrace EBM through the development of a comprehensive Integrated Ecosystem Assessment program (Levin et al., 2009, 2013; Samhouri et al., 2013). Within the GOM Integrated Ecosystem Assessment program, several spatially explicit ecosystem models have been designed, including an Atlantis model for the entire Gulf of Mexico (Atlantis-GOM) and an OSMOSE model for the West Florida Shelf (OSMOSE-WFS), to simulate predator–prey dynamics and the potential impacts of management measures in the GOM. One major challenge for developing Atlantis-GOM and OSMOSE-WFS has been the construction of distribution maps despite the availability of several large fisheries-independent survey databases.

We developed delta generalized additive models (GAMs; Hastie and Tibshirani, 1990; Guisan et al., 2002) for predicting the spatial distribution of different life stages of multiple functional groups over the entire GOM shelf, which can then be used to define distribution maps for the OSMOSE-WFS model. In the following, we: (1) briefly review how distribution maps have been produced and utilized in spatially explicit ecosystem models to date, focusing on the widely used OSMOSE and Atlantis models; (2) discuss the use of GAMs to construct distribution maps for spatial ecosystem models; and (3) give an outline of the content and objectives of the present study.

1.1. *Distribution maps in spatially explicit ecosystem models*

Spatial ecosystem models usually explicitly consider a large number of functional groups whose spatial distribution in the real world can vary substantially within life stages and between seasons. However, the generation of distribution maps for spatially explicit ecosystem models is usually constrained by the availability of survey data and the total number of samples available. Spatial abundance and biomass data are typically collected for species of high economic importance. Moreover, available spatial data generally cover only a fraction of the total habitat area used by functional groups of interest. Given these limitations, a single, simple framework is desired to produce distribution maps for the multiple functional groups represented in spatial ecosystem models. The spatial distribution of functional groups in an ecosystem model at the start of simulations or at the beginning of each time step constitutes an important step in capturing ecosystem dynamics. Fish movements implemented after this step ultimately affect the predation mortality rates and diet composition of functional groups.

OSMOSE is a two-dimensional, individual-based, multi-species model whose basic units (‘super-individuals’) are schools, which consist of organisms belonging to the same functional group and the same life stage, which have the same length, weight, and, at a given time step, the same spatial coordinates (Shin and Cury, 2004, 2001). Schools are distributed in space at each time step using a set of maps of presence/absence or density maps created for specific functional groups, life stages and seasons. When the distribution of schools remains static (within a season or if the distribution is constant throughout the year), schools move to immediately adjacent cells within their distribution area following a random walk. Maps of presence/absence used in OSMOSE have generally been produced from the literature and experts' opinion (e.g., Shin et al., 2004; Travers et al., 2009; Brochier et al., 2013) or directly from research surveys and commercial fisheries data (Fu et al., 2013). Marzloff et al. (2009) created density maps for the eight functional groups represented in their OSMOSE model directly from acoustic and trawl survey data.

Atlantis is a sophisticated biogeochemical marine ecosystem model (Fulton et al., 2004, 2007). This model integrates ecological, fisheries, physical and chemical dynamics in a three-dimensional, spatially explicit domain. Distribution maps are employed in Atlantis for defining the allocation of functional groups biomass over space at the start of simulations. These distribution maps are habitat preference maps or density maps, produced directly from research survey data or the literature (e.g., Fulton et al., 2007; Horne et al., 2010; Kaplan et al., 2010). Ainsworth et al. (2011) took a different approach and used a habitat similarity matrix to extrapolate research survey data to the entire spatial footprint of their Atlantis model for the northern Gulf of California.

All the above-mentioned methods used to generate distribution maps for spatial ecosystem models are convenient ways to create maps rapidly. However, these methods limit the spatial coverage of spatially explicit ecosystem models to those areas that are consistently sampled. Furthermore, with the exception of Ainsworth et al. (2011), extrapolations are not an objective process and instead rely heavily on individual opinion.

1.2. *Using GAMs to produce distribution maps for spatially explicit ecosystem models*

Data-driven statistical models such as GAMs offer a valuable, objective way to predict abundance and biomass over extensive geographical regions. However, the potential of GAMs for producing distribution maps for spatially explicit ecosystem models has not been exploited until recently (Drexler and Ainsworth, 2013). GAMs relate an ecological response to a suite of predictors using non-linear smoothing functions (Hastie and Tibshirani, 1990; Guisan et al., 2002). One major disadvantage of GAMs is that they require a relatively large amount of data to have the high degrees of freedom that guarantee their flexibility (Wood, 2006). One of their major advantages is that they can be used to estimate spatial patterns of abundance or biomass over a broad geographic region *spanning both sampled and unsampled areas* (e.g., Koubbi et al., 2006; Vaz et al., 2006; Loots et al., 2007; Planque et al., 2007).

Drexler and Ainsworth (2013) developed a GAM approach to predict the relative abundance of multiple functional groups in shelf areas across the entire Gulf of Mexico, based on abundance estimates coming from a fisheries independent dataset, the SEAMAP groundfish/trawl dataset (GSMFC, 2011; SEDAR, 2011), and regional environmental and habitat features. There is an overdispersion of abundance estimates in the SEAMAP groundfish/trawl dataset linked to the high number of zero data, as is frequently the case with research survey data and other ecological data (e.g., Barry and Welsh, 2002; Koubbi et al., 2006; Vaz et al., 2006; Loots et al., 2010). To account for this, Drexler and Ainsworth (2013) used a negative binomial GAM approach (Barry and Welsh, 2002; Zeileis et al., 2008). The authors utilized this approach to generate distribution maps for 40 functional groups represented in the Atlantis-GOM model.