**Instructions**:

The abstracts should be selling pitches for the chapters, with a focus on what the chapter is about, and what the reader can be expected to gain from reading it. They tend to be 100-200 words long, written in the third person with no abbreviations, footnotes or incomplete references.

Chapter 1:

Chapter 1 illustrates that ecological dynamics can be expressed by describing individual organisms and changes in their marks (e.g., location, size, maturity, etc.) over time. It specifically illustrates this with two examples: (1) by simulating individual timelines (birth and death timing) and resulting population size, and (2) simulating individual locations and deriving population habitat utilization. The chapter then shows how to analyze these individual (Lagrangian) dynamics by discretizing space and time and fitting a gridded (Eulerian) statistical model. To for these gridded models, it introduces the components of a Generalized Linear Model (GLM) and shows how to fit GLMs using either basic R functions or by defining a likelihood function and using Template Model Builder to identify parameters that maximize this likelihood. Readers will also learn basic tools to visualize output and evaluate model diagnostics.

Chapter 2:

Chapter 2 proposes that ecological dynamics typically depend upon state-variables that cannot be directly observed, and these unobserved variables complicate defining a likelihood function that can be used to estimate parameters. It then introduces the concept of random effects, where these are marginalized across (using an integral or summation) to calculate a marginal likelihood that is useful for estimation. To facilitate computing this integral, Chapter 2 introduces the Laplace approximation and shows how this can be implemented in basic R functions or automatically using Template Model Builder (TMB). In particular, the chapter presents a simplified example involving a known probability distribution, and then illustrates the Laplace approximation for fitting a Generalized Linear Mixed Model (GLMM). Finally, Chapter 2 introduces basic considerations when using TMB to implement the Laplace approximation, including the concept of separable random effects, and common errors in coding these models.

Chapter 3:

Chapter 3 introduces a simple (Gompertz) model predicting changes in population abundance over time. It then uses it to illustrate general concepts regarding autoregressive models. In particular, the chapter demonstrates the Gompertz model using multidecadal surveys for flathead sole in the eastern Bering Sea, and compares measurement-error and state-space approaches to model fitting. The chapter then demonstrates that the covariance for an autocorrelated random effect can be specified either as a series of conditional distributions, or by defining the joint distribution for all random effects. Finally, it also introduces the concept of semi-variance and correlation functions, as well as different ways of forecasting state-space models.

Chapter 4:

Chapter 4 introduces statistical models for the movement of individual organisms, specifically emphasizing multivariate state-space models. It specifically decomposes movement into three processes: drift (passive movement along a known vector-field), taxis (directional movement towards preferred habitat) and diffusion (otherwise unexplained movement that is treated as random). Using this decomposition, it simulates movement for a central-place forager that initially moves away from the centroid of its range, and then subsequently moves back towards this centroid. It then presents methods to fit these simulated data either using a pure diffusion process, or including a spline to represent directional movement. Finally, it shows how tracks for multiple individuals can be analyzed simultaneously, and presents two practical approaches (either factor or structural equation models) to represent the covariance among variables.

Chapter 5:

Chapter 5 builds progressively from simple to general methods for estimating spatially correlated variables. To do so, it introduces basis expansion using splines, and emphasizes tensor splines to implement basis expansion for two spatial coordinates. It then introduces generalized additive models (GAMs), and briefly outlines how generalized linear mixed models (GLMMs) and GAMs can both estimate the wiggliness associated with a tensor spline. Then, using point-count data for bald eagles in western North America, it compares four different ways of constructing the covariance or precision matrix for a two-dimensional spatial variable in a GLMM. Specifically, it first extends time-series methods to define a conditional distribution for log-densities on a two-dimensional grid, and then extends this by jointly constructing the gridded spatial covariance. It then contrasts this with either a conditional autoregressive process or the stochastic partial differential equation (SPDE) method for specifying the precision matrix for over an irregular spatial domain. In each case, the chapter shows that these specifications result in similar spatial basis functions, and also similar estimates of bald-eagle densities in the case study example.

Chapter 6:

Chapter 6 introduces spatial sampling designs and illustrates how results from a spatial model can be weighted to infer a spatially integrated total such as population abundance. To do so, it first introduces two ways of calculating uncertainty when estimating a quantity derived from spatial random effects. The chapter also introduces the concept of retransformation bias, where the simplest plug-in estimator for a derived quantity is biased, and then introducing a generic solution called the “epsilon bias-correction”. Using these methods, it compares plug-in and epsilon estimators for a real-world case study involving ozone concentrations in the southern United States. It shows that the epsilon estimator results in a higher estimate of population-weighted ozone, as expected given the specified model structure. Using a simulation study based on these data, the chapter next introduces the concept of “preferential sampling bias,” occurring when sampling probabilities are correlated with the spatially correlated variable being estimated. It specifically shows that this bias can be mitigated by including appropriate covariates. Finally, the chapter introduces multi-stage sampling designs, and briefly outlines the class of “occupancy” models that are widely used to estimate detection probabilities in ecological sampling designs.

Chapter 7:

Chapter 7 introduces the many complex topics that arise when including covariates in a spatial model. To do so, it first highlights the difference between extrapolation (when predicting sampling units that are similar to those that are fitted) and counter-factual prediction (where the relationship among covariates might differ systematically from those that are fitted). Using vocabulary from graphical modelling, it shows that standard regression methods can perform well for extrapolation but still poorly for counter-factual prediction, while structural equation models can in some cases resolve the difficulties arising with counter-factual prediction. The chapter then highlights the distinction between habitat covariates (which affect the target variable being estimated) vs. detectability covariates (which affect the sampling process). It first uses a simulated case study to highlight that density covariates can improve statistical performance for extrapolation in a spatial model. Next, it uses a real-world case study involve multiple sampling gears for red snapper in the Gulf of Mexico to highlight how detectability covariates can be used to integrate multiple data sets in a spatial model.

Chapter 8:

Chapter 8 introduces spatial models that include changes over time (“spatio-temporal models”). It first reviews ecological mechanisms that give rise to spatio-temporal dynamics, and how these can be summarized using a Stommel diagram that visualizes the spatial and temporal scales having largest variance. Chapter 8 then introduces the distinction between adding new data within a fixed spatial domain (“infill asymptotics”) vs. maintaining a constant sampling density but expanding the spatial domain (“sprawl asymptotics”). It uses a simulation study to show that these two designs have different implications for the precision of estimated parameters or random effects, and highlights that seasonal variation can be repeatedly sampled (i.e., subject to infill asymptotics) while interannual variation often cannot (i.e., is subject to sprawl asymptotics). The chapter then introduces seasonal adjustment methods for time-series models, and shows how spatially varying coefficients can extend seasonal adjustment within spatial models. It highlights this seasonal spatial adjustment by fitting a cyclic spline with spatially varying coefficients to seasonal ozone concentrations in the southeastern United States. Finally, it introduces alternative versions of a spatio-temporal model for interannual densities of Alaska pollock in the eastern Bering Sea. Using this example, it highlights how density changes can be summarizes to visualize local trends in density.

Chapter 9:

Chapter 9 introduces the concept of ecological teleconnections, whereby individual movement or other mechanisms cause densities to by strongly correlated at geographically distant locations. It then introduces Empirical Orthogonal Functions (EOF), where spatio-temporal dynamics are summarized as the product of a spatial response map and an estimated temporal index. It then generalizes this conventional EOF using a generalized linear latent variable model (EOF-GLLVM). Using a case study involving summer sea ice concentrations in the Arctic Ocean, the chapter shows that EOF-GLLVM can accurately reconstruct aggregate spatio-temporal dynamics while also highlighting dominant modes of ecosystem variability. Finally, it introduces “confirmatory factor models” (CFA) where EOF indices are replaced with an hypothesized time-series covariate. Using this CFA, Chapter-9 highlights that the spatial extent of near-freezing water at the bottom of the eastern Bering Sea can explain multi-decadal dynamics for eastern Bering Sea pollock.

Chapter 10:

Chapter 10 revisits the topic of individual movement, extending (Lagrangian) methods from Chapter 4 to now estimate (Eulerian) movement fractions for population density. It specifically provides a partial differential equation (PDE) that includes terms for drift (passive movement along a known vector-field), taxis (directional movement towards preferred habitat) and diffusion (otherwise unexplained movement that is treated as random). It then illustrates how this PDE can be solved by defining an instantaneous movement rate matrix, and then integrating time by approximating the matrix exponential. It first illustrates this using simulated dispersal for an introduced species on the east coast of Madagascar. It then introduces a Hidden Markov Model (HMM) fitting to locational data from archival tags for a tagged Pacific cod in the Aleutian Islands. Finally, it fits the model to point-count data for bald eagles in the northeast North America. Using these examples, Chapter 10 highlights that the drift-taxis-diffusion PDE provides a generic framework for analyzing gridded movement processes.

Chapter 11:

Chapter 11 illustrates how multispecies spatial models can be applied to understand community assembly and biogeography. It first introduces phylogenetic trees (representing evolutionary relatedness of different taxa) and functional traits, and shows how these can be converted to a design matrix and fitted within a spatial regression. It then introduces a joint species distribution model (JSDM) that includes phylogenetic, trait, environmental, and residual spatial variation. Fitting the JSDM to point-count data for 20 bird species in the western United States, it shows how to calculate the proportion of variance explained by each of these spatial components. It then demonstrates various post-hoc analyses that are feasible using a JSDM. In particular, it shows spatial cluster analysis to identify geographic areas, beta diversity to calculate species turnover, and functional diversity to highlight spatial variation in functional composition. In particular, it emphasizes how these post-hoc metrics can be interpreted by reference to species-specific estimates of population density.