Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments

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Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments

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ABSTRACT

Fisheries scientists provide stock, ecosystem, habitat, and climate assessments to support interdisplinary fisheries management in the US and worldwide. These assessment activities have evolved different models, using different review standards, and are communicated using different vocabulary. Recent research shows that spatio-temporal models can estimate population density for multiple locations, times, and species, and that this is a "common currency" for addressing core goals in stock, ecosystem, habitat, and climate assessments. I therefore review the history and "design principles" for one spatio-temporal modelling package, the Vector Autoregressive Spatio-Temporal (VAST) package. I then provide guidance on fifteen major decisions that must be made by users of VAST, including: whether to use a univariate or multivariate model; when to include spatial and/or spatio-temporal variation; how many factors to use within a multivariate model; whether to include density or catchability covariates; and when to include a temporal correlation on model components. I finally demonstrate these decisions using three case studies. The first develops indices of abundance, distribution shift, and range expansion for arrowtooth flounder (*Atheresthes stomias*) in the Eastern Bering Sea, showing the range expansion for this species. The second involves "species ordination" of eight groundfishes in the Gulf of Alaska bottom trawl survey, which highlights the different spatial distribution of flathead sole (*Hippoglossoides elassodon*) relative to sablefish (*Anoplopoma fimbria*) and dover sole (*Microstomus pacificus*). The third involves a short-term forecast of the proportion of coastwide abundance for five groundfishes within three spatial strata in the US West Coast groundfish bottom trawl survey, and predicts large interannual variability (and high uncertainty) in the distribution of lingcod (*Ophiodon elongatus*). I conclude by recommending further research exploring the benefits and limitations of a "common currency" approach to stock, ecosystem, habitat, and climate assessments, and discuss extending this approach to optimal survey design and economic assessments.

1. The broad scope for spatio-temporal models

Over the past hundred years, lawmakers in the United States and worldwide have entrusted fisheries scientists with an increasing role in informing fisheries management policy (Smith, 2007). The US Magnuson-Stevens Act (with subsequent amendment and interpretation) stipulates a role for biological information in several fisheries management activities including: setting an upper limit on allowable catches (Methot et al., 2014); identifying the likely impact of ecosystem components on optimal yield (Patrick and Link, 2015); and the designation of essential fish habitat (Rosenberg et al., 2000). Providing scientific information regarding the likely impact of climate change on changing fish productivity is also a growing task in many US regions and worldwide (Hare et al., 2016). Scientific information is therefore needed to assess stock status and productivity, ecosystem considerations, essential habitat, and climate impacts.

Stock, ecosystem, habitat, and climate assessments have historically been conducted using a wide variety of model types (Link and Browman, 2014), in part because these different assessments aim to measure different biological quantities, ranging from: the maximum sustainable yield for a population (stock assessment); the impact of species interactions on population productivity (ecosystem assessment); the richness and productivity of different locations (habitat assessment); and the likely impact of changing climate on fish productivity (climate assessment). However, these quantities can all be estimated by developing a model using a single common currency: the population density of one or more species at multiple locations within an ecosystem and how this changes over time. The quantities sought by

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Table 1
Goals, objectives, and questions that can be addressed using the VAST package (or its precursors), along with example references for each question.

Assessment type	Common activities	Questions	Example reference
Stock assessment	Estimate trends in abundance	Is abundance increasing after management changes?	(Thorson et al., 2015b)
	Standardize fishery-dependent catch per unit effort (CPUE)	How to disentangle fishery targeting from population abundance when analyzing fishery CPUE data?	(Thorson et al., 2017a)
	Estimate proportion at size/age/sex from subsampling data	What is the proportion of abundance in different size/age classes?	(Thorson and Haltuch, 2018)
Habitat assessment	Identify habitat associations	Is body size greater in areas with higher primary productivity?	(Thorson, 2015a)
	Identify preferred habitat for multiple stages	Where do juvenile or adult individuals typically occur?	(Kai et al., 2017)
	Estimate range expansion/contraction	Does occupied habitat expand during stock rebuilding?	(Thorson et al., 2016c)
Climate assessment	Estimate distribution shifts	Is the distribution of species changing interannually or directionally?	(Thorson et al., 2016b)
	Forecast distribution under future climate conditions	How will distribution change under future temperature scenarios?	(Thorson, 2018)
	Attribute historical distribution shift to multiple hypothesized drivers	How much of previous distribution shifts is caused by temperature or size-structure?	(Thorson et al., 2017b)
Ecosystem assessment	Identify species with similar dynamics (“ordination”)	Which species are consistently co-occur within the ecosystem?	(Dolder et al., 2018; McClatchie et al., 2018)
	Estimate species distribution/density for use as input to ecosystem model	How best to approximate species interactions using information about co-occurrence?	(Grüss et al., 2018a; Grüss et al., 2018b)
	Visualize dominant patterns of ecosystem dynamics	How is an ecosystem changing over time?	(Thorson et al., 2016a)
	Estimate covariation between multiple components of an ecosystem	Are fishes consistently associated with biogenic or abiotic ecosystem features?	(Thorson and Barnett, 2017)

different assessment types can then typically be computed from estimates of population density and dynamics for multiple species across space and time.

Fortunately, population density and its change over time for multiple locations, times, and species can now be efficiently estimated using spatio-temporal models, an emerging class of statistical model that estimates variation in one or more response variable (wind speed and temperature; human exposure to diseases; density of invasive species) across multiple locations and time periods (e.g., Cressie and Wikle, 2011). Critically, these models predict a response variable and its evolution over time (for example, weather conditions in the Pacific Northwest) while acknowledging the potential role for known processes (to continue our example, physics for atmospheric dynamics), unmeasured processes (unknown initial conditions for the atmosphere), and imperfect system measurements (mis-calibrated sensors in wind gauges). Spatio-temporal models follow a long tradition of “state-space models” that incorporate both process variability and measurement errors in fisheries models (e.g., Walters and Hilborn, 1978; Gudmundsson, 1994; Punt, 2003), but extend this tradition by accounting for the Law of Geography: the tendency for process and/or measurement errors to be more similar at nearby sites than geographically distant locations (Tobler, 1970).

Recent research in fisheries science indicates that spatio-temporal models can provide useful input to stock, ecosystem, habitat, and climate assessments conducted in the US and worldwide. In particular, a body of recent research has shown how the Vector-Autoregressive Spatio-temporal (VAST) package available in the R statistical environment (R Core Team, 2017) can be used to answer many common questions in these multiple assessment types (Table 1). Using a single software package for multiple assessment types has several potential benefits, e.g., sharing expertise and review-standards between teams, sharing costs for model development and testing, and improved communication and corroboration of results within and among teams.

However, there is little guidance available to researchers who would like to apply the VAST package. In this paper, I therefore provide guidance on decisions (including a decision tree) when using a VAST model for different assessments types. To do so, I first review the history of the VAST package, with the aim of justifying its current structure and default settings. I then list fifteen decisions that must be made in every application, while providing guidance regarding default decisions for different assessment types. Finally, I demonstrate this decision tree via application to three case studies, representing index standardization (stock assessment), species ordination (ecosystem assessment), and forecasting spatial distribution (climate assessment). I then conclude by reviewing potential future research to extend spatio-temporal models to emerging demands for fisheries science, including economic assessments and optimal survey design.

2. Introduction to VAST

The vector autoregressive spatio-temporal (VAST) model can be implemented using package *VAST* that is publicly available (www.github.com/james-thorson/VAST) within the R statistical environment.[2] Package *VAST* includes several forms of documentation to help analysts, including: (1) Doxygen documentation that can accessed through the standard R-help interface when the library is loaded within R[3]; (2) a “VAST model structure and user interface” document that describes the model equations while linking them to the R interface (www.github.com/james-thorson/VAST/manual); (3) two separate Rmarkdown “tutorials” that provide annotated code illustrating how to run VAST for single- or multi-species example using real-world data (www.github.com/james-thorson/VAST/examples); (4) a searchable “issue tracker” available through GitHub; and (5) peer-reviewed articles describing development, testing, and applications for each feature. I include a list of all model equations and notation (Tables 2 and 3), and the decision guidance (including decision tree) that is presented here will be maintained as a separate “living document” to complement these existing help-file, model-structure, R-markdown example, issue-tracking, and peer-reviewed resources.

The initial development of VAST was motivated by applied problems for the Pacific Fisheries Management Council (PFMC), which manages fisheries in federal waters off the US West Coast. The Northwest Fisheries Science Center uses a spatially-stratified bottom trawl survey to sample groundfish densities for this region (Keller et al., 2017). One major product from this effort is an “index of abundance” that is intended to be proportional to population biomass for many individual species, where a stock assessment model is then fitted to

[2] VAST automatically installs its dependencies including package *TMB*. For successful usage, *TMB* requires installation of Rcpp tools, which on a windows operating system requires installation of Rtools. Further details regarding *TMB* can be found in its repository: www.github.com/kaskr/adcomp.

[3] For example, users can read an overview of the package using:

Table 2
Equations defining the model VAST (while ignoring features that are implemented but have not yet been documented).

Name	Equation	Num
First linear predictor	$p_1(i) = \beta_1(c_i, t_i) + \sum_{f=1}^{n_{\omega 1}} L_{\omega 1}(c_i, f)\omega_1(s_i, f) + \sum_{f=1}^{n_{\varepsilon 1}} L_{\varepsilon 1}(c_i, f)\varepsilon_1(s_i, f, t_i)$ $+ \sum_{f=1}^{n_{\eta 1}} L_1(c_i, f)\eta_1(v_i, f) + \sum_{p=1}^{n_p} \gamma_1(c_i, t_i, p)X(x_i, t_i, p) + \sum_{k=1}^{n_k} \lambda_1(k)Q(i, k)$	2.1
Second linear predictor	$p_2(i) = \beta_2(c_i, t_i) + \sum_{f=1}^{n_{\omega 2}} L_{\omega 2}(c_i, f)\omega_2(s_i, f) + \sum_{f=1}^{n_{\varepsilon 2}} L_{\varepsilon 2}(c_i, f)\varepsilon_2(s_i, f, t_i)$ $+ \sum_{f=1}^{n_{\delta 2}} L_2(c_i, f)\eta_2(v_i, f) + \sum_{p=1}^{n_p} \gamma_2(c_i, t_i, p)X(x_i, t_i, p) + \sum_{k=1}^{n_k} \lambda_2(k)Q(i, k)$	2.2
Link functions for conventional delta or zero-inflated model	$r_1(i) = logit^{-1}(p_1(i))$ $r_2(i) = a_i \times log^{-1}(p_2(i))$	2.3
Link functions for Poisson-link delta model (only appropriate for biomass-sampling data)	$r_1(i) = 1 - exp(-a_i \times exp(p_1(i)))$ $r_2(i) = \frac{a_i \times exp(p_1(i))}{r_1(i)} \times exp(p_2(i))$	2.4
Probability distribution function for biomass (real-value) data	$Pr(B = b_i) = \begin{cases} 1 - r_1(i) & if\ B = 0 \\ r_1(i) \times g\{B = b_i \mid r_2(i), \sigma_m^2(c)\} & if\ B > 0 \end{cases}$	2.5
Probability density function for abundance (count) data	$Pr(B = b_i) = \begin{cases} (1 - r_1(i)) + g\{B = 0 \mid r_2(i), ...\} & if\ B = 0 \\ r_1(i) \times g\{B = b_i \mid r_2(i), ...\} & if\ B > 0 \end{cases}$	2.6
Matérn correlation function (smoothness $\varphi = 1$)	$\boldsymbol{R}_1(s_n, s_m) = \frac{1}{2^{\varphi-1}\Gamma(\varphi)} \times (\kappa_1\ \lvert\boldsymbol{d}(s_n, s_m)\boldsymbol{H}\rvert)^{\varphi} \times K_\nu(\kappa_1\ \lvert\boldsymbol{d}(s_n, s_m)\boldsymbol{H}\rvert)$ $\boldsymbol{R}_2(s_n, s_m) = \frac{1}{2^{\varphi-1}\Gamma(\varphi)} \times (\kappa_2\ \lvert\boldsymbol{d}(s_n, s_m)\boldsymbol{H}\rvert)^{\varphi} \times K_\nu(\kappa_2\ \lvert\boldsymbol{d}(s_n, s_m)\boldsymbol{H}\rvert)$ $\boldsymbol{H} = \begin{bmatrix} exp(h_1) & h_2 \\ h_2 & exp(-h_1)(1 + h_2^2) \end{bmatrix}$	2.7
Exponential correlation function	$\boldsymbol{R}_1(i, j) = exp(-\kappa_1\ \lvert\boldsymbol{d}(s_n, s_m)\rvert)$ $\boldsymbol{R}_2(i, j) = exp(-\kappa_2\ \lvert\boldsymbol{d}(s_n, s_m)\rvert)$	2.8
Probability density function for spatial factors	$\omega_1(\bullet, f) \sim MVN(0, \boldsymbol{R}_1)$ $\omega_2(\bullet, f) \sim MVN(0, \boldsymbol{R}_2)$	2.9
Probability density function for spatio-temporal factors	$\varepsilon_1(\bullet, f, t) \sim \begin{cases} MVN(0, \boldsymbol{R}_1) & if\ t = 1 \\ MVN(\rho_{\varepsilon 1}\varepsilon_1(\bullet, f, t-1), \boldsymbol{R}_1) & if\ t > 1 \end{cases}$ $\varepsilon_2(\bullet, f, t) \sim \begin{cases} MVN(0, \boldsymbol{R}_2) & if\ t = 1 \\ MVN(\rho_{\varepsilon 2}\varepsilon_2(\bullet, f, t-1), \boldsymbol{R}_2) & if\ t > 1 \end{cases}$	2.10
Probability density function for overdispersion	$\eta_1(v, f) \sim Normal(0,1)$ $\eta_2(v, f) \sim Normal(0,1)$	2.11
Autoregressive structure on intercepts	$\beta_1(t) \sim \begin{cases} Normal(0, \sigma_{\beta 1}^2) & if\ t = 1 \\ Normal(\rho_{\beta 1}\beta_1(t-1), \sigma_{\beta 1}^2) & if\ t > 1 \end{cases}$ $\beta_2(t) \sim \begin{cases} Normal(0, \sigma_{\beta 2}^2) & if\ t = 1 \\ Normal(\rho_{\beta 2}\beta_2(t-1), \sigma_{\beta 2}^2) & if\ t > 1 \end{cases}$	2.12
Predicted density	$d^*(s, c, t) = r_1^*(s, c, t) \times r_2^*(s, c, t)$ Where r_1^* and r_2^* are calculated from Eq. (2).1–2.4, except fixing $\eta_1 = \eta_2 = \lambda_1 = \lambda_2 = 0$	2.13
Index of abundance	$I(c, t, l) = \sum_{x=1}^{n_x} (a(s, l) \times d^*(s, c, t))$	2.14
Center of gravity for stratum $l = 1$	$Z(c, t, m) = \sum_{x=1}^{n_x} \frac{(z(s, m) \times a(x, 1) \times d^*(s, c, t))}{I(c, t, 1)}$	2.15
Average density	$D(c, t, l) = \sum_{x=1}^{n_x} \left(\frac{a(x, l) \times d^*(x, c, t)}{I(c, t, l)} d^*(x, c, t)\right)$	2.16
Effective area occupied	$A(c, t, l) = \frac{I(c, t, l)}{D(c, t, l)}$	2.17
Covariance among categories	$\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^T$ Where $\boldsymbol{L}$ is $\boldsymbol{L}_{\omega 1}$, $\boldsymbol{L}_{\omega 2}$, $\boldsymbol{L}_{\varepsilon 1}$, $\boldsymbol{L}_{\varepsilon 2}$, $\boldsymbol{L}_1$, or $\boldsymbol{L}_2$	2.18
Varimax rotation	$\boldsymbol{B} = argmax_{\boldsymbol{B}}(\sum_{c2=1}^{n_c} \sum_{c1=1}^{n_c} b(c1, c2)^2)$ given that $\boldsymbol{B}$ is a rotation matrix	2.19
PCA rotation	$\boldsymbol{L}^* = \boldsymbol{V}\boldsymbol{\Lambda}^{0.5}$ Where $\boldsymbol{V}$ and $\boldsymbol{\Lambda}$ are, respectively, the first n_f eigenvectors and eigenvalues of $\boldsymbol{\Sigma}$ $\boldsymbol{B} = inv(\boldsymbol{L}^*)\boldsymbol{L}$ Where $inv(\boldsymbol{L}^*)$ is the Moore-Penrose pseudo-inverse of $\boldsymbol{L}^*$	2.20
Factors and loading matrix after rotation	$\boldsymbol{\psi}^* = \boldsymbol{B}\boldsymbol{\psi}$ Where $\boldsymbol{\psi}$ is $\boldsymbol{\omega}_1(s)$, or $\boldsymbol{\omega}_2(s)$, or $\boldsymbol{\varepsilon}_1(s, t)$, or $\boldsymbol{\varepsilon}_2(s, t)$, or $\boldsymbol{\eta}_1(v)$, or $\boldsymbol{\eta}_2(v)$ $\boldsymbol{L}^* = \boldsymbol{L}\boldsymbol{B}^{-1}$ Where $\boldsymbol{\psi}^*$ and $\boldsymbol{L}^*$ are rotated factors and loadings	2.21

Table 3
Definition of mathematical notation, including the symbol used, its type (Index, Data, fixed effects "FE", random effects "RE", intermediate quantity computed internally "IQ", and derived quantities that are outputted for users "DQ"), and its dimension.

Name	Symbol	Type	Dimensions
Observation number	i	Index	–
Spatial location number	s	Index	–
Time interval number	t	Index	–
Category number	c	Index	–
Factor number	f	Index	–
Habitat covariate number	p	Index	–
Catchability covariate number	k	Index	–
Stratum number	l	Index	–
Index number for measures of center-of-gravity	m	Index	–
Index number for other book-keeping	z	Index	–
Sample response	b_i	Data	n_i
Location for each sample	s_i	Data	n_i
Time interval for each sample	t_i	Data	n_i
Category for each sample	c_i	Data	n_i
Overdispersion level for each sample	v_i	Data	n_i
Area covered by each sample	a_i	Data	n_i
Distance between locations s_n and s_m	$d(s_n, s_m)$	Data	$n_s \times n_s$
Habitat covariates for each location, time, and variable	$X(s, t, p)$	Data	$n_s \times n_t \times n_p$
Catchability covariates for each sample and variable	$Q(i, k)$	Data	$n_i \times n_k$
Area associated with location in each stratum	$a(s, l)$	Data	$n_s \times n_l$
Statistic for each location used to calculate center of gravity	$z(s, m)$	Data	$n_s \times n_m$
Intercept for 1st linear predictor	$\beta_1(c, t)$	FE/RE	$n_c \times n_t$
Intercept for 2st linear predictor	$\beta_2(c, t)$	FE/RE	$n_c \times n_t$
Loadings matrix for spatial covariation for 1st linear predictor	$L_{\omega 1}(c, f)$	FE	$n_c \times n_{\omega 1}$
Loadings matrix for spatial covariation for 2nd linear predictor	$L_{\omega 2}(c, f)$	FE	$n_c \times n_{\omega 2}$
Loadings matrix for spatio-temporal covariation for 1st linear predictor	$L_{\varepsilon 1}(c, f)$	FE	$n_c \times n_{\varepsilon 1}$
Loadings matrix for spatio-temporal covariation for 2nd linear predictor	$L_{\varepsilon 2}(c, f)$	FE	$n_c \times n_{\varepsilon 2}$
Loadings matrix for overdispersion covariation for 1st linear predictor	$L_1(c, f)$	FE	$n_c \times n_{\eta 1}$
Loadings matrix for overdispersion covariation for 2nd linear predictor	$L_2(c, f)$	FE	$n_c \times n_{\eta 2}$
Impact of habitat covariates on 1st linear predictor	$\gamma_1(c, t, p)$	FE	$n_c \times n_t \times n_p$
Impact of habitat covariates on 2nd linear predictor	$\gamma_2(c, t, p)$	FE	$n_c \times n_t \times n_p$
Impact of catchability covariates on 1st linear predictor	$\lambda_1(k)$	FE	n_k
Impact of catchability covariates on 2nd linear predictor	$\lambda_2(k)$	FE	n_k
Parameters governing residual variation	$\sigma_m^2(c, z)$	FE	$n_c \times 2$
Decorrelation rate for 1st linear predictor	κ_1	FE	1
Decorrelation rate for 2nd linear predictor	κ_2	FE	1
Autocorrelation for intercepts of 1st linear predictor	$\rho_{\beta 1}$	FE	1
Autocorrelation for intercepts of 2nd linear predictor	$\rho_{\beta 2}$	FE	1
Conditional variance for intercepts of 1st linear predictor	$\sigma_{\beta 1}^2$	FE	1
Conditional variance for intercepts of 2ndlinear predictor	$\sigma_{\beta 2}^2$	FE	1
Autocorrelation for spatio-temporal covariation of 1st linear predictor	$\rho_{\varepsilon 1}$	FE	1
Autocorrelation for spatio-temporal covariation of 2nd linear predictor	$\rho_{\varepsilon 2}$	FE	1
Parameters governing geometric anisotropy	$h(z)$	FE	2
Spatial factors for 1st linear predictor	$\omega_1(s, f)$	RE	$n_s \times n_{\omega 1}$
Spatial factors for 2nd linear predictor	$\omega_2(s, f)$	RE	$n_s \times n_{\omega 2}$
Spatio-temporal factors for 1st linear predictor	$\varepsilon_1(s, f, t)$	RE	$n_s \times n_{\varepsilon 1} \times n_t$
Spatio-temporal factors for 2nd linear predictor	$\varepsilon_2(s, f, t)$	RE	$n_s \times n_{\varepsilon 1} \times n_t$
Overdispersion factors for 1st linear predictor	$\eta_1(v, f)$	RE	$n_v \times n_{\eta 1}$
Overdispersion factors for 2nd linear predictor	$\eta_2(v, f)$	RE	$n_v \times n_{\eta 2}$
1st linear predictor	$p_1(i)$	IQ	n_i
2nd linear predictor	$p_2(i)$	IQ	n_i
1st link-transformed predictor	$r_1(i)$	IQ	n_i
2nd link-transformed predictor	$r_2(i)$	IQ	n_i
Spatial correlation matrix for 1st linear predictor	$\boldsymbol{R}_1$	IQ	$n_s \times n_s$
Spatial correlation matrix for 2nd linear predictor	$\boldsymbol{R}_2$	IQ	$n_s \times n_s$
Anisotropy matrix	$\boldsymbol{H}$	IQ	2×2
Predicted density	$d^*(s, c, t)$	DQ	$n_s \times n_c \times n_t$
Index of abundance	$I(c, t, l)$	DQ	$n_c \times n_t \times n_l$
Center of gravity	$Z(c, t, m)$	DQ	$n_c \times n_t \times n_m$
Average density	$D(c, t, l)$	DQ	$n_c \times n_t \times n_l$
Effective area occupied	$A(c, t, l)$	DQ	$n_c \times n_t \times n_l$
Rotation matrix for spatial covariation for 1st linear predictor	$\boldsymbol{B}_{\omega 1}$	DQ	$n_c \times n_c$
Rotation matrix for spatial covariation for 2ndlinear predictor	$\boldsymbol{B}_{\omega 2}$	DQ	$n_c \times n_c$
Rotation matrix for spatio-temporal covariation for 1st linear predictor	$\boldsymbol{B}_{\varepsilon 1}$	DQ	$n_c \times n_c$
Rotation matrix for spatio-temporal covariation for 2ndlinear predictor	$\boldsymbol{B}_{\varepsilon 2}$	DQ	$n_c \times n_c$
Rotation matrix for overdispersion covariation for 1st linear predictor	$\boldsymbol{B}_1$	DQ	$n_c \times n_c$
Rotation matrix for overdispersion covariation for 2ndlinear predictor	$\boldsymbol{B}_2$	DQ	$n_c \times n_c$
Rotated loadings matrix for spatial covariation for 1st linear predictor	$L_{\omega 1}^*(c, f)$	DQ	$n_c \times n_{\omega 1}$
Rotated loadings for spatial covariation for 2nd linear predictor	$L_{\omega 2}^*(c, f)$	DQ	$n_c \times n_{\omega 2}$
Rotated loadings for spatio-temporal covariation for 1st linear predictor	$L_{\varepsilon 1}^*(c, f)$	DQ	$n_c \times n_{\varepsilon 1}$
Rotated loadings for spatio-temporal covariation for 2nd linear predictor	$L_{\varepsilon 2}^*(c, f)$	DQ	$n_c \times n_{\varepsilon 2}$
Rotated loadings for overdispersion covariation for 1st linear predictor	$L_1^*(c, f)$	DQ	$n_c \times n_{\eta 1}$
Rotated loadings for overdispersion covariation for 2nd linear predictor	$L_2^*(c, f)$	DQ	$n_c \times n_{\eta 2}$
Rotated spatial factors for 1st linear predictor	$\omega_1^*(s, f)$	DQ	$n_s \times n_{\omega 1}$
Rotated spatial factors for 2nd linear predictor	$\omega_2^*(s, f)$	DQ	$n_s \times n_{\omega 2}$
Rotated spatio-temporal factors for 1st linear predictor	$\varepsilon_1^*(s, f, t)$	DQ	$n_s \times n_{\varepsilon 1} \times n_t$
Rotated spatio-temporal factors for 2nd linear predictor	$\varepsilon_2^*(s, f, t)$	DQ	$n_s \times n_{\varepsilon 1} \times n_t$
Rotated overdispersion factors for 1st linear predictor	$\eta_1^*(v, f)$	DQ	$n_v \times n_{\eta 1}$
Rotated overdispersion factors for 2nd linear predictor	$\eta_2^*(v, f)$	DQ	$n_v \times n_{\eta 2}$

each abundance-index to estimate changes in population density over time. Scientists in this region have used a model-based framework to develop the abundance-index in part because the survey is conducted using equipment and staff from contracted fishery vessels and previous research showed the importance of accounting for differences in catchability among vessels (Helser et al., 2004). Index standardization for 2013 PFMC stock assessments was conducted using an R package *nwfscDeltaGLM*, and subsequent research using this package suggested that treating the interaction of spatial stratum and year as a random effect was a robust approach to account for spatial variability and low sample sizes in some strata (Thorson and Ward, 2013). However, a random interaction of stratum and year still required defining spatial strata a priori, and this approach did not include any information regarding which strata were adjacent to one another. Subsequently, Shelton et al. (2014) demonstrated that a spatially-explicit model could explain a substantial portion of residual variation by accounting for variable population density within existing spatial strata, but this approach required long run-times relative to spatially-stratified methods.

VAST then grew out of several software packages developed by collaborative research over the past decade. Most importantly, Kristensen et al. (2014) demonstrated new statistical software for mixed-effects models, which would subsequently be called Template Model Builder using package *TMB* (Kristensen et al., 2016). Similarly, the *R-INLA* package (Illian et al., 2012) had recently demonstrated a computationally efficient "stochastic partial differential equation" (SPDE) approximation to spatio-temporal processes (Lindgren et al., 2011). Thorson et al. (2014b) documented how to efficiently implement the SPDE approximation within the new TMB software, and Thorson et al. (2015b) subsequently introduced an R package *SpatialDeltaGLMM* that could fit single-species index standardization models while including both spatial variation that is constant among years (spatial effects) and spatial variation that varies among years (spatio-temporal effects). Simultaneously, Thorson et al. (2015a) introduced spatial factor analysis (SFA, using package *Spatial_FA*), which could estimate covariation for multiple species in a single time interval, and Thorson et al. (2016a) extended this to spatial dynamic factor analysis (SDFA, using package *SpatialDFA*), which could account for both spatial and spatio-temporal covariation. Finally, Thorson and Barnett (2017) merged all features from *SpatialDeltaGLMM*, *Spatial_FA*, and *SpatialDFA* within a single R package, which they called the vector autoregressive spatio-temporal (VAST) model. VAST has subsequently merged features for estimating species interactions from package *MIST* (Thorson et al., 2017c), although we do not discuss those features here. This package continues to evolve to include new features, but is generally designed to be backwards compatible (i.e., previous code can be re-run with no or minimal modifications to accommodate subsequent updates). Analysts are recommended to use package *VAST* for any task that might previously have involved *SpatialDeltaGLMM*, *Spatial_FA*, *SpatialDFA*, and *MIST* packages.

Since the development of package *SpatialDeltaGLMM* in 2015, VAST and its precursors have been used for both research and operations, and I briefly summarize when it has been presented to fisheries managers and/or peer-reviewers hired to review materials for fisheries managers (Table 4). By this measure, usage of VAST had a slow start (with 4 reports in 2015–2016), but subsequently has seen increased use (with 13 reports in 2017–June 2018). This includes inclusion in nine stock assessments in the "base case" model and six stock assessments in a "sensitivity" model, as well as for seven taxa within two ecosystem-considerations reports. So far VAST has had little usage within habitat or climate assessments, although this could partly reflect a lower annual rate of reports for habitat and climate assessments. Applications for fisheries management are limited to the Gulf of Alaska, Eastern Bering Sea, US West Coast, and South Africa.

3. VAST design principles

VAST represents four main design principles. Although there are many other implementation details that distinguish VAST from previous index-standardization methods, I believe that these four design principles represent the features that any future replacement should include.

3.1. Area weighting

VAST is built around the principle that analysts typically seek to estimate variables occurring over a pre-defined spatial domain. VAST predicts population density for all locations within this spatial domain, and then predicts derived quantities (e.g., total abundance, spatial concentration, or the centroid of spatial distribution) by aggregating population density across the spatial domain while weighting density estimates by the area associated with each estimate (see discussion of year x area interactions in Maunder and Punt (2004)). Ideally, this spatial domain represents the spatial boundaries for a given stock, ecosystem, habitat, or climate assessment. In this case, the estimate of total abundance can be treated as an "abundance index" that is directly comparable to other data sources and model estimates of population biomass developed at this spatial scale.

3.2. Distinct catchability and habitat covariates

VAST makes an explicit distinction between habitat and catchability covariates. Both types of covariates contribute to variation in expected catch rates, but VAST uses only habitat covariates when predicting population density within the spatial domain. VAST therefore "controls for" the effect of catchability covariates (i.e., filters out these components of covariation) and "conditions upon" the effect of habitat covariates (i.e., uses information about habitat covariates to improve performance when predicting population density). Previous index standardization methods have typically involved fitting a regression model including a year intercept and covariates, and then treated the year intercept as the abundance index. This approach implicitly treated all covariates as "catchability covariates", even when these variables were likely associated with increases in local population density. By

Table 4
List of reports (including taxa, region, year, type, usage and reference) using VAST or its precursors for documents presented specifically to fisheries management agencies or authorities, including whether the report is regarding ecosystem or single-species management decisions (USWC: US West Coast; GOA: Gulf of Alaska; EBS: Eastern Bering Sea).

Year	Region	Type	Taxon	Usage	Reference
2015	USWC	Stock	Canary	Base	(Monk et al., 2018)
2015	USWC	Stock	Darkblotched	Base	(Gertseva et al., 2015)
2015	GOA	Stock	Dusky	Sensitivity	(Lunsford et al., 2015)
2016	EBS	Stock	Walleye pollock	Sensitivity	(Ianelli et al., 2016)
2017	USWC	Stock	Lingcod	Base	(Haltuch et al., 2017)
2017	USWC	Stock	Yelloweye	Base	(Gertseva and Cope, 2017)
2017	USWC	Stock	Pacific Ocean perch	Base	(Wetzel et al., 2017)
2017	USWC	Stock	Arrowtooth	Base	(Sampson et al., 2017)
2017	South Africa	Stock	Hake complex	Sensitivity	(Fairweather et al., 2017)
2017	EBS	Stock	Blue King crab	Sensitivity	(The Plan Team for the King and Tanner Crab Fisheries of the Bering Sea and Aleutian Islands, 2017)
2017	South Africa	Stock	Groundfish complex	Base	(Winker et al., 2017)
2017	GOA	Stock	Arrowtooth	Sensitivity	(Spies et al., 2017)
2017	EBS	Ecosystem	Forage fish, groundfish, jellyfish, salmon (4 documents)	Base	(Moss et al., 2017)
2017	GOA	Ecosystem	Forage fish, groundfish, salmon (3 documents)	Base	(Moss et al., 2017)
2018	USWC	Stock	Bocaccio	Sensitivity	(He and Field, 2018)
2018	USWC	Stock	California scorpionfish	Base	(Monk et al., 2018)
2018	USWC	Stock	Yellowtail	Base	(Stephens and Taylor, 2018)

enforcing an explicit distinction between habitat and catchability covariates, VAST seeks to eliminate the common ambiguity between habitat and catchability covariates. VAST typically cannot identify whether a given variable should be treated as affecting catchability or density, and this decision generally requires theoretical insight from analysts.

3.3. Condition on missing covariates

VAST estimates the effect of measured processes (habitat and catchability covariates), approximates the effect unmeasured processes (unobserved variables or processes that affect local density), and uses both when predicting derived quantities. Previous research has explored algorithms for imputing unobserved processes (e.g., imputing biomass in unsampled areas; Carruthers et al. (2011)), while VAST approximates the net effect of unmeasured processes using spatially correlated random effects. These random effects serve two main purposes: (A) inclusion of random effects is used to represent the spatial correlation in available data, which would otherwise invalidate statistical tests for covariates or confidence intervals for derived quantities; (B) predictions of these spatial random effects are a useful approximation of the aggregate effect of unobserved variables and processes. VAST predicts population density based on both habitat covariates and spatial and spatio-temporal random effects, and in this way it "conditions upon" the missing processes and covariates that inform these random effects (Thorson and Ward, 2013; Shelton et al., 2014). I recommend further research comparing statistical imputation (using random effects) and algorithmic imputation (using assumptions about sampled locations), but in either case recommend careful consideration of how this is done (also see Section 5: Dealing with Interactions in Maunder and Punt, 2004).

3.4. Bridge between univariate and multivariate applications

Previous index-standardization models have generally focused on single-species applications (univariate data). However, analysts will need to model multiple species to interpret transitions in community composition (Hovel et al., 2017), multiple sizes to interpret ontogenic habitat shifts (Kristensen et al., 2014; Kai et al., 2017), and multiple ages to expand age-composition samples (Hocking et al., 2018; Thorson and Haltuch, In press). VAST allows analysts to explore simplified models for individual species, but also to transition analyses to include multiple species/age/size/stage categories whenever this becomes necessary.

4. Fifteen major decisions when using package VAST

Analysts must make many decisions when running VAST for a given assessment process. Although these decisions are listed in the various papers introducing new features of VAST (e.g., Table 1), there is no single document providing guidance regarding all of these decisions or how they relate to one-another. I therefore summarize these major decisions, while noting the specific inputs used to implement decisions in footnotes (for further details regarding software usage, please see the User Manual and R help files). I also organize these decisions into a decision tree (Fig. 1), where analysts can start either with inputs (data characteristics) or outputs (desired quantities to estimate) and identify relationships among major decisions.

4.1. Spatial domain used when calculating derived quantities

The first decision is what spatial domain to define. Many fishery surveys use stratified-random sampling within a pre-defined domain, and in this case the analysis will typically be restricted to that spatial domain so that estimates of abundance are directly comparable to design-based indices. In other cases, analysts may analyze fishery catch-per-unit-effort (CPUE) or other types of opportunistic data, where there is no pre-defined spatial domain. VAST requires analysts to define the area over which densities are to be extrapolated when calculating derived quantities, and VAST installs an "extrapolation grid" defined for surveys that have been previously analyzed. When analyzing data from a region for which no "extrapolation grid" has already been developed, VAST attempts to guess at an appropriate area by using all areas within a specified distance from the nearest sample[4].

When analyzing opportunistic data, I recommend that analysts define the area that is included in any stock assessment for that fishery as spatial domain, even if there are no sampling data available for a portion of that spatial domain. For example, fishery CPUE data are often not available for all areas that are included in a stock assessment, and VAST will have higher predictive uncertainty when predicting density in these areas with low/zero sample sizes. The variance of many derived quantities is an increasing function of the variance and covariance for predicted density (Kass and Steffey, 1989). Consequently, the resulting abundance index will generally be more precise in years where a greater proportion of area had CPUE data available, and I believe that this is a reasonable default behavior for any CPUE abundance index. If opportunistic data only sample a very small portion of the area occupied by a stock, then this is likely an indication that these data are not appropriate to generate an abundance index for that stock. In this case, I recommend integrating multiple data sources to achieve a reasonable spatial coverage of the stock area (e.g., Grüss et al., 2017).

4.2. Which categories (species/sizes) to include

Next, analysts must decide which categories (species/size/age/stage) are modeled. This decision can easily be revised later, but affects subsequent decisions in this decision tree. I recommend starting with as simple a model as possible (e.g., using several univariate models for a multispecies analysis), and add model complexity gradually (in this case, by transitioning to a multivariate model). This simple-to-complex model building process is useful to diagnose issues, e.g., if a problem arises when analyzing data for one particular category. An increase in the number of categories generally increases model complexity (number of possible model configurations to explore) and computational cost (model run time). I therefore recommend including multiple categories only when it is likely useful to share information among categories (Thorson and Barnett, 2017), or when study goals are intrinsically linked to a multivariate analysis, e.g., when seeking to estimate covariation among species (Thorson et al., 2016a; Dolder et al., 2018)[5].

4.3. Identify whether to analyze encounter, abundance, and/or biomass-sampling data

Analysts must decide whether to analyze encounter/non-encounter (binary), abundance (count), or biomass (real-valued) data, and this decision dictates what distribution and link-functions should be used (see section 4.12). It is also possible to fit VAST using multiple data types, and this feature is currently being tested (A. Grüss, personal communication). Many fisheries analyses are conducted using population biomass, and VAST uses a delta-model (Table 2, Eq. (2.5)) for biomass-sampling data that separately estimates encounter-probability

[4] Analysts specify an "extrapolation grid" that defines the spatial domain using input 'Region' to function 'FishStatsUtils::make_extrapolation_info'. Inputting 'Region = "Other' generates an extrapolation grid based on the location of sampling data and 'FishStatsUtils::Prepare_User_Extrapolation_Data_Fn' can be used to specify a user-defined extrapolation grid.

[5] The user specifies the response (e.g., sampled biomass) for each sample using vector `b_i`, where vector `c_i` indicates the category (species, age, etc) for each sample. Both `b_i` and `c_i` are passed to `?VAST::Data_Fn`.

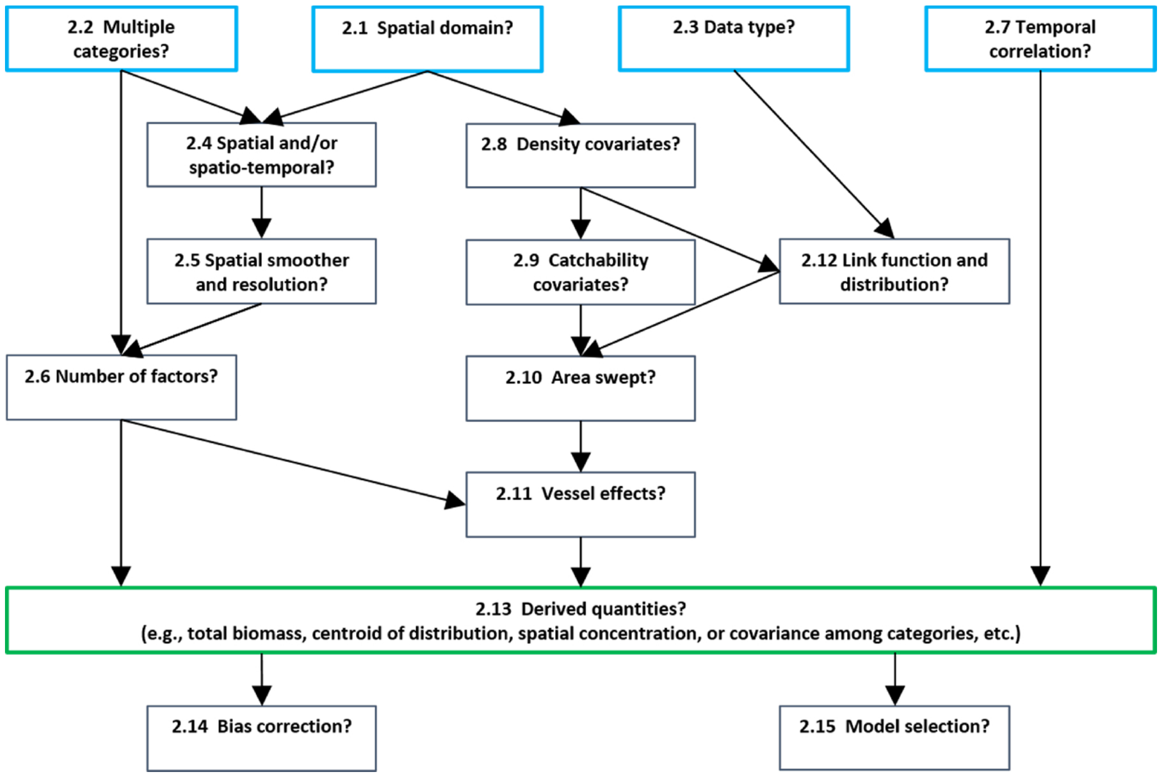

Fig. 1. Decision tree representing the relationship between decisions (boxes) listed in the main text. Analysts are advised to start either with inputs (blue boxes) or outputs (green box) and proceed via arrows to related decisions; the direction of each arrow is chosen to visualize the recommended path when starting with inputs, but can be reversed to indicate the path when starting with outputs. Arrows indicate that a given decision (box) has a strong dependency upon earlier decisions (arrows flowing in) and strong effect on later decisions (arrows flowing out); weak dependencies are not explicitly represented but do in some cases exist. The order of boxes is chosen to simplify drawing of arrows, whereas the order in the main text is chosen to simplify textual description (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

and positive catch rates. Analysts may instead analyze abundance (counts), and VAST uses a zero-inflated model (Eq. (2.6)) that separately estimates the probability that sampling occurs in habitat where the species will never occur ("zero-inflation probability"), and the expected abundance within occupied habitat ("abundance-density"). VAST includes features for analyzing biomass-sampling data that does not include zeros in one or more years, and also for count-data that is not zero-inflated, and users are directed to the R-help documentation for dealing with these instances. The delta-model and zero-inflated models involve two separate "linear predictors" that are then transformed to predict available data. Each linear predictor can include an intercept, spatial and spatio-temporal variation, habitat and catchability covariates, and a random effect representing overdispersion (see section 5. Model Structure for a detailed explanation). Finally, VAST has been fitted to encounter/non-encounter (binary) data, and in this case it is only necessary to estimate parameters for one of the two linear predictors (Grüss et al., 2017, 2018a). I recommend analyzing as many data as are available, while accounting for differences in sampling design or sampling vessels as catchability covariates or vessel-effects (e.g., Dolder et al. (2018), see later sections for details).

4.4. Including spatial and/or spatio-temporal variation

Spatial autocorrelation (i.e., a spatial pattern in model residuals) will often arises when a statistical model does not account for all of the processes (either environmental drivers, or intrinsic biological dynamics) that drive autocorrelated variation in population density. Proper statistical inference (testing significance of covariates, or estimating confidence intervals for derived quantities) requires accounting for spatial autocorrelation (Dormann et al., 2007), and the presence of autocorrelation can be explored by including a spatial random effect and estimating whether its estimated variance is substantially greater than zero. Furthermore, conditioning model predictions upon residual patterns, e.g., as is done when kriging (Petitgas, 2001), can substantially improve predictions of population abundance (Bahn and McGill, 2007).

For these two reasons, I recommend by default that analysts include variation in population density that is constant over time ("spatial variation") and that varies among modeled time-intervals ("spatio-temporal variation") for both linear predictors in either a delta-model or zero-inflated model. This involves making a decision about four model components (spatial and spatio-temporal variation for both linear predictors). Spatial variation represents a species' "fundamental niche" (its expected spatial distribution on average over time), while spatio-temporal variation represents a species' environmental response (response to transient, unmeasured environmental conditions). The estimated magnitude of spatial variation will be greater than spatio-temporal variation whenever species have stable patterns in spatial distribution, and vice-versa whenever spatial distribution varies greatly among years. It is necessary to include spatio-temporal variation to accurately characterize shifts in distribution (Thorson et al., 2017b). If the estimated standard deviation of spatial or spatio-temporal variation approaches zero (i.e., < 0.001), then it may hinder model convergence and I recommend that this component be removed[6]. In some cases,

[6] This decision is made by specifying the input `FieldConfig`, passed to function `VAST::Data_Fn`, where e.g., `FieldConfig = c("Omega1" = 1, "Epsilon1" = 1, "Omega2" = 0, "Epsilon2" = 0)` indicates that VAST should include spatial and spatio-temporal variation in the 1st linear predictor (Omega1 and Epsilon1, respectively), and should remove spatial and spatio-temporal variation for the 2nd linear predictor (Omega2 and Epsilon2, respectively).

model selection may indicate that a spatial or spatio-temporal component is not parsimonious even though its variance is greater than zero (Tolimieri et al., 2015).

However, there are several cases where it is useful to remove spatial or spatio-temporal variation by default. For example, many count-data models do not have sufficient information to estimate spatial or spatio-temporal variation in zero-inflation probability. In these cases, the analyst may choose to remove spatial and spatio-temporal variation for the first linear predictor, and instead deal with an excess of zeros using options for estimating overdispersion in the 2nd linear predictor. An analyst may also seek to conduct species ordination (categorize species based on similar dynamics), and this task could be difficult when estimating all four spatial/spatio-temporal covariance matrices. In this case, the analyst may choose a priori to only include spatial or spatio-temporal variation (see the 2nd case study below). Finally, any analysis that includes only a single time period requires removing spatio-temporal variation a priori.

4.5. Choosing the spatial smoother and resolution

Spatial models generally shrink the value of a random effect towards its value at nearby locations. VAST accomplishes this in a computationally efficient manner using three options for a spatial smoother. The default option uses a stochastic partial differential equation (SPDE) approximation to a Matérn correlation function (Lindgren et al., 2011), which is applicable for any set of points within two spatial dimensions (a “2D mesh”). This SPDE approach is widely used in the popular R-INLA software (Illian et al., 2012), and VAST allows users to specify a Matérn function that is either isotropic (where correlations decline at the same rate in any direction) or follows geometric anisotropy (where the rate at which correlations decline depends upon the direction of movement). Geometric anisotropy is common in marine ecosystems, where correlations decline slowly when moving along a depth contour but rapidly when moving perpendicular to the depth contour (Thorson et al., 2015b). As an alternative, VAST also allows users to specify an isotropic exponential correlation function, defined at equally spaced locations within a given spatial domain (called a “2D grid” in VAST). I recommend exploring the 2D grid as a sensitivity analysis, to explore whether the decision about spatial smoother causes a substantial change in model results. VAST includes a new, fourth option to model spatial correlations using network distance within rivers and streams (Hocking et al., 2018), although documentation and examples for this feature are a work in progress (M. Rudd, personal communication).

VAST also achieves computational efficiency by defining spatial variables at a specified number of “knots” within a “predictive process” statistical framework (Banerjee et al., 2008). The user specifies the number of knots a priori, and VAST defines the location of knots to minimize the average distance between samples and knots. Any location is assumed to have all spatial variables equal to their value at the nearest knot, so the number of knots implicitly defines the spatial resolution at which VAST estimates spatial variation in population density. I recommend that users start with a small number of knots during model testing and development (perhaps 50–100), and then increase the number to the maximum that is feasible on a given machine. For applications being used for fisheries management, I also recommend that users work with their regional review organizations (e.g., Scientific and Statistical Committees in the US) to pre-define a number of knots, so that decisions about the number of knots are made independently of any opportunity to look at model results.[7] In cases with spatially unbalanced data (e.g., fishery-dependent CPUE), research suggests that it is important to place knots evenly over the modeled spatial domain rather than in proportion to available data (A. Grüss, personal communication)[8].

4.6. Choosing the number of spatial and spatio-temporal factors

VAST can be fitted to both univariate (single response) and multivariate (multiple response) data sets, and VAST models covariation among multiple categories using a factor-modelling approach (Thorson et al., 2015a; Warton et al., 2015a) where this notation is presented later (see section 5. Model Structure). For a model with C categories, the number of factors F can be any whole number $F \in \{0,1, 2, \ldots, C\}$, and this decision must be made separately for four separate components (spatial and spatio-temporal variation for each linear predictors)[9]. Specifying $F = 0$ implies that a given spatial/spatio-temporal component has been “turned off”, and a univariate model involves turning on ($F = 1$) or turning off ($F = 0$) each component. Deciding upon the appropriate number of factors is clearly more complicated in a multivariate model. For example, in a model with $C = 3$ categories and $F = 1$ factors for spatial variation in the linear predictor affecting encounter probability, VAST estimates a single factor representing spatial variation in encounter probability, and estimates a 3-by-1 “loadings matrix” representing the impact of that factor on encounter probability for each category. Continuing this example, if the analyst next explores $F = 3$, VAST then estimates three factors for spatial variation in encounter probability and a 3-by-3 loadings matrix representing the impact of each factor on each category. To ensure that each parameter has a unique value (is “identifiable”) all upper-triangle elements of the loadings matrix are fixed at zero. This factor-modelling approach can greatly reduce model complexity: a “full-rank” model (where $F = C$) must estimate many more covariance parameters than a “reduced rank” model (where $F < C$), particularly when modelling many categories[10].

4.7. Specifying temporal correlation on model components

In addition to specifying correlations across space (using spatial and spatio-temporal random effects) and among species (using a factor-modelling approach), VAST allows users to specify a correlation structure across time. Specifically, users can separately specify a temporal correlation for both annual intercepts and/or spatio-temporal variation for each of the two linear predictors (i.e., four separate model decisions)[11].

The intercept for each linear predictor is a fixed effect for each year by default. This default ensures that estimates of abundance are essentially independent for each modeled year, which is appropriate when estimating an abundance index to be used as data in a subsequent stock assessment model (see case study #1 below). However, users can instead specify that intercepts follow a first-order autoregressive process, a random-walk process, a random process that is independent

[7] Users specify the default smoother using input `Method="Mesh"`, where the number of knots is then specified using input `n_x`. Both are inputted to function `FishStatsUtils::make_spatial_info`.

[8] For case-by-case features like this, the model structure may vary in the future and interested users should read the Rhelp documentation for relevant functions.

[9] This decision is again made by specifying the input `FieldConfig` where e.g., `FieldConfig = c("Omega1"=4, "Epsilon1"=3, "Omega2"=0, "Epsilon2"=0)` indicates that VAST should use four factors for spatial variation in the 1st linear predictor, three factors for spatio-temporal variation in the 1st linear predictor, and turn off spatial and spatio-temporal variation in the 2nd linear predictor (this input would only make sense when analyzing data for four or more categories).

[10] The full rank model estimates $0.5C(C + 1)$covariance parameters, which scales as C^2, while the reduced rank model estimates $CF + 0.5F(F + 1)$ covariance parameters, which scales as CF.

[11] This decision is made by specifying the input `RhoConfig`, which by default is `RhoConfig = c("Beta1"=0, "Beta2"=0, "Epsilon1"=0, "Epsilon2"=0)` but where codes for alternative options described in the text are listed in the R help file, `?VAST::Data_Fn`

among years, or be constant for all years. Specifying a constant intercept ensures that all changes over time are attributed to spatio-temporal variation, density, and catchability covariates, and therefore is useful when using spatio-temporal covariation to define species similarity ("species ordination"). Similarly, specifying an autoregressive or random-walk structure on intercepts is useful when interpolating an abundance index into years when data are not available (which is impossible when treating the intercept as a fixed effect), or when forecasting abundance in future years (Thorson, In press; see section 6.3 Forecasting species allocations).

Meanwhile, the spatio-temporal component is independent among years by default, but users can instead specify that it follows an autoregressive or random walk process. Estimating a temporal correlation for spatio-temporal components allows VAST to estimate whether "hotspots" in population density typically persist from one year to the next. I recommend estimating a temporal correlation for spatio-temporal variation whenever some areas are not sampled in every year and the analyst wants to ensure that "hotspots" estimated in sampled areas are propagated into unsampled areas in adjacent years. For example, the Bering Arctic Subarctic Integrated Survey sampled the northern but not the southern portion of their standard sampling area in 2015 (Yasumiishi et al., 2017). However, both northern and southern portions were sampled in 2014 and 2016, so the relative population density in northern vs. southern areas in those years could be used to predict the relative density in 2015, despite the lack of sampling data in the southern portion. Similarly, the Gulf of Alaska bottom trawl survey is conducted every other year (Von Szalay and Raring, 2016), and to interpolate density in unsampled years it is necessary to estimate a temporal correlation for spatio-temporal variation.

4.8. *Including density covariates as a semi-parametric model*

VAST allows users to specify covariates that affect population density, and consequently affect expected catch rates (termed "density covariates"). However, VAST uses density covariates twice: (I) in the two linear predictors to calculate the probability of each sample, and (II) in the prediction of population density within the spatial domain, to be used when calculating derived quantities. Therefore, VAST requires the value of density covariates at every location within the spatial domain. This requirement is notably different from sampling data, which are not needed at all locations in a given year; the response variable (sampling data) can be missing for some locations while predictor variables (the density covariate) cannot be missing for any location. To simplify this process, VAST requires users to input the value of density covariates at every knot and in every year, and it uses these values twice to accomplish steps I and II above[12].

Density covariates are particularly useful for three common tasks: extrapolation, attribution, and variance partitioning. When samples are not available at a fine spatial scale or in some areas of the modeled spatial domain, a density covariate can be useful to interpolate/extrapolate population density. This usage is common in semi-parametric models, where a biological model (e.g., estimated response to a density covariate) can improve precision when combined with a non-parametric smoother (Shelton et al., 2014; Thorson et al., 2014a). It can also be useful to compare models with and without covariates to determine what proportion of variance in a derived quantity is explained by a given covariate. When there is a strong biological or mechanistic argument for how the covariate drives variation in population density or a derived quantity, this approach can attribute observed patterns to one or more covariates (Thorson et al., 2017b). Finally, including a density covariate will generally decrease the variance of residual spatial and spatio-temporal variation, and the degree to which this happens can be used to determine the variance explained by a given covariate. This variance explained can then be used to evaluate the strength of evidence for competing biological hypotheses regarding population density (e.g., Thorson, 2015a).

By incorporating density covariates for each knot and year, VAST involves an important assumption: that density covariates are effectively constant for all locations associated with a given knot. This implies that users cannot include variation in density covariates that occurs at a finer spatial scale than the scale implied by the number of knots. Future research could relax this requirement (e.g., by specifying density covariates at a finer spatial scale than spatial autocorrelation), but for now users must increase the number of knots if they want to decrease the spatial scale for density covariates.

4.9. *Accounting for catchability covariates and confounding variables*

In addition to habitat covariates, users can also specify covariates that affect expected catch rates that are not associated with changes in population density (termed "catchability covariates"). VAST requires a value for catchability covariates for every datum, so the user is required to specify a matrix of catchability covariates with a row for every sample[13], and catchability covariates are not needed at locations where sampling is not conducted. This format differs from the input format for density covariates because density covariates are needed not just for samples, but also for all locations within the modeled spatial domain.

I recommend exploring as catchability covariate any variable that could plausibly affect catch rates but not reflect variation in population density. For example, weather conditions and vessel characteristics can affect bottom trawl gear performance (Stewart et al., 2010; Thorson and Ward, 2014), hook spacing can affect hook-and-line performance (Monnahan and Stewart, 2018), and longline characteristics can affect the vertical distribution of hooks in and outside of a species' vertical distribution (Bigelow and Maunder, 2007). These examples all involve characteristics of fishing operations, and it is therefore easy to argue that these variables affect catchability but not population density.

However, other covariates could plausibly affect either population density or catchability. For example, light levels near bottom could be associated with increased/decreased nutrient concentrations in the water column, thus affecting habitat suitability and population density, or alternatively could affect the vertical distribution of visual-foraging groundfishes (Casey and Myers, 1998). In these cases, I recommend that analysts explore including these covariates (to determine if they are associated with variation in catch rates), and it they are significant then use either experiments, paired sampling of multiple gears, or validated conceptual models to distinguish between the hypothesis that a given variable affects catchability or affects population density. To continue our example, paired acoustic and bottom trawl sampling suggests that light levels are associated with vertical distribution (and hence bottom trawl catchability) in walleye pollock in the Eastern Bering Sea (Kotwicki et al., 2015).

Catchability covariates can be important for two main reasons. First, ignoring a catchability variable that varies systematically over space or time will result in a biased estimate of spatio-temporal variation in population density. This occurs because ignoring systematic variation in catchability will cause estimates of population density to include variation in both catchability and density. Second, including a catchability covariate will often reduce the estimate of residual variation in catch rates. Reducing residual variation will, in turn, result in more

[12] Density covariates are inputted as object \`X_xtp\` passed to \`VAST::Data_Fn\`, where the notation indicates that \`X_xtp\` has three dimensions with length number of knots (\`n_x\`), number of years (\`n_t\`) and number of covariates (\`n_p\`)

[13] Catchability covariates are inputted as object \`Q_ik\` passed to \`VAST::Data_Fn\`, where the notation indicates that \`Q_ik\` has two dimensions with length number of samples (\`n_i\`) and number of catchability covariates (\`n_k\`)

precise estimates of population density, and therefore improve estimates of any derived quantities (i.e., an index of abundance). However, including catchability covariates can also make it more complicated to build, maintain, communicate, or replicate a spatio-temporal model, so it is generally useful to include only when it explains a substantial portion of variation in catch rates.

4.10. Treating area swept as a catchability covariate or offset

The most common type of "catchability covariate" is survey effort. Historically, many fisheries models have analyzed a survey response (catch in biomass) divided by survey effort (e.g., area swept by a bottom trawl) as their response variable. If using a conventional delta-model and a scale-free distribution for the response (i.e., the lognormal distribution), then this treatment is identical to analyzing the response (catch in biomass) while treating survey effort as an "offset" for positive catch rates. However, these two treatments are not identical in many other cases, e.g., when analyzing "count data" such that dividing a count by effort will often result in a non-integer number that cannot be analyzed using standard count-data models.

VAST allows users to include an effort offset and I recommend doing so whenever effort is measured in units of area[14], so that resulting abundance indices will have units of numbers (for count data) or biomass (for biomass data). This approach is appropriate when analyzing gears with a known "area swept," e.g., bottom trawls, acoustic samples, or visual samples where distance-sampling methods have been used to estimate an effective area. However, many data sets will involve sampling gears where the area swept is unknown or not measured, e.g., for hook-and-line or baited visual sampling where the "area of attraction" is unknown (Runnebaum et al., 2017). In these cases, a user of VAST can input a value of one for the effort offset. Ignoring the area of attraction for a sampling gear implies that some derived quantities will have a scale that is not directly interpretable (e.g., resulting abundance indices will be proportional to abundance with an unknown proportionality constant), while others will be unaffected (e.g., indices of distribution shift are invariant to multiplying area-swept for all samples by a positive constant). Analysts can divide the abundance-index by its mean (creating a log-centered index) without loss of information when an abundance-index has a scale that is not interpretable (e.g., when derived from sampling data without a meaningful area swept). This log-centered index can then be compared with other log-centered indices (e.g., the same abundance-index derived from other techniques) to evaluate the change in index precision when using VAST.

VAST also allows users to analyze data from multiple sampling gears and/or designs. When combining data from multiple gears, I recommend that analysts estimate a "catchability coefficient" for all but one gear (e.g., Grüss et al., 2017). When using a delta-model, it may be necessary to include two "catchability coefficients" for each additional gear (e.g., for encounter probability and positive catch rates in a conventional delta-model). In most cases, estimating the difference in catchability will require that both gears sample nearby locations in the same year, where differences in the survey response at these "calibration samples" can inform the difference in catchability among gears (Miller et al., 2010). However, VAST users can use model-based methods to intercalibrate gears operating at the same location in adjacent years when specifying some temporal structure for model intercepts (Runnebaum et al., 2017). However, the performance of model-based calibration methods has not received sufficient research or simulation testing to recommend its wide use.

I generally recommend that authors analyze "raw" data (e.g., the survey response) while treating effort as an offset, rather than transforming data prior to analysis (O'Hara and Kotze, 2010; Warton, 2018). However, I do recommend that analysts explore including effort as a catchability covariate in addition to using it as an effort offset. This can be important whenever expected catch is a nonlinear function of survey effort, e.g., due to different rates of gear saturation in hook-and-line gears, or different rates of fish falling into the codend of bottom trawl gears for short vs. long trawl tows.

4.11. Including vessel effects as overdispersion

VAST allows users to specify random variation in catchability among different levels of a grouping variable. When the grouping variable identifies different survey and/or commercial sampling vessels, then this random variation is typically called a "vessel effect" (Helser et al., 2004), and research suggests that vessel effects can be substantial even when using standardized sampling gears within a designed survey (Thorson et al., 2015b). VAST requires users to specify a level of this grouping variable for each sample, and it uses a factor modelling approach to model covariation in vessel effects, where analysts can specify $F = \{0,1,\ 2,\ \dots, C\}$ factors when modelling C categories in a multivariate model[15]. Covariation in vessel effects can be useful to distinguish vessel targeting (due to differences in fishing location at fine scales or unmeasured differences in gear operations) from covariation in species densities (Thorson et al., 2017a).

4.12. Choosing among link functions and distributions

VAST typically estimates two linear predictors, and transforms linear predictors to predict encounter probability and positive catch rates (in a delta model) or zero-inflation probability and count rates (in a zero-inflated model). By default, VAST uses a logit link function to calculate encounter or zero-inflation probability, and a log link function to calculate positive catch and count rates (Eq. 2.3). However, analysts can instead specify a log-link for both linear predictors when using the Foster and Bravington (2013) parameterization of the Tweedie distribution, although this distribution is computationally expensive (and therefore slow) to estimate. Similarly, analysts can specify a "Poisson link delta model," which approximates the Tweedie distribution without requiring additional computational resources relative to the conventional delta-model (Eq. 2.4). Recent research suggests that the Poisson-link often provides a better fit to bottom trawl data than the conventional delta-model, and this model also allows easier interpretation of covariate effects and effort offsets (Thorson, 2017). I therefore recommend comparing performance of the Poisson-link and conventional delta models for biomass-sampling data.

It is necessary to specify a probability distribution for available data[16]. Options for count data include a Poisson, negative-binomial, Conway-Maxwell Poisson, or lognormal-Poisson. The Poisson distribution is a "null" model for count data, while the negative binomial is useful to account for overdispersion (Lindén and Mäntyniemi, 2011) and the Conway-Maxwell Poisson accounts for both under- and overdispersion (Lynch et al., 2014). In our experience, a lognormal-Poisson distribution is more computationally stable than the negative binomial when estimating overdispersion, so I recommend using it by default when fitting count data. Options for continuous data include the normal, lognormal, and gamma distributions. For both data types, I

[14] The area offset for each sample is inputted as object `a_i` passed to `VAST::Data_Fn`, where the notation indicates that `a_i` has one dimension with length number of samples (`n_i`)

[15] The level of an "overdispersion factor" (e.g., vessel effect) for each sample is inputted as object `v_i` passed to `VAST::Data_Fn`, where the notation indicates that `v_i` has one dimension with length number of samples (`n_i`). The covariance in the overdispersion factor is inputted as object `OverdispersionConfig`, which by default is turned off using `OverdispersionConfig = c("Eta1" = 0, "Eta2" = 0)`.

[16] Users specify both the link function and distribution for data using input `ObsModel` passed to `VAST::Data_Fn`, and codes for different options can be found in the R help file `?VAST::Data_Fn`.

recommend exploring multiple distributions. If it is necessary to identify a single model, I recommend using standard model selection tools (see section 4.15 Model Selection) to identify the distribution that results in a parsimonious fit to the data (e.g., Dick, 2004).

4.13. Derived quantities

By default, VAST estimates population density at each knot and year for every category, and also estimates an index of abundance for each modeled category. However, VAST can be used to generate many other derived quantities that can be useful in specific circumstances[17].

When conducting climate assessments, VAST can be configured to estimate the biomass-weighted average for a variable defined at each knot. This is typically used to estimate the centroid of the population's distribution ("center of gravity", COG), measured as kilometers in Eastings and Northings, to identify distribution shifts. While sample-based measures of COG area also available, these sample-based measures confound shifts in the location of sampling (whether random or systematic) with shifts in population density. By contrast, VAST accounts for spatially unbalanced designs during parameter estimation, and therefore avoids this source of potential bias (Thorson et al., 2016b). Similarly, VAST estimates the area needed to contain each category given its average density (termed "effective area occupied"), and changes in effective area indicate range expansion/contraction e.g. for species that are expanding into a given ecosystem (Thorson et al., 2016c).

VAST can be configured to calculate the proportion of total population biomass that belongs to each modeled category in a multivariate model. This could be useful in stock assessments, e.g., when applied to biomass for multiple size/age categories to estimate the proportion of total biomass within each size/age class (Hocking et al., 2018; Thorson and Haltuch, In press). It is also possible to specify multiple spatial strata, and VAST will estimate the total population biomass within each specified stratum. Specifying spatial strata has no effect on parameter estimates, and only affects the portion of the spatial domain that is used when calculating each abundance index (see case study #3 below).

VAST can also be configured to rotate estimated spatial and spatio-temporal factors to identify dominant modes of community dynamics, and this could be useful in ecosystem assessments. This rotation has no impact on parameter estimates or model parsimony, and instead is useful to visualize important features of the resulting model. Specifically, a "varimax rotation" is useful to identify factors that are associated with a small subset of species (so that the spatial distribution or spatio-temporal variation in each subset can be visualized and interpreted). Alternatively, a "PCA rotation" is defined such that the first axis represents the maximum proportion of community-level variation, and is therefore useful to visualize the dominant pattern of spatio-temporal dynamics within a given ecosystem (Thorson et al., 2016a). I recommend using "PCA rotation" to summarize and visualize community-level patterns of covariation, so that analysts can identify a factor that explain the maximum proportion of variance possible (McClatchie et al., In press). By contrast, I recommend using "varimax rotation" when conducting species ordination, so that analysts can identify groups of species that strongly covary.

Finally, analysts may want to visualize the standard error of predicted density for each category at each knot and year by plotting them on a map. Estimating many standard errors is somewhat time-consuming, but can be useful to identify areas where estimates are relatively more or less precise. Each of these derived quantities can also be calculated using alternative techniques (e.g., generalized linear models for index standardization; non-metric multidimensional scaling to identify modes of community dynamics). I recommend ongoing studies to compare model performance, and note a growing literature suggestion model-based inference for these different types of analysis (e.g., Warton et al., 2015b).

4.14. Bias correction for derived quantities

VAST uses maximum-likelihood methods to identify an optimal estimate for model parameters. VAST then predicts random-effects based on maximum-likelihood estimates for parameters, and calculates derived quantities via nonlinear transformation of fixed and random effects. However, any nonlinear transformation of a random effect will result in a biased estimator, known as "retransformation bias" when it occurs within spatial models. Although VAST implements the "epsilon bias-correction estimator" (Thorson and Kristensen, 2016) to correct for retransformation bias, this bias-corrected estimator is computationally expensive to calculate. Analysts must therefore decide which variables to bias-correct. I recommend bias-correcting any derived quantity that is interpreted for ecological or management purposes, including abundance indices, center-of-gravity, and effective area occupied. However, time can be saved by not bias-correcting other variables (e.g., local predictions of density) that are not used to make decisions. The magnitude of bias-correction depends on (1) how nonlinear is the transformation being applied to random effects, and (2) how uncertain are the estimates of random effects being transformed. Therefore, it is particularly important to use bias-correction when derived quantities have large differences in standard error, e.g., when estimating an abundance index for years where the survey samples a different proportion of the spatial domain in different years.

4.15. Model selection

Given the many decisions that must be made when applying VAST to a new data set, I envision that analysts will sometimes identify multiple models that could be appropriate. In these cases, I recommend exploring each model in detail, including diagnostics of model fit and numerical experiments fitting to new data that are simulated with either the correct or a mis-specified model. After discarding models that have poor fit, I recommend presenting results from multiple models, perhaps within a model ensemble (Stewart and Martell, 2015). However, if it is necessary to select only a single model, I recommend using conventional model selection tools to identify the optimal model, including the Akaike Information Criterion (Burnham and Anderson, 2002), k-fold crossvalidation (Gelman et al., 2014; Hooten and Hobbs, 2015), retrospective skill-testing (Thorson, In press), or a simulation experiment conditioned upon estimated parameters for each model. This latter options is available in VAST using a "bootstrap simulator" that simulates new random effects and data based on the maximum-likelihood estimate of fixed effects, where this new data set can then be fitted again within a replicated experiment to explore likely model performance.

5. Model structure

Having read guidance for these fifteen decisions, some readers will be curious about how these decisions are translated into statistical model structure. I therefore provide a high-level outline of the VAST model, and readers are directed to the User Manual for additional details.

At its core, VAST estimates fixed and random effects that govern two linear predictors. The two linear predictors each include the impact of annual intercepts, density covariates, catchability covariates, vessel effects, spatial random effects, and spatio-temporal random effects for one or more category. For example, the first linear predictor $p_1(i)$ for sample i is calculated as:

[17] Calculating derived quantities such as COG and effective area is done by specifying object `Options`, e.g., ` Options = c("Calculate_Range"=1, "Calculate_effective_area"=1)` passed to `VAST::Data_Fn`.

$$p_1(i) = \overbrace{\beta_1(c_i, t_i)}^{Intercept} + \overbrace{\sum_{f=1}^{n_{\omega 1}} L_{\omega 1}(c_i, f)\omega_1(s_i, f)}^{Spatial\ effect} + \overbrace{\sum_{f=1}^{n_{\varepsilon 1}} L_{\varepsilon 1}(c_i, f)\varepsilon_1(s_i, f, t_i)}^{Spatio-temporal\ effect}$$
$$+ \overbrace{\sum_{f=1}^{n_{\eta 1}} L_1(c_i, f)\eta_1(v_i, f)}^{Vessel\ effect} + \overbrace{\sum\nolimits_{p=1}^{n_p} \gamma_1(c_i, t_i, p)X(s_i, t_i, p)}^{Density\ covariate}$$
$$+ \overbrace{\sum\nolimits_{k=1}^{n_k} \lambda_1(k)Q(i, k)}^{Catchability\ covariate} \quad (1)$$

where c_i is the category sampled, t_i is the year, and s_i is the knot for sample i, the second linear predictor $p_2(i)$ is defined similarly, and other symbols are defined in Table 3. This linear predictor includes the summation across n_p density covariates $X(s, t, p)$ defined at every location and year, and n_k catchability covariates $Q(i, k)$ defined at every sample. However, it also includes a "factor model" for spatial, spatio-temporal, and vessel terms, and these terms are likely unfamiliar for many analysts who do not commonly conduct multivariate analysis. Looking at the spatial term $\sum_{f=1}^{n_{\omega 1}} L_{\omega 1}(c_i, f)\omega_1(s_i, f)$ in detail, $\omega_1(f)$ is a vector of random effects that has a mean of zero and standard deviation of 1.0, representing unmeasured spatial variation $\omega_1(s, f)$ in the first linear predictor for location s as represented by factor f, and the impact of each factor on species c is estimated as a parameter $L_{\omega 1}(c, f)$ in loadings matrix $\boldsymbol{L}_{\omega 1}$. Spatial and spatio-temporal random effects are shrunk towards a spatial (and optionally temporal; see section 4.7) correlation function that is specified by the analyst. When specifying a univariate model, the model can only include one factor and the notation reduces to $\sigma_{\omega 1}\omega_1$ such that $L_{\omega 1}(c_i, f)^2 = \sigma_{\omega 1}^2$. When specifying a multivariate model, the estimated loadings matrix and factors (e.g., $\boldsymbol{L}_{\omega 1}$ and $\omega_1(f)$ for spatial variation in the 1st linear predictor) can be rotated to ease interpretation without otherwise impacting the model likelihood (see section 4.13).

Linear predictors are then transformed to predict sample data. When using a conventional delta-model, for example, they are transformed to predict encounter probability $r_1(i)$ and positive catch rates $r_2(i)$:

$$r_1(i) = logit^{-1}(p_1(i))$$

$$r_2(i) = a_i \times exp(p_2(i)) \quad (2)$$

where a_i is the effort offset. When using a lognormal distribution to continue our example, the probability of biomass sampling data is calculated as:

$$\Pr(B = b_i) = \begin{cases} 1 - r_1(i) & if\ B = 0 \\ r_1(i) \times Lognormal\{B = b_i | r_2(i), \sigma_m^2(c_i)\} & if\ B > 0 \end{cases} \quad (3)$$

where b_i is observed biomass, and $\sigma_m^2(c_i)$ is the residual variance in positive catch rates.

Finally, VAST predicts population density $d(s, c, t)$ for each location, category, and time from both transformed linear predictors when dropping terms affecting catchability. Continuing our example with the conventional-delta model, density is predicted as:

$$d(s, c, t) = \text{logit}^{-1}\left(\beta_1(c_i, t_i) + \sum_{f=1}^{n_{\omega 1}} L_{\omega 1}(c_i, f)\omega_1(s_i, f) + \sum_{f=1}^{n_{\varepsilon 1}} L_{\varepsilon 1}(c_i, f)\varepsilon_1(s_i, f, t_i) + \sum\nolimits_{p=1}^{n_p} \gamma_1(c_i, t_i, p)X(x_i, t_i, p)\right)$$
$$\times \exp\left(\beta_2(c_i, t_i) + \sum_{f=1}^{n_{\omega 1}} L_{\omega 2}(c_i, f)\omega_2(s_i, f) + \sum_{f=1}^{n_{\varepsilon 1}} L_{\varepsilon 2}(c_i, f)\varepsilon_2(s_i, f, t_i) + \sum\nolimits_{p=1}^{n_p} \gamma_2(c_i, t_i, p)X(x_i, t_i, p)\right) \quad (4)$$

VAST then calculates derived quantities from its predictions of local density $d(s, c, t)$. For example, an abundance index $I(c, t, l)$ for category c in time t for spatial stratum l is calculated as:

$$I(c, t, l) = \sum_{s=1}^{n_s} (a(s, l) \times d(s, c, t)) \quad (5)$$

where $a(s, l)$ is the area associated with knot s that is within that stratum l. This area $a(s, l)$ is used to weight the relative weighting of density estimates at different knots when calculating derived quantities, and depends upon the spatial domain defined for the model, hence explaining the importance of carefully defining the spatial domain (see section 4.1). For the calculation of other derived quantities please see Table 2. Standard errors for any derived quantity are calculated by TMB using the delta-method (Kass and Steffey, 1989), and this approach propagates uncertainty about predictions of density $d(s, c, t)$ as well as estimated parameters; previous simulation experiments suggest that these standard errors accurately represent predictive uncertainty (Thorson et al., 2015b; Thorson and Haltuch, In press).

6. Applying the decision-tree to three hypothetical assessments

Here I provide three worked examples of this decision-tree for hypothetical applications for use in stock, ecosystem, and climate assessments. These three examples involve publicly available survey data from the North Pacific. Code to replicate these analyses is available online (Supporting Information 1), and data are downloaded from regional databases and harmonized to follow a common data format using package *FishData* (Thorson, 2015b).

6.1. Index standardization

Many analysts seek to estimate an index of abundance that is proportional to population biomass, and default settings are generally appropriate for this usage. I therefore illustrate how to estimate an abundance index using data from the Eastern Bering Sea shelf bottom trawl survey, conducted annually since 1982 (Lauth and Conner, 2016). This survey uses a fixed station design, and I use as 'spatial domain' the 496,000 square-kilometer area of ocean habitat that is also considered when applying design-based estimators to this data set. I analyze biomass-sampling data for a single species, arrowtooth founder (*Atheresthes stomias*), and include both spatial and spatio-temporal variation for both linear predictors in a Poisson-link delta model, while using a gamma distribution for positive catch rates (i.e., replacing the conventional delta-model with different link-functions in Eqs. (2) and (4). Given that this is a univariate data set, it is computationally practical to analyze density changes at a relatively fine spatial scale. I therefore use the "2D mesh" smoother including geometric anisotropy, with 1,000 knots that are located to minimize the average distance between a grid overlaid on the spatial domain and the 1,000 knots. Given that analysts often use the resulting abundance index as data within a stock assessment model, I minimize covariance in the estimated index by excluding any temporal correlation on model components (i.e., the intercept is a fixed effect in each year, and the spatio-temporal term is independent in each year). For simplicity of presentation, I do not include any density or catchability covariates (i.e., removing those terms from Eq. (1), but do include the area-swept by the bottom trawl as an effort offset (specify a_i in Eq. (2). Following standard practice when analyzing data from this survey, I do not include survey vessel as a source of overdispersion, and calculate three main derived quantities (abundance index, center of gravity, and effective area occupied) while bias-correcting each of these[18] (i.e., using Eq. (5), and 2.15/2.17 in Table 2).

Inspection of the resulting abundance index, center-of-gravity, and

[18] These decisions are implemented using the following inputs (with # indicating comments in R):

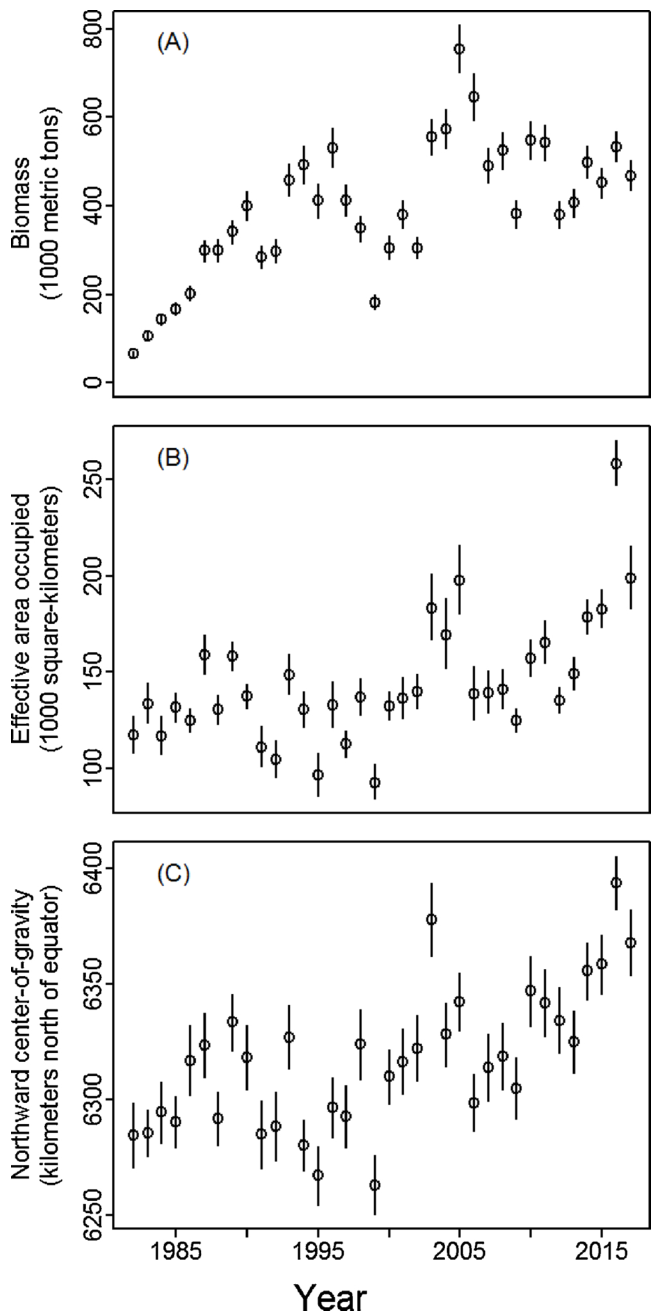

Fig. 2. Abundance index (panel A; representing total biomass in the chosen spatial domain), effective area occupied (panel B; representing area needed to contain the population at average biomass-density), and northward center-of-gravity (panel C; representing centroid of the population), each showing bias-corrected maximum likelihood estimate (circles) and +/− one standard error (whisker) for each year of survey data 1982–2017 for arrowtooth flounder (*Atheresthes stomias*) when using the default configuration for VAST.

effective area occupied for arrowtooth flounder in the Eastern Bering Sea (Fig. 2) illustrates tremendous changes in this stock over the past 30 years. Its estimated survey biomass has risen from < 100,000 to nearly 500,000 metric tons, while the population has increased its effective area occupied from 120,000 to 180,000 square kilometers, and the centroid of the population has shifted over 100 km northward. These derived quantities all highlight the expansion of this predatory species into the Eastern Bering Sea shelf ecosystem (e.g., Spencer et al., 2016).

6.2. Species ordination

Analysts may instead use VAST to identify groups of species that have similar or different spatio-temporal dynamics (called "species ordination"), such that these assemblages could be studied or managed differently. Therefore, I next illustrate model settings for species ordination by using data for eight groundfishes from the Gulf of Alaska bottom trawl survey, which has been conducted every third year from 1984 to 1999 and every second year from 1999-2017. As spatial domain, I select all areas that are within the sampling-frame for the survey. I model biomass for each species separately using a multivariate model with eight categories. However, I fix the intercept for each species to be constant over time, and eliminate spatial and spatio-temporal variation in the 2nd linear predictor of the Poisson-link delta model while using a gamma distribution for positive catch rates. I avoid including density or catchability covariates, and analyze biomass divided by area swept as the response without an effort offset (this is the form in which data are publicly available). This model specification ensures that variation among sites and years is explained entirely by spatial and spatio-temporal variation in the "numbers density" of the Poisson-link model, such that species can be "ordinated" by interpreting these two model components, which represent differences in long-term distribution (spatial niche) vs. short-term patterns (shared response to environmental variation). I again use the 2D mesh smoother with geometric anisotropy, and this time use 500 knots. I include two factors for spatial and spatio-temporal variation in the 1st linear predictor, because this is as many factors as can be easily displayed on a 2-dimensional ordination plot, and specify a 1st order autoregressive process on spatio-temporal variation.[19] As a derived quantity, I apply a "varimax rotation" to the 8-by-2 loadings matrices (for spatial and spatio-temporal variation) to visualize associations of each species with the two estimated spatial and spatio-temporal terms. I also apply the inverse-rotation matrix to spatial and spatio-temporal factors, so that I can visualize patterns in average spatial distribution (represented by spatial variation) and changes in density among years (represented by spatio-temporal variation). Given that the loadings matrix is only a function of fixed effects and visualizing rotated factors does not require a nonlinear transformation, bias-correction is not necessary and I skip it to conserve computational resources.

Species ordination results show that the average spatial distribution of *Hippoglossoides elassodon* (flathead sole), which is positively associated with factor 1, is largely independent of the average spatial distribution of *Microstomus pacificus* (Dover sole), *Anoplopoma fimbria* (sablefish), and *Glyptocephalus zachirus* (rex sole), which are positively associated with factor 2 (Fig. 3 top panel). Factor 1 is associated with increased population densities inshore from Kodiak island to the start of the Aleutian Islands and decreased densities in Southeast Alaska (Fig. 4 left panel), while factor 2 is associated with increased densities from Prince William Sound to Southeast Alaska. Meanwhile, species ordination based on spatio-temporal variation (Fig. 3 bottom panel) shows that *Hippoglossus stenolepis* (Pacific halibut) and *Gadus microcephalus* (Pacific cod) have correlated dynamics from a shared, positive association with factor 2, while other species have strongly correlated dynamics (from a positive association with factor 1). Visualizing these factors shows, e.g., that densities of *H. stenolepis* and *G. microcephalus* were elevated (relative to their average density) to the east of Kodiak Island in 1984 (Fig. 5; red area in top-right panel), and were depressed relative to their long-term average from Prince William Sound to Southeast Alaska in 2001 and again in 2017. These estimates highlight how patterns of elevated or depressed densities are correlated among multiple species, and could be used to communicate with local communities regarding fishing opportunities for groundfish assemblages

[19] These decisions are implemented using the following inputs (with # indicating comments in R):

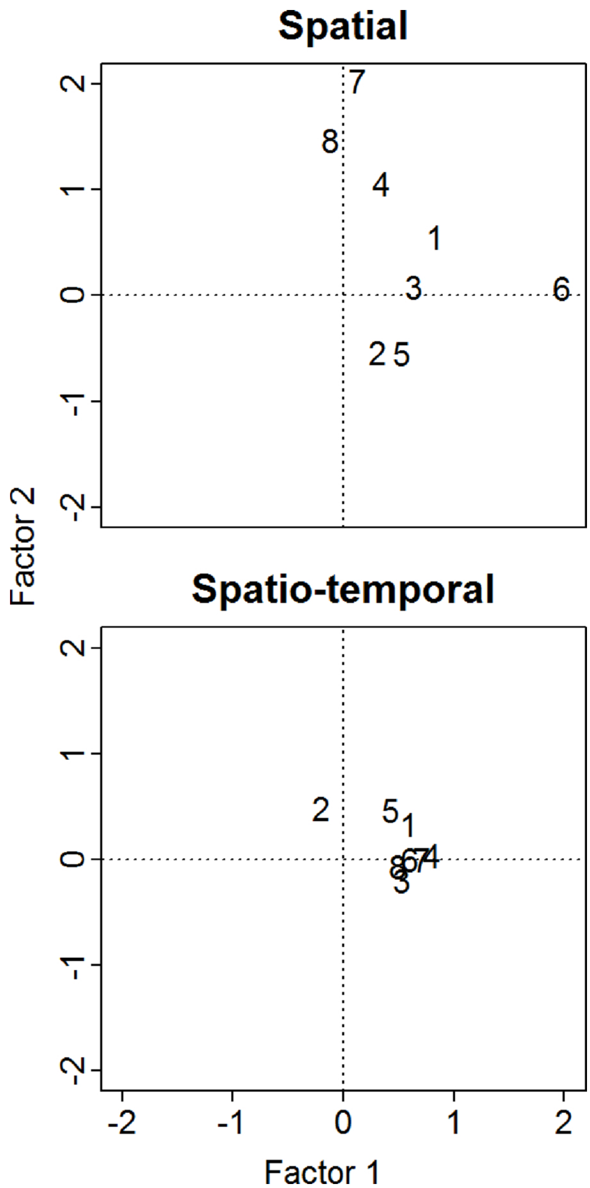

Fig. 3. Loadings matrix after varimax rotation (which rotates the loadings matrix $\boldsymbol{L}$ in Eq. (1) such that each factor has strong loadings for as few species as possible, see decision 4.13)for spatial variation (top panel) or spatio-temporal variation (bottom panel) affecting the 1st linear predictor of a Poisson-link delta model (representing variation in log-numbers density) for eight groundfishes in the Gulf of Alaska bottom trawl survey 1984–2017 (1: *Atheresthes stomias*, arrowtooth flounder; 2: *Hippoglossus stenolepis*, Pacific halibut; 3: *Gadus chalcogrammus*, Walleye pollock; 4: *Glyptocephalus zachirus*, rex sole; 5: *Gadus microcephalus*, Pacific cod; 6: *Hippoglossoides elassodon*, flathead sole; 7: *Microstomus pacificus*, Dover sole; 8: *Anoplopoma fimbria*, sablefish). The absolute-value of each element of the loadings matrix represents the standard deviation for the associated spatial or spatio-temporal process, and the sign indicates whether it has a positive or negative association with a given spatial or spatio-temporal process.

that have similar dynamics.

6.3. Forecasting spatial allocations

Finally, I envision that analysts may seek to forecast changes in species distribution and how that impacts the optimal allocation of fishing quota among multiple spatial strata (e.g., Thorson, In press). I therefore illustrate model settings when using VAST to forecast the proportion of coastwide abundance that occurs within different spatial strata. Output from such an analysis could be used to inform the allocation of allowable catch to fleets based in different strata, while using the forecasts to account for distribution changes that are likely to occur during a lag between scientific advice and management implementation. Specifically, I fit to survey data for five commercially important groundfishes off the US West Coast, obtained using the West Coast groundfish bottom trawl survey, WCGBTS (Keller et al., 2017). As of writing (June 19, 2018), data were publicly available from 2003 to 2015, and I envision a hypothetical scenario where fisheries managers might want information on the proportion of coastwide biomass within federal waters for each of three states in 2016 and 2017. This activity therefore involves fitting data for 13 years and then forecasting future changes over the following two years.

As spatial domain, I select the US West Coast waters from 55 m to 1280 m depth while specifying three spatial strata (California: 32–42°N; Oregon: 42–46°N; Washington: 46–49°N Latitude) to use when calculating derived quantities. I apply a multivariate model with five categories, and fit to biomass-sampling data for each using a Poisson-link delta model and a gamma distribution. I include both spatial and spatio-temporal variation in both linear predictors, and use a “saturated” factor model (5 factors) for each component such that VAST estimates the full 5-by-5 covariance matrix for each spatial and spatio-temporal component. To accommodate data for five species, I use a relatively coarse spatial resolution (100 knots), and again use a 2D mesh smoother with geometric anisotropy. To allow VAST to forecast biomass in years with no data, I specify a temporal structure on model intercepts, i.e., a random walk process. I also specify a 1st-order autoregressive process for spatio-temporal variation, such that hotspots in population density decay towards the average spatial distribution during forecast years, where the rate of decay (a.k.a. strength of spatio-temporal autocorrelation) is estimated based on dynamics during years with available data. This autoregressive process for spatio-temporal variation means that hotspots in population density in 2015 will decay towards the average density for that species during forecast years. I do not include density or catchability covariates, but do include area-swept by the bottom trawl as an effort offset. Importantly, the WCGBTS contracts 3–4 commercial fishing vessels to conduct survey operations in each year, and previous research suggests that it is important to include a random effect for each unique combination of vessel and year, called a “vessel-year effect” (Helser et al., 2004; Thorson and Ward, 2014). I therefore include each vessel-year combination as an overdispersion term, using five factors to approximate the full covariance among species in vessel-year effects for each linear predictor. To save computational resources, I do not calculate any derived quantities except an abundance index for each species, which I bias-correct for each spatial stratum.[20]

Forecasts of groundfish distribution (Fig. 6) show considerable variability in the proportion of coastwide abundance in state waters for *Eopsetta jordani* (Petrale sole) and *Ophiodon elongatus* (lingcod), and little variability for *Sebastolobus alascanus* (shortspine thornyhead). As expected, the proportion in each state’s waters during forecast years (2016–2017) decays towards its average value over years when data are available (2003–2015). This is particularly evident for *O. elongatus*, e.g., where the proportion in Washington waters is high in 2014, but declines in 2015 and is forecasted to continue declining in 2016–2017. Also as expected, the predictive interval for each species increases in the 1st and then 2nd forecast year relative to the period with available data. This increase in uncertainty is appropriate, as the model is forecasting future distribution shifts during these years, and the increase in interval width is greatest for species with highly variable distributions (i.e., *O. elongatus* and *E. jordani*).

[20] These decisions are implemented using the following inputs (with # indicating comments in R):

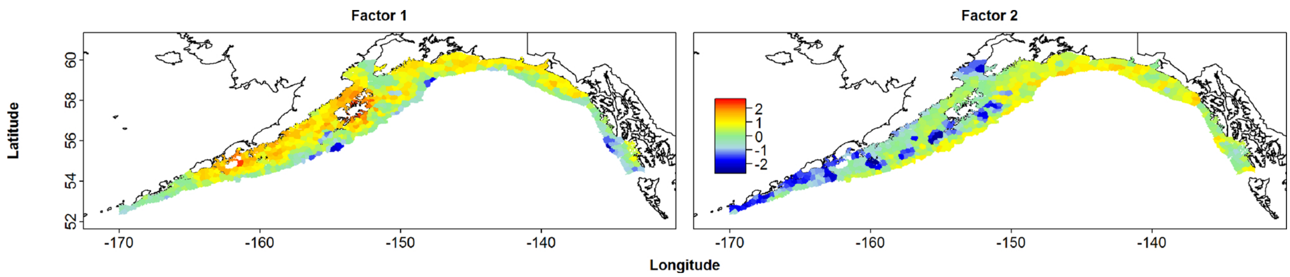

Fig. 4. Plot of two factors for spatial variation in the 1st linear predictor of a Poisson-link delta model ($\omega_1(f)$ from Eq. (1), representing log-numbers-density) for ten groundfishes in the Gulf of Alaska bottom trawl survey, visualized after varimax rotation (see Fig. 3 for association of each factor with each species and description of varimax rotation).

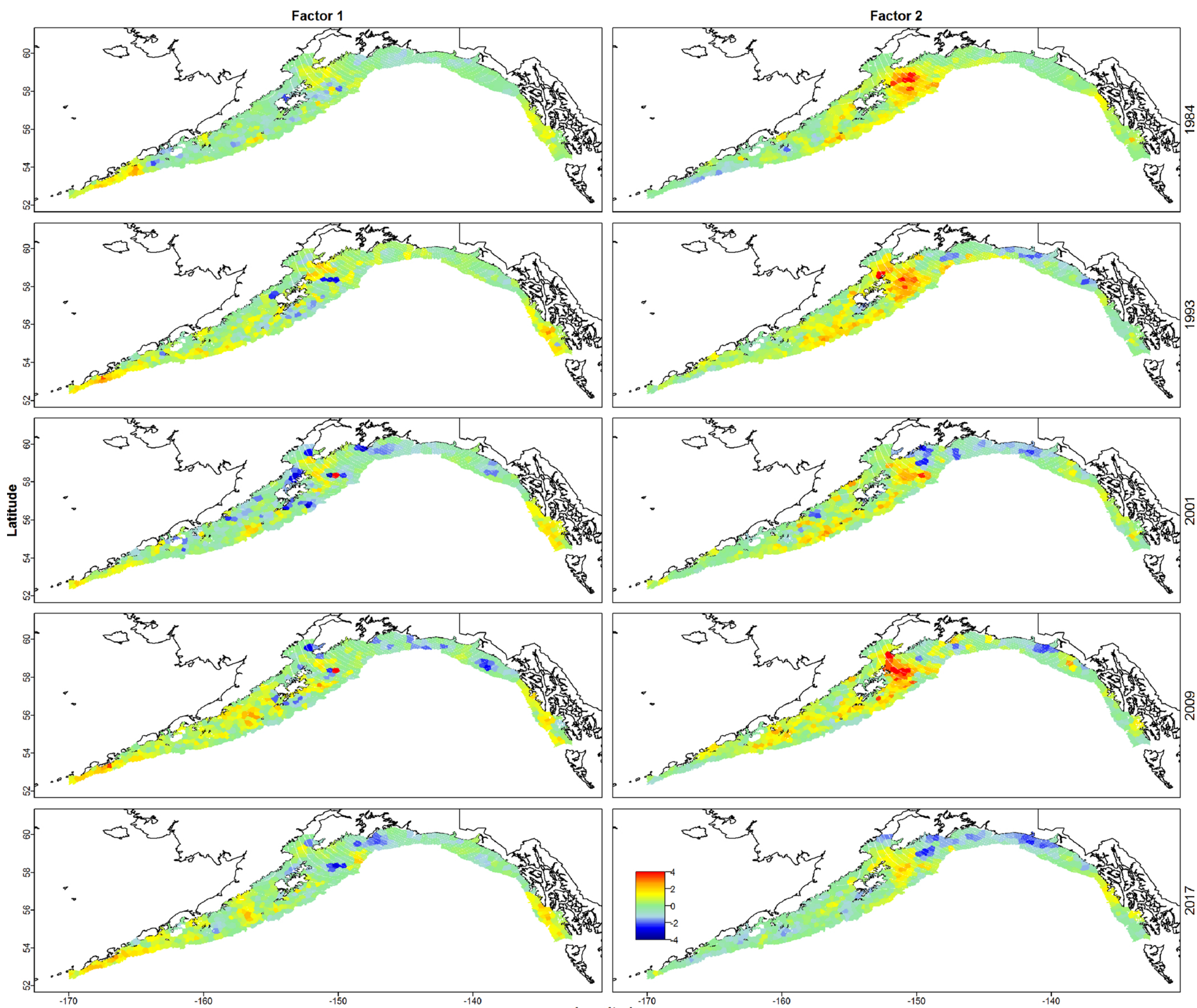

Fig. 5. Plot of two factors for spatio-temporal variation ($\varepsilon_1(f, t)$ from Eq. (1) in five years when bottom trawl sampling was conducted (1984, 1993, 2001, 2009, 2017), visualized after varimax rotation (see Fig. 4 caption for details) (For interpretation of the references to colour in the text, the reader is referred to the web version of this article).

7. Limitations and future developments

There are many potential applications of spatio-temporal models to common activities within fisheries science and management. I therefore conclude by briefly summarizing a few potential directions that have not been extensively investigated in hopes of stimulating future research, and also discuss ongoing limitations.

7.1. Optimal survey design

Fisheries scientists are often tasked with prioritizing funding for a portfolio of different field-sampling programs. This task could be

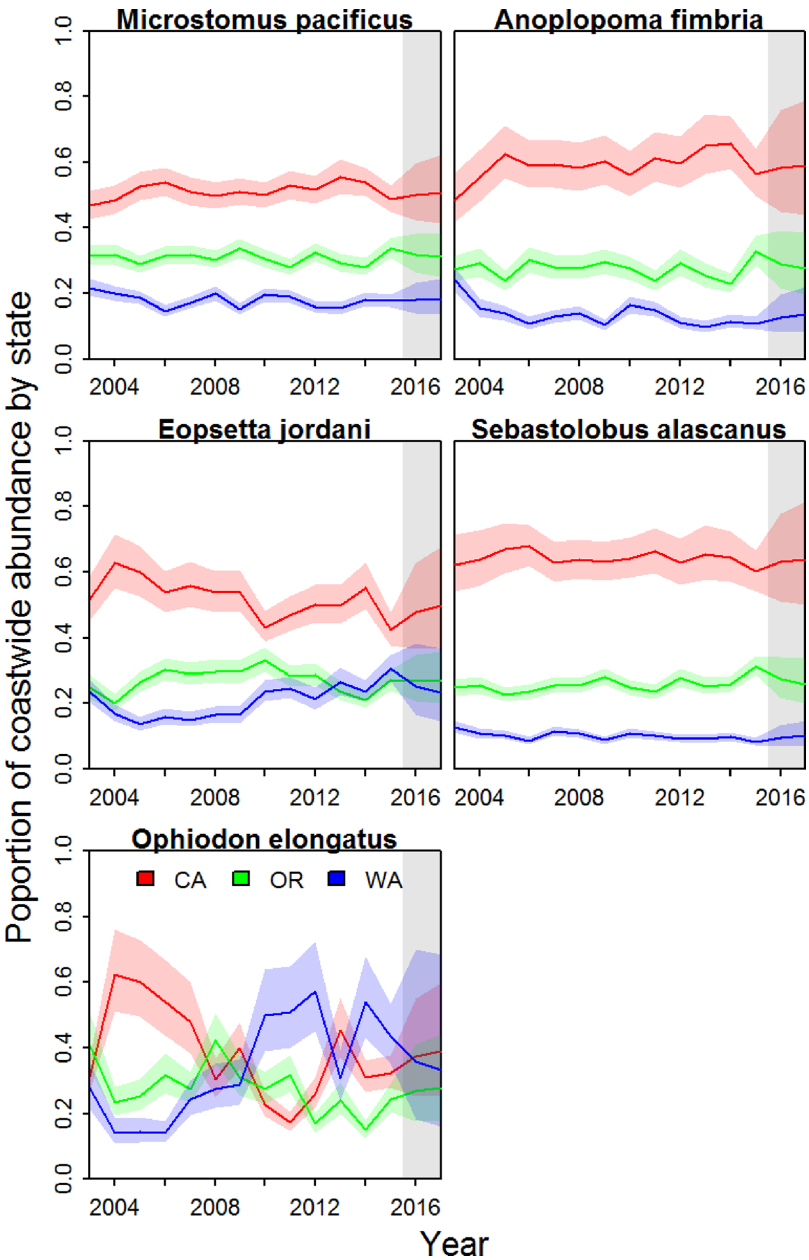

Fig. 6. Estimates of the proportion of coastwide biomass within federal waters of three states (y-axis) in each year 2003–2017 (x-axis) for five groundfishes (figure panels) as estimated using the US West Coast groundfish bottom trawl survey for years with publicly available survey data (2003–2015) as well as forecasted years without publicly available data (2016–2017; indicated by a grey shaded area), where each panel shows the estimated proportion (lines) in each state (red: California; green: Oregon; blue: Washington) as well as +/− one standard error (shaded area) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

informed by using spatio-temporal models to optimize sampling designs given funding constraints and management goals, or at least to eliminate designs that are clearly suboptimal relative to some multi-objective criteria. This activity requires three main tasks: (1) estimate spatial variation in biomass (and associated uncertainty) for multiple species/stages across the spatial domain; (2) develop multiple potential survey designs, or some constraints defining a feasible set of survey protocols; (3) define one or more performance criteria that can be used to assess relative performance of these different survey designs. Critically, evaluating these performance criteria requires simulating new data sets (based on estimates of population density and its uncertainty from Step #1), applying candidate survey designs to each simulated data set, and evaluating the performance of survey designs while averaging across all simulation replicates (Reich et al., 2018). Useful performance criteria range from relatively simple (e.g., precision for resulting abundance indices) to complex (e.g., risk of poor economic performance due to mis-allocating quota among different spatial regions). In particular, I recommend future research to explore the use of spatio-temporal models within a closed-loop simulation context, where previous model estimates and management decisions can impact future performance outcomes. This is conceptually similar to management strategy evaluation (Sainsbury et al., 2000), although survey optimization could include a wide range of closed-loop simulations without explicitly modelling a management procedure.

7.2. Economic assessment

Similarly, there has been surprisingly little previous research applying spatio-temporal models to economic assessments of fishery performance, despite the many clear avenues for research (e.g., Abbott et al., 2015; Thorson et al., 2018). Expanding upon our third case-study example (section 3.3), spatio-temporal models could be used to estimate the proportion of population biomass that was within the spatial domain fished by a given fleet or fishing port. This proportion could then be compared with port-specific landings to identify the degree to which fishing fleets can buffer against resource availability while seeking positive economic outcomes. Recent research has shown the importance of species portfolios when analyzing economic performance for different fleet segments (Anderson et al., 2017), but this work generally has not involved estimates of resource density at the fine spatial scales that are available for targeting by local fishing fleets. Similarly, spatio-temporal methods could be used to generate short-term forecasts of resource distribution, and this information could be used when forecasting impacts of alternative management actions on profits and employment.

7.3. Analyzing opportunistic data

There is growing interest in using spatio-temporal methods to synthesize data from one or more opportunistic data sources, e.g., to combine catch-per-unit-effort (CPUE) data from fishers with sampling data from resource surveys. Recent research has developed several news ways to analyze fisher targeting (Winker et al., 2013; Thorson et al., 2017a; Okamura et al., 2017), so I am hopeful that methods could be developed to estimate resource density by simultaneously analyzing both fishery-dependent and –independent data sources. Similarly, populations will sometimes range across the spatial domain sampled by different resource surveys, e.g., by latitude (sablefish in US West Coast, Canadian, and Gulf of Alaska waters) or by vertical distribution (Alaska pollock in areas accessed by both bottom trawl and acoustic sampling gears; (Kotwicki et al., 2015)). Although some studies have integrated data from multiple surveys with overlapping spatial footprints (Dolder et al., 2018; Grüss et al., 2018a), there is a need for more methods to account for spatial differences in catchability between different surveys and to diagnose instances when data should or should not be combined.

7.4. Limitations

There are many avenues for improving inference when estimating spatio-temporal variation using VAST, and I hope that these will be resolved after further development and testing. For example, population density may vary over smaller spatial scales in some habitats than others; however, VAST smooths spatial variation using a spatial correlation function that is constant spatially. Recent statistical research has developed new approaches to model spatial variation wherein covariates could be used to identify areas where spatial correlations decay rapidly or slowly with distance (Risser and Calder, 2015), and VAST contributors are currently exploring these options for inclusion in VAST (J. Best, pers. comm.). If computationally efficient, these methods could be used to specify that spatial correlations decay quickly over land, e.g., such that two locations on separate sides of an island are correlated only via the distance separating them along the coastline and not by distance over land. Analysts have also noted instances where estimates of biomass are consistently greater or less than design-based estimators for a sequence of years. As a result, there are ongoing questions about the magnitude of bias arising when the model structure in VAST (e.g., the distribution of residual variation, spatial smoother, etc.) is highly mis-specified relative to the data-generating process. Therefore, I highly recommend further simulation testing in the presence model mis-specification. Relatedly, there is a pressing need for better statistical diagnostics of model fit, which could hopefully identify cases where the model is sufficiently mis-specified that resulting estimates should not be trusted.

7.5. Synopsis

I have argued that estimates of local density for multiple locations, years, and species can serve as a common currency to unify disparate approaches to stock, ecosystem, habitat, and climate assessments. This common currency can be estimated using multivariate spatio-temporal models, such as the package *VAST* that I have highlighted here. However, spatio-temporal models are a relatively new tool, and involve many unfamiliar decisions for analysts. For this reason, I described fifteen major decisions that must be made when applying VAST, and demonstrated these decisions using three novel, real-world case studies.

These case studies illustrate that a common currency can be used to hindcast and forecast changes in abundance, distribution, area occupied, covariation among species, and dominant patterns of community variation, and these derived quantities can address many different questions for fisheries management. Such questions have previously been addressed using many distinct models, within different teams, with different vocabulary and communication methods. I hypothesize that increased adoption of a spatio-temporal modelling framework will help to integrate these disparate assessment communities over the next 10 years.

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