Update

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# Model review

The proposed model uses a zero-inflated log-normal likelihood with a Poisson link function. The linear predictors for numbers density, , and weight per group, , are

Where each linear predictor may include:

* : abundance fixed effects (e.g. year)
* : abundance spatial effects
* : abundance spatiotemporal effects
* : catchability fixed effects (e.g. vessel/fleet)
* : catchability spatial effects
* : catchability spatiotemporal effects

The spatial and spatiotemporal effects parameter vectors take multivariate normal distributions, each of which depends on independent parameters and . These parameters can be difficult to estimate. In two dimensions and fixing the Matérn smoothness parameter to ,

where is the distance where correlation drops to roughly . This parameter cannot be consistently estimated under in-fill asymptotics (adding additional observations within a fixed domain). The parameter on the other hand *can* be consistently estimated under in-fill asymptotics[[1]](#footnote-20). It is the essential the ratio of the marginal standard deviation and the correlation range,

The intuition here is that a field with short correlation range and small variance will generate similar realizations to a field with long correlation range and large marginal variance. In a model that includes all the specified spatial and spatiotemporal effects, eight and eight parameters must be estimated.

# Progress

## Bugs

At the beginning of the summer I was struggling to fit models with spatial and spatiotemporal random fields for abundance, i.e. to be on par with the basic functionality of VAST. I discovered and fixed two major bugs in my TMB model. One covariance parameter was mis-indexed so that one parameter was shared by two random fields and another was not used by the model at all. This fix was straightforward once discovered. The second was a misunderstanding of how the Eigen library can reshape a two-dimensional matrix into a vector. My spatiotemporal random fields were originally two-dimensional matrices, with mesh nodes as rows and years as columns. This was based on my understanding of the facilities in TMB for separable spatiotemporal random fields and made calculating the final indices of abundance simpler. However, I still needed a single vector in order to calculate my linear predictor and project the field to the observation locations.

## Fitting data generated by the estimation model

The TMB model includes the ability to simulate observations from the estimation model given a set of parameter values and observation locations. This simulated data was used to test the model’s ability to recover generative parameters. The model did well recovering parameter values, with some important caveats. The primary issue is that the optimizer often gets stuck in areas of parameter space where the Hessian is not positive definite. This can indicate that the parameter values are at a saddle rather than a maximum, or be the result of numerical issues when calculating the eigenvalues of a poorly conditioned matrix. The optimizer consistently finds parameter values with a positive definite Hessian when spatial and spatiotemporal abundance and spatial catchability are estimated, along with their and parameters. Including spatiotemporal catchability usually results in a non-positive definite Hessian. It is also important to note that parameter values with positive definite Hessians are most often found when the initial parameter values are very close to the final values. In the case of data generated from the estimation model, the generative values were used to initialize the optimization procedure.

## Where are the negative eigenvalues coming from?

For model fits whose hessian is not positive definite, # Future

At this point I would like to focus on fitting models with spatial and spatiotemporal abundance random fields and spatial catchability random fields. I may consider including spatiotemporal catchability random fields later, but I would like to push forward in the direction that seems most promising.

I have started fitting models using data simulated from the operating model I have specified. Without

## Dealing with initial values

I am experimenting with using phasing (estimating fixed effects, then including spatial abundance, then spatiotemporal abundance, and finally spatial catchability).

## Regularizing random field parameter estimates

Including a penalty term to keep the correlation range and marginal standard deviation under control can stabilize the estimation of these parameters. The penalized complexity framework aims to specify prior distributions for Bayesian analysis that shrink models toward simpler “base” models[[2]](#footnote-27). In the case of the Gaussian random fields used here, penalized complexity priors can be used as penalty terms for the and parameters. This prior/penalty tends to shrink the Gaussian random field toward having an infinite correlation range and zero variance, i.e. a constant. These priors are intuitively parameterized, so that for some correlation range and tail probability ,

Similarly, for a marginal standard deviation and tail probability ,

The joint prior can be calculated in terms of and , even when it is parameterized in terms of and . Attempts to use this prior as a penalty term have been promising, resulting in positive definite Hessians, but more work is needed to validate the code and choose appropriate values of and for each estimated Gaussian random field.

1. Fuglstad et al., 2018. *Constructing priors that penalize the complexity of Gaussian random fields*. J Am Stat Assoc. <https://doi.org/10/ggkqqb> [↑](#footnote-ref-20)
2. Simpson et al., 2017. *Penalising model component complexity: a principled, practical approach to constructing priors*. J Am Stat Assoc. <https://doi.org/10.1214/16-STS576> [↑](#footnote-ref-27)