Spatial density surface estimation from distance sampling surveys

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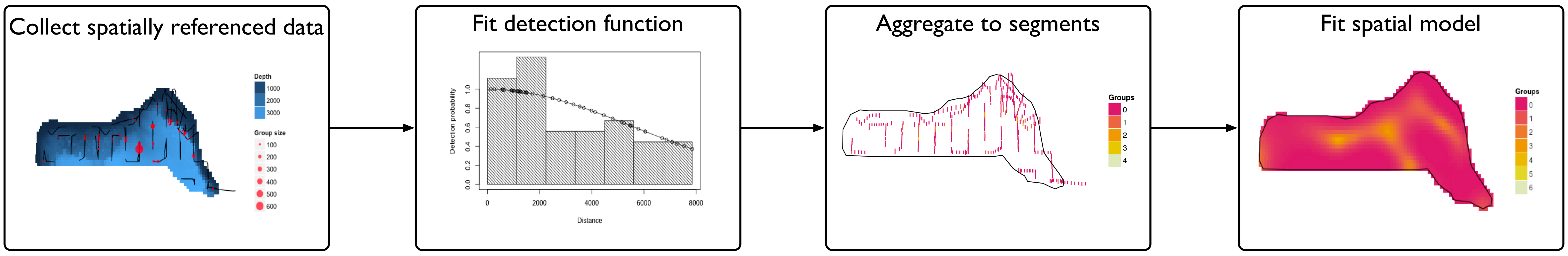
Density surface modelling



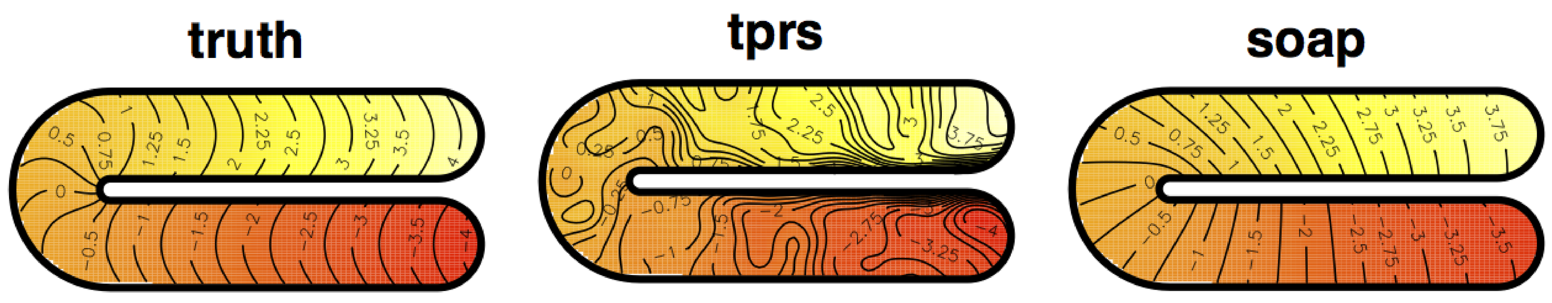
In Distance we follow the approach of Hedley and Buckland (2004). Having fit a detection function, we aggregate the effective strip widths (CDS) or estimated abundances to segments (MCDS). We then fit a spatially referenced model to the segment data. Models include:

$$\mathbb{E}(\mathbf{n_j}) = \exp\left[\log_e(2\hat{\mu}\mathbf{l_j}) + \sum_k \mathbf{f_k}(\mathbf{z_{jk}})\right] \text{ (CDS models)} \quad \textit{or} \quad \mathbb{E}(\hat{\mathbf{N}}_\mathbf{j}) = \exp\left[\log_e(2w\mathbf{l_j}) + \sum_k \mathbf{f_k}(\mathbf{z_{jk}})\right] \text{ (MCDS models)}$$

where $\mathbf{n_j}$ is count per segment, $\hat{\mu}$ is the effective strip width, $\mathbf{l_j}$ is the length of the segment, $\hat{\mathbf{N}}_\mathbf{j}$ is the (Horvitz-Thompson) estimated abundance in the segment and $\mathbf{w}$ is the truncation distance. $\mathbf{j = 1, \ldots, J}$ index the segments. The $\mathbf{f_k}$s are smooths of environmental covariates $\mathbf{z_{jk}}$.

Recent developments

Complex region smoothers



- Often the study region has an odd shape.
- This can lead to incorrect inference.
- Recent advances in spatial modelling allow us to work around this.
- We opt for the soap film smoother approach of Wood et al. (2008).

Variance propagation

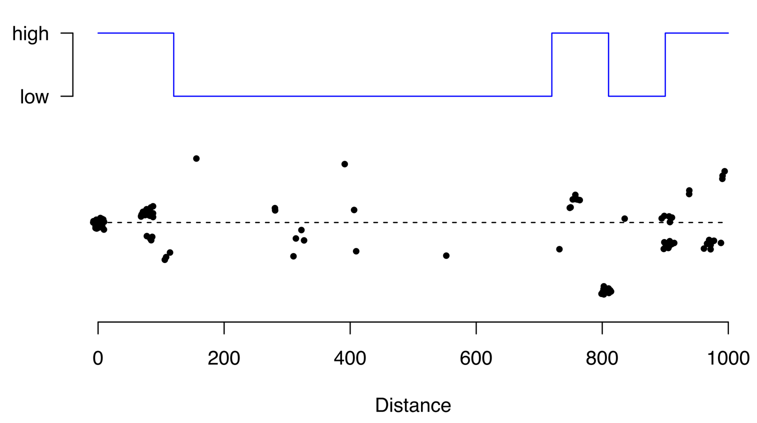
- Uncertainty in detection function estimation and the spatial model must be combined.
- Usually achieved using the *delta method* $\Rightarrow$ independence between detection process and the spatial process
- Clearly this is not the case!
- Williams et al. (2011) propose a method of *variance propagation*:
  - Fit a spatial model with

$$\mathbb{E}(\mathbf{n_j}) = \exp\left[\log_e(2\hat{\mu}\mathbf{l_j}) + \left[\frac{\partial \log_e \widehat{\mathbf{P_a}}(\theta; \mathbf{z_j})}{\partial \theta}\right]_{\theta=\hat{\theta}} \cdot \gamma + \sum_k \mathbf{f_k}(\mathbf{z_{jk}})\right]$$

  where $\gamma = \theta - \hat{\theta}$ ($\hat{\theta}$ is the MLE of θ).
  - Derivative term can then be thought of as a random effect with parameter $\gamma \sim \text{MVN}(\mathbf{0}, -\mathbf{H}_{\hat{\theta}}^{-1})$.
  - Resulting variance from the GAM *includes* detection function variability.
- Only works with detection functions with no covariates (CDS).

Markov modulated Poisson process – Skaug (2006)

- Often observe clustering
- 2-state (high/low) process
- Biologically motivated
- Can include GLM/GAM components



New R package: `dsm`

- Individual (MCDS) as well as environmental covariates
- Binned and continuous & group and individual data
- Faster bootstrap
- New bootstrap method incorporating detection function uncertainty
- Soap film smoothing for complex regions (see left)
- Variance propagation (see left)
- CV plotting
- Tutorial available at `http://github.com/dill/dsm/wiki/Examples`
- Talks to `mrds` and the new package `Distance`
- In Distance 7.0, on CRAN soon!

Other approaches

- DSpat - Johnson et al. (2010)
  - Directly model the point process
  - Setection function as thinning of the process
  - (Spatial) mixture of detection functions
  - Over-dispersion handled by post-hoc correction
- `unmarked`
  - Not full spatial modelling but can use transect-level spatial covariates
  - Hierarchical approach
  - Binned data only
- Bayesian point processes via (RJ)MCMC - Niemi and Fernández (2010)
  - Intensity function – product of a parametric function of the covariates
  - Mixture of Gaussian kernels as a spatial smooth (priors on knots select smoothing)
  - Single precision parameter $\Rightarrow$ cannot accommodate both small- and large-scale variation
  - "Known" detection function as a thinning of the process

Coming soon!

A review paper incorporating all this information and **more**: *Spatial models for distance sampling data: recent developments and future directions.* David L. Miller, Louise Burt, Eric Rexstad and Len Thomas.

References

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