`dsm` version 2 – what's new?

David L. Miller (University of Rhode Island)

RUWPA seminar, University of St Andrews

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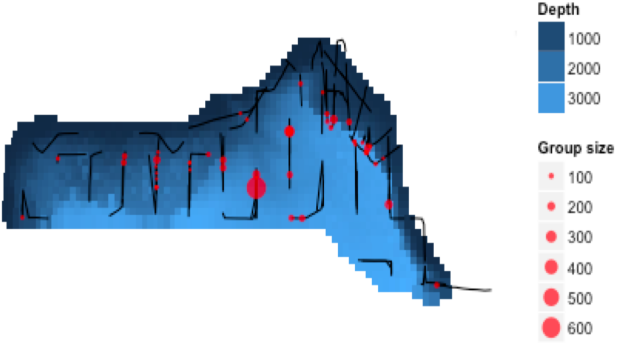
- variance estimation
- other tricks

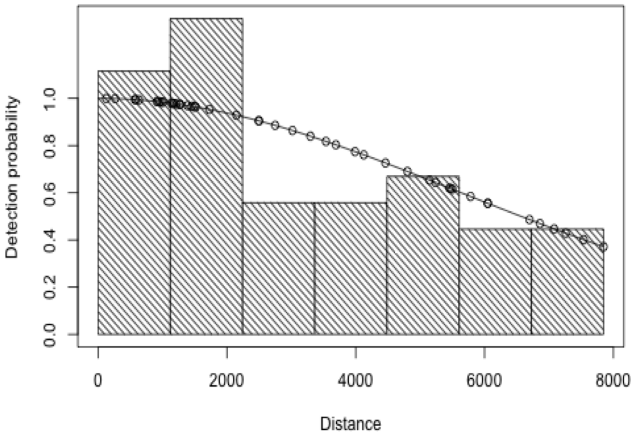
a very brief overview of density surface modelling

Collect spatially referenced data



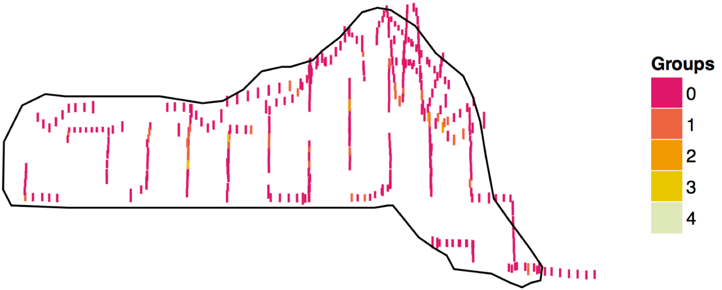
. . .

Fit detection function



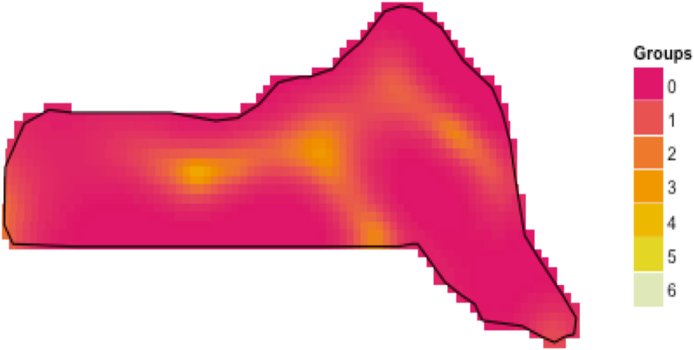
...

Aggregate to segments



. . .

Fit spatial model



dsm version 2

models look like:

```
dsm(N ~ s(x,y), ddf.obj,
    segment.data, observation.data,
    family=quasipoisson(), ...)
```

the `...` is where the magic happens

`mgcv`-like syntax

`dsm` features

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- `gam.check`, `predict`, `summary` all do sensible things
- also: documentation *and* examples (on CRAN)

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  - combine with $\text{CV}^2(\hat{N}) = \text{CV}^2(\hat{p}) + \text{CV}^2(\hat{N}_{\text{GAM}})$

uncertainty estimation issues

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- propagation of uncertainty from detection function

GAM confidence intervals

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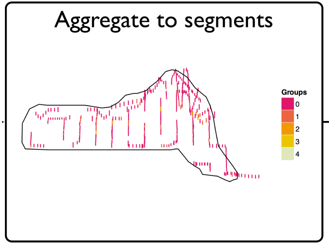

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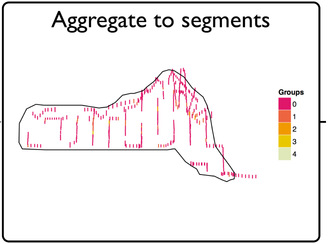

GAM confidence intervals

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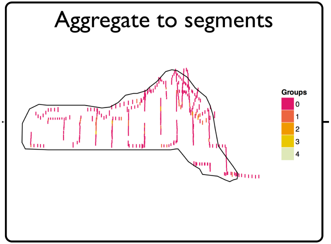
- not *more* assumptions but *different* ones



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- non-linear links more complicated...

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  2. Calculate the appropriate summary statistics, e.g. median, 95% quantiles etc over b.
- MVB, suggests that this is unneccessary: *"once you've got a CV so big that the delta-method doesn't work, then your estimate is officially Crap and there is not much point in expending extra effort to work out exactly how Crap!"*

analytic approximate solution

beef up the variance based (roughly) on the uncertainty in the linear predictor:

$$\left(\frac{\partial^2 \log_e \eta}{\partial \eta^2} \bigg|_{\eta=\hat{\eta}} \circledast \mathbf{X}_p \right) \mathbf{V}_\beta \left(\frac{\partial^2 \log_e \eta}{\partial \eta^2} \bigg|_{\eta=\hat{\eta}} \circledast \mathbf{X}_p \right)^\mathsf{T}$$

where $\frac{\partial^2 \log_e \eta}{\partial \eta^2} \big|_{\eta=\hat{\eta}}$ is the vector of second derivatives evaluated at the values of the linear predictor

and $\circledast$ denotes R-style matrix-vector multiplication

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- in `dsm` as `dsm.var.gam`

variance propagation

Trick from MVB to get detection function uncertainty into the GAM

Our model is of the form:

$$\log(\mathbb{E}[N_j]) = \log(2 l_j w \hat{p}(\theta)) + \sum_k f_k(z_k)$$

add in a derivative of $\hat{p}(\theta)$:

$$\log(\mathbb{E}[N_j]) = \log(2 l_j w \hat{p}(\theta)) + \frac{d \log(\hat{p}(\theta))}{d\theta}\Big|_{\theta=\hat{\theta}} . \gamma + \sum_k f_k(z_k)$$

should have no effect on $\mathbb{E}[N_j]$

variance propagation (2)

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variance propagation (2)

- Detection function uncertainty now included
- in `dsm` as `dsm.var.prop`
- only works when there are no covariates in d.f.

summary – uncertainty estimation

- Wood (2006) and Augustin et al. (2009) for more on uncertainty in GAMs

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- faster than MBB, in (limited) simulations marginally "better"
- See Williams et al. (2010) for the detection function uncertainty trick (there is an error in the paper!)

select

option `select=TRUE`

extra shrinkage allows smooths to be removed from the model

effective degrees of freedom can be shrunk to zero

```
Approximate significance of smooth terms:
                     edf Ref.df      F  p-value    
s(roughness)   1.401e+00      6  0.661   0.0531 .  
s(gchl_winter) 5.999e-07      6  0.000   0.2947    
s(depthm)      8.322e-01      6  3.651 4.83e-08 ***
s(x)           5.399e+00      6 15.571  < 2e-16 ***
s(y)           3.909e+00      6 13.928  < 2e-16 ***
```

here `gchl_winter` has been “removed” from the model

more info in `?gam`

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- `?Tweedie` or Candy (2004)

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- `?negbin` has more information

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- example analysis at http://github.com/dill/dsm/wiki

References

Augustin, N., Musio, M., Wilpert, von, K., Kublin, E., Wood, S.N. & Schumacher, M. (2009) Modeling spatiotemporal forest health monitoring data. Journal of the American Statistical Association, 104, 899–911.

Candy, S. (2004) Modelling catch and effort data using generalised linear models, the Tweedie distribution, random vessel effects and random stratum-by-year effects. CCAMLR Science, 11, 59–80.

Williams, R., Hedley, S.L., Branch, T.A., Bravington, M.V., Zerbini, A.N. & Findlay, K.P. (2011) Chilean blue whales as a case study to illustrate methods to estimate abundance and evaluate conservation status of rare species. Conservation Biology, 25, 526–535.

Wood, S.N. (2006) Generalized Additive Models: an Introduction with R. Chapman & Hall/CRC.