Lecture 3: Multivariate smoothing & model selection

University of St Andrews

The story so far...

- How GAMs work
- How to include detection info
- Simple spatial-only models

Life isn't that simple

- Which enivronmental covariates?
- Which response distribution?
- Which response?

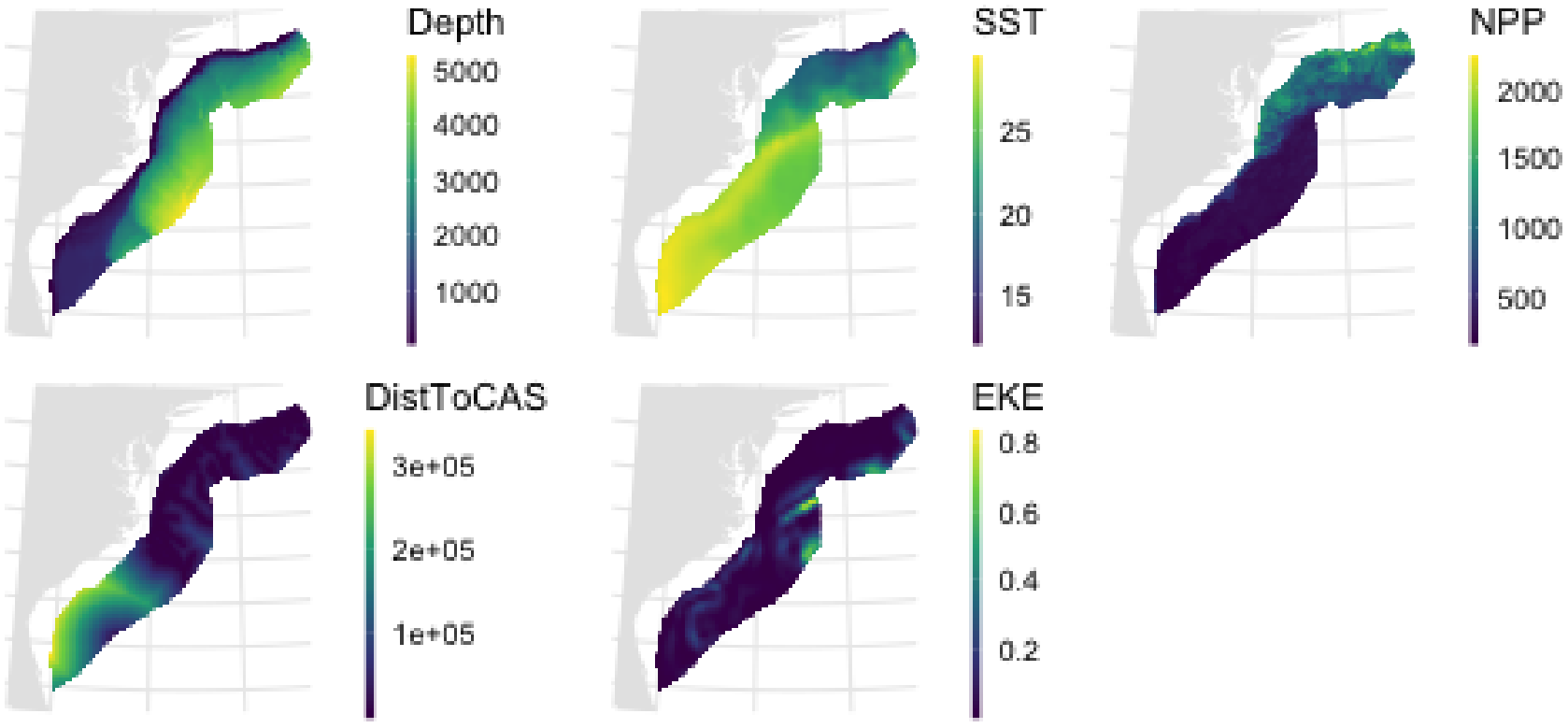
How to select between possible models?

Adding covariates

Model formulation

- Pure spatial, pure environmental, mixed?
- Prior knowledge of biology/ecology of species
- What are drivers of distribution?
- What data is available?

Sperm whale covariates

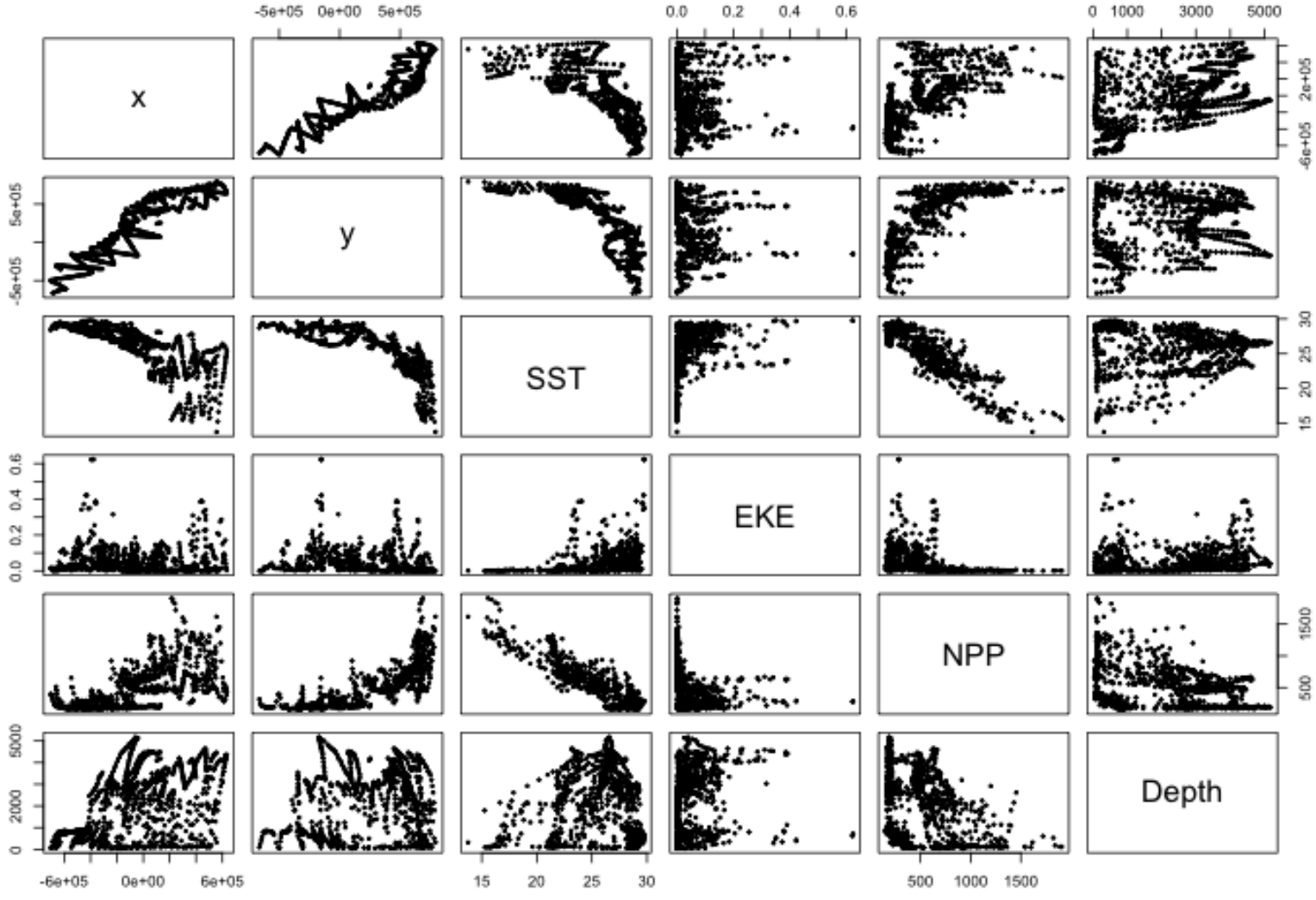


Tobler's first law of geography

"Everything is related to everything else, but near things are more related than distant things"

Tobler (1970)

Implications of Tobler's law



Adding smooths

- Already know that + is our friend
- Can build a big model...

```
dsm_all <- dsm(count~s(x, y) +
                     s(Depth) +
                     s(DistToCAS) +
                     s(SST) +
                     s(EKE) +
                     s(NPP),
                   ddf.obj=df_hr,
                   segment.data=segs, observation.data=obs,
                   family=tw())
```

Each `s()` has its own options

- `s(..., k=...)` to adjust basis size
- `s(..., bs="...")` for basis type
- lots more options (we'll see a few here)

Now we have a huge model, what do we do?

Term selection

Two popular approaches (using *p*-values)

Stepwise selection - path dependence

All possible subsets - computationally expensive (fishing?)

p-values

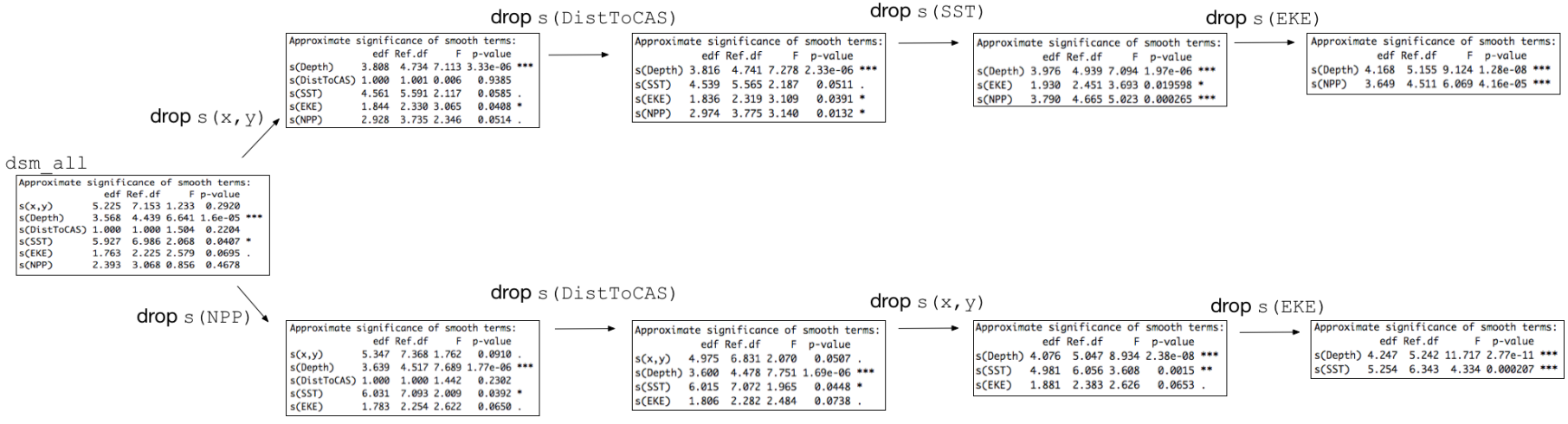
- Test for *zero effect* of a smooth
- They are **approximate** for GAMs (but useful)
- Reported in `summary`

summary(dsm_all)

```
##
## Family: Tweedie(p=1.25)
## Link function: log
##
## Formula:
## count ~ s(x, y) + s(Depth) + s(DistToCAS) + s(SST) + s(EKE) +
##     s(NPP) + offset(off.set)
##
## Parametric coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -20.6368     0.2751     -75   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                edf Ref.df     F p-value
## s(x,y)       5.225  7.153 1.233  0.2920
## s(Depth)     3.568  4.439 6.641 1.6e-05 ***
## s(DistToCAS) 1.000  1.000 1.504  0.2204
## s(SST)       5.927  6.986 2.068  0.0407 *
## s(EKE)       1.763  2.225 2.579  0.0695 .
## s(NPP)       2.393  3.068 0.856  0.4678
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Path dependence is an issue here

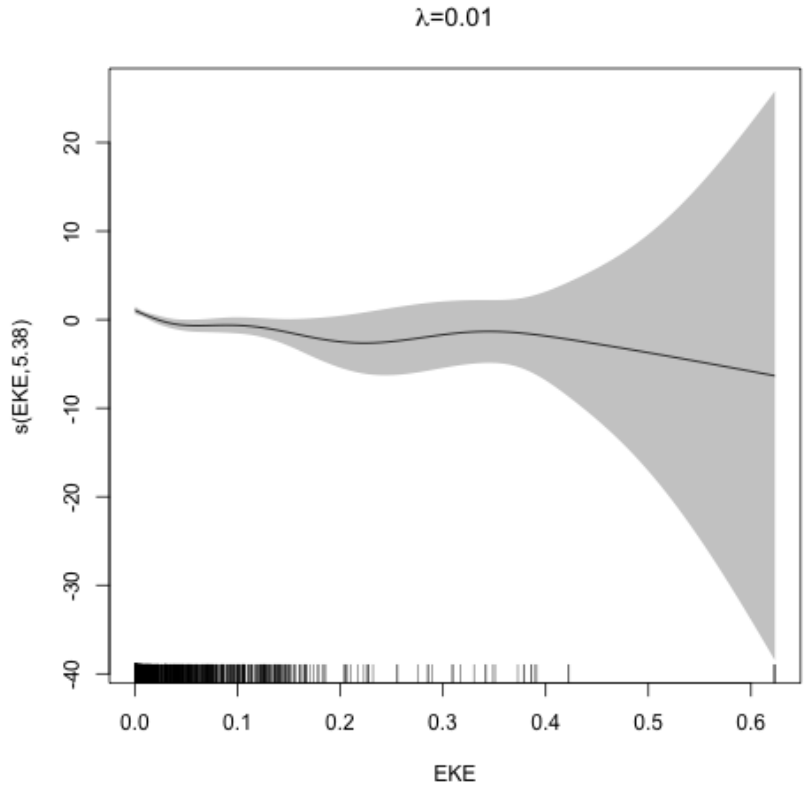
- (silly) Strategy: want all $p \approx 0$ ($***$), remove terms 1-by-1
- Two different universes appear:



This isn't very satisfactory!

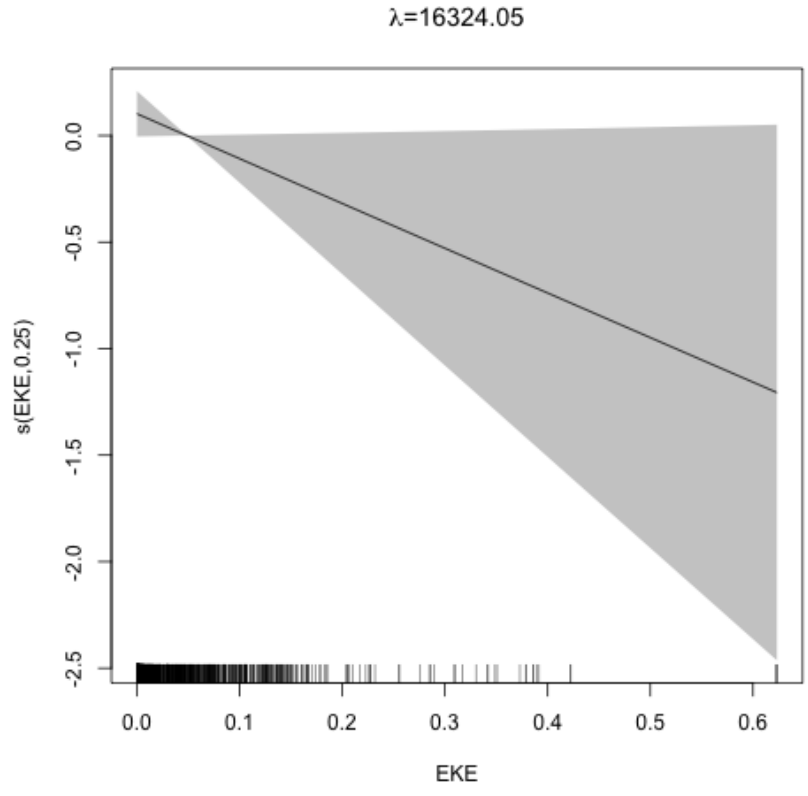
Term selection during fitting

- Already selecting wigglyness of terms
- (via a penalty)
- What about using it to remove the whole term?



Shrinkage approach

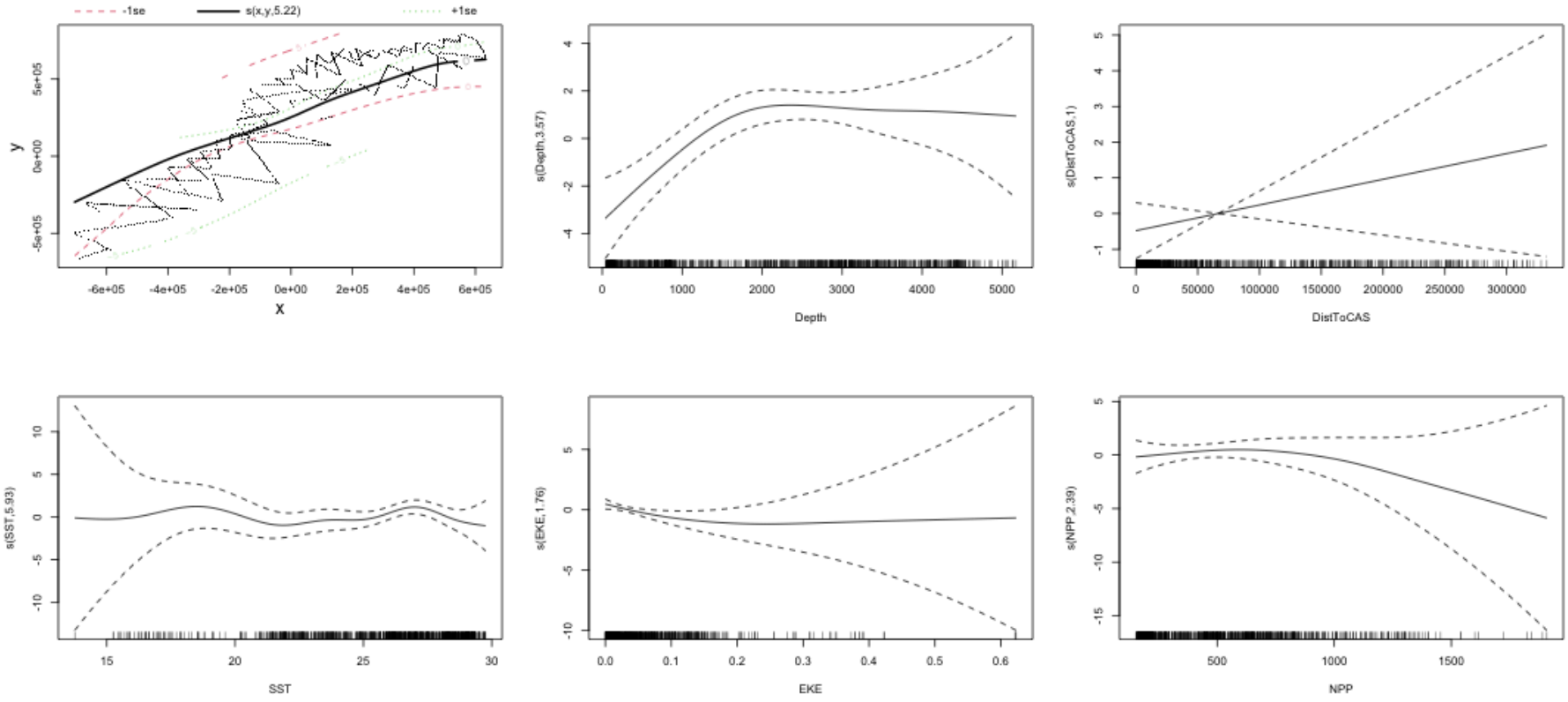
- Basis `s(..., bs="ts")` - thin plate splines *with shrinkage*
- remove the wiggles **then** remove the "linear" bits
- nullspace should be shrunk less than the wiggly part



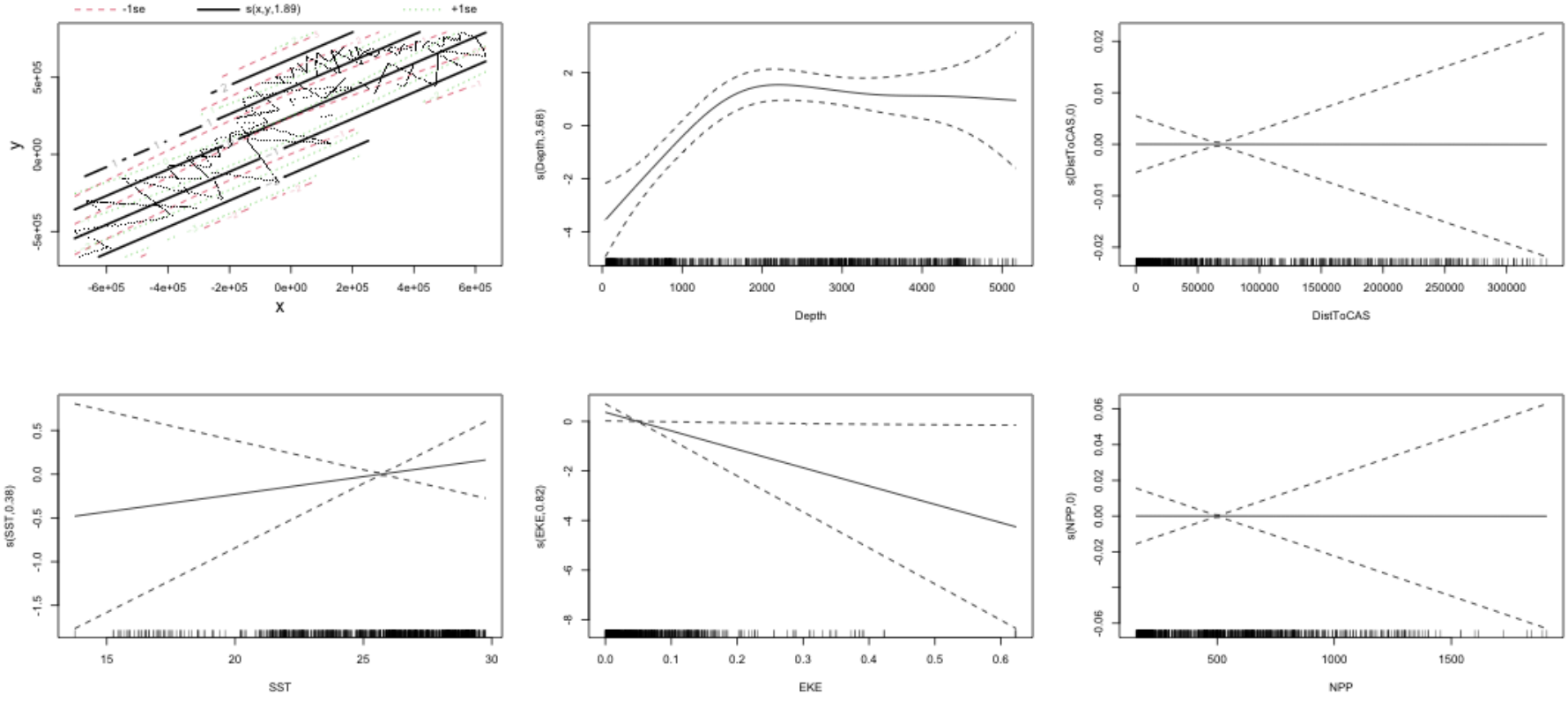
Shrinkage example

```
dsm_ts_all <- dsm(count~s(x, y, bs="ts") +
                        s(Depth, bs="ts") +
                        s(DistToCAS, bs="ts") +
                        s(SST, bs="ts") +
                        s(EKE, bs="ts") +
                        s(NPP, bs="ts"),
                  ddf.obj=df_hr,
                  segment.data=segs, observation.data=obs,
                  family=tw())
```

Model with no shrinkage



... with shrinkage



summary(dsm_ts_all)

```
##
## Family: Tweedie(p=1.277)
## Link function: log
##
## Formula:
## count ~ s(x, y, bs = "ts") + s(Depth, bs = "ts") + s(DistToCAS,
##     bs = "ts") + s(SST, bs = "ts") + s(EKE, bs = "ts") + s(NPP,
##     bs = "ts") + offset(off.set)
##
## Parametric coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -20.260      0.234  -86.59   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                   edf Ref.df     F  p-value
## s(x,y)       1.8875209     29 0.705 3.56e-06 ***
## s(Depth)     3.6794182      9 4.811 2.15e-10 ***
## s(DistToCAS) 0.0000934      9 0.000   0.6797
## s(SST)       0.3826654      9 0.063   0.2160
## s(EKE)       0.8196256      9 0.499   0.0178 *
## s(NPP)       0.0003570      9 0.000   0.8359
## ---
```

EDF comparison

	tp	ts
s(x,y)	5.2245	1.8875
s(Depth)	3.5679	3.6794
s(DistToCAS)	1.0001	0.0001
s(SST)	5.9267	0.3827
s(EKE)	1.7631	0.8196
s(NPP)	2.3931	0.0004

Removing terms?

1. EDF
    - Terms with EDF<1 may not be useful (can we remove?)
2. non-significant p-value
    - Decide on a significance level and use that as a rule

(In some sense leaving "shrunk" terms in is more "consistent" in terms of variance estimation, but can be computationally annoying)

Comparing models

Comparing models

- Usually have >1 option
- How can we pick?
- Even if we have 1 model, is it any good?

(This can be subtle, more in model checking tomorrow!)

Akaike's "An Information Criterion"

- As for many other models, we can get an AIC from our model
- Comparison of AIC fine (but not the end of the story)

```
AIC(dsm_all)
```

```
## [1] 1238.288
```

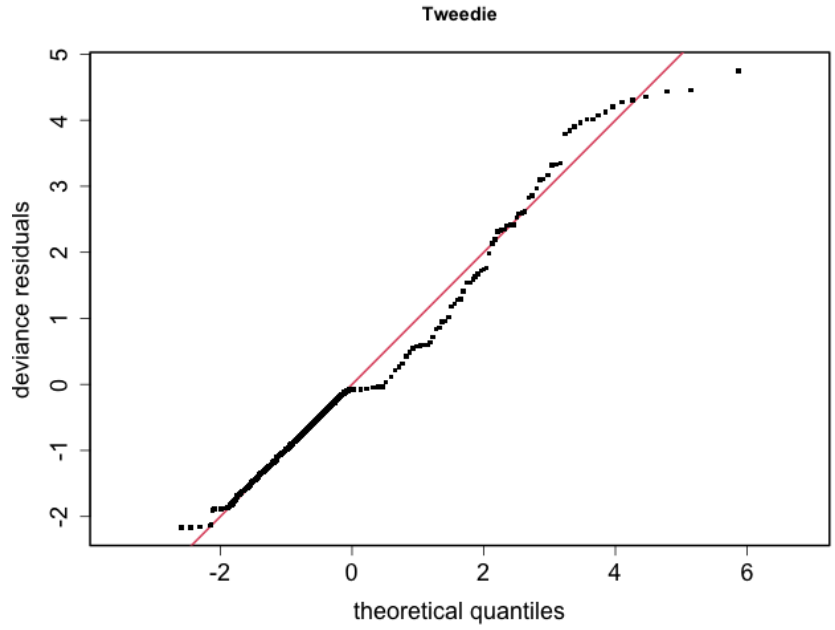
```
AIC(dsm_ts_all)
```

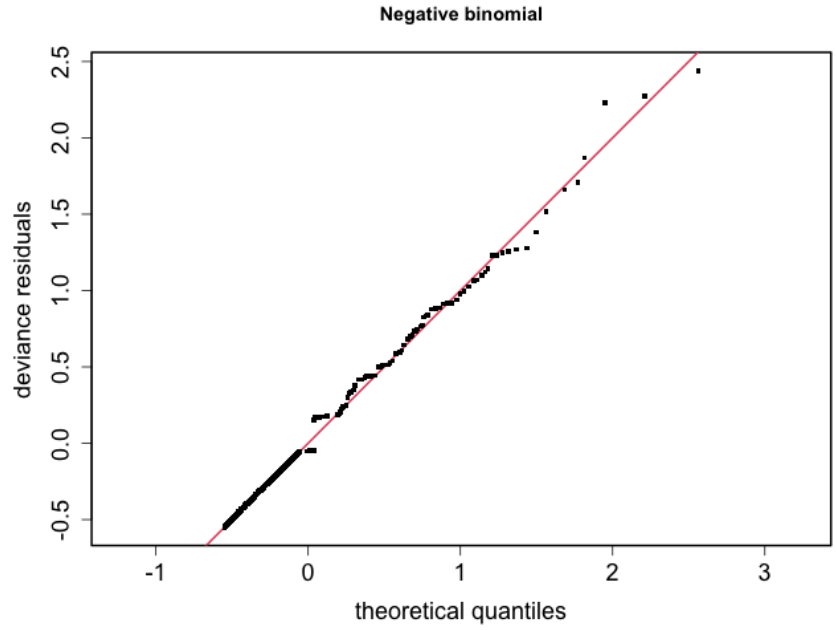
```
## [1] 1225.822
```

Selecting between response distributions

Goodness of fit

- Q-Q plots
- Closer to the line is better
- But what does "close" mean?

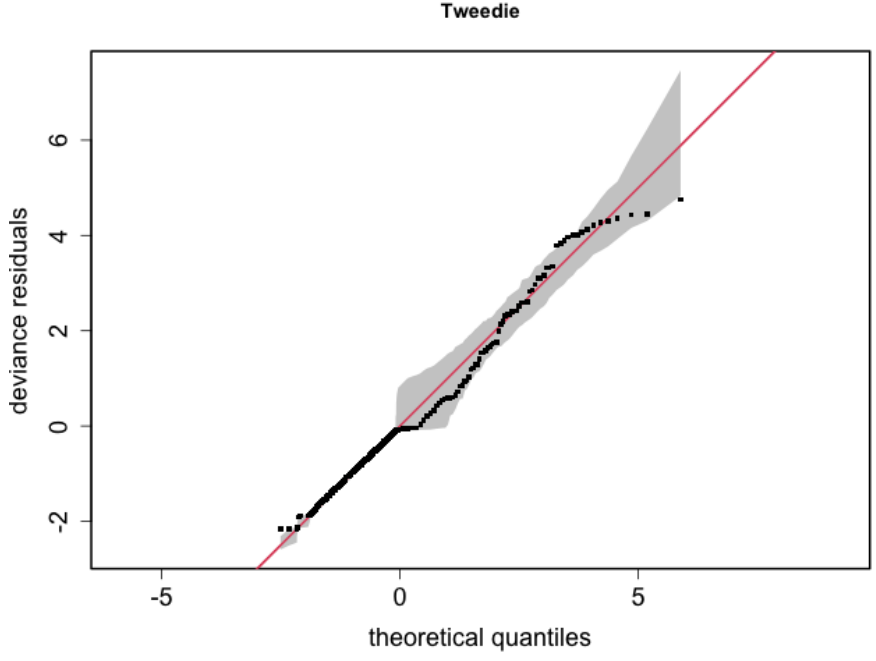


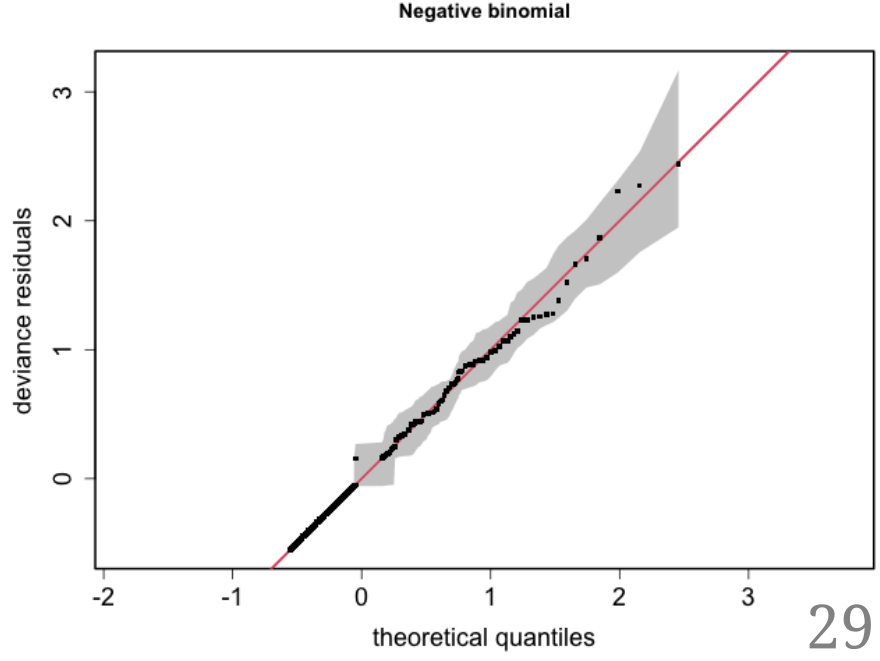


Using reference bands

- What is down to random variation?
- Where does the model actually fail?
- Resampling the response, generate bands

```
qq.gam(dsm_all, asp=1, main="Tweedie",
       cex=5, rep=100)
```

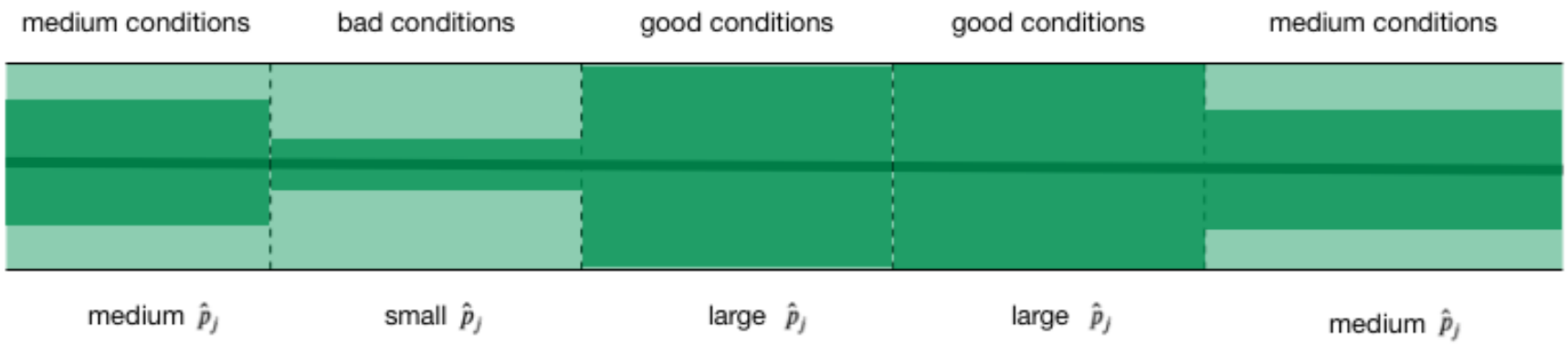




Which response type?

Count model `count~...`

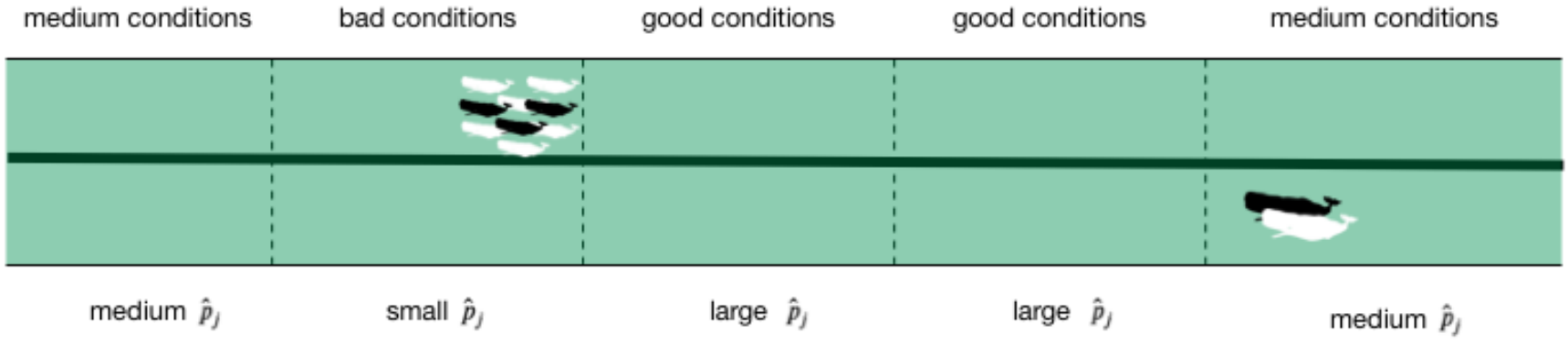
- Effort is effective effort
- Response is count per segment



Estimated abundance

`abundance.est~...`

- Effort is area of each segment
- Response is estimated abundance per segment

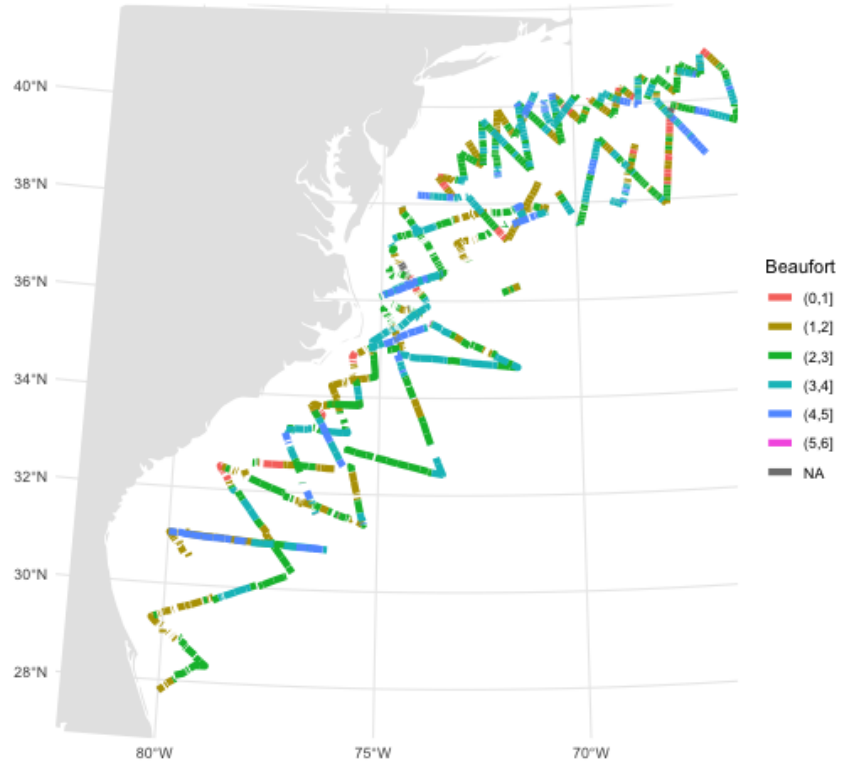


When to use each approach?

- *Practical choice*
- 2 detection function covariate "levels"
  - "Observer"/"observation" -- change **within** segment
  - "Segment" -- change **between** segments
- "Count model" only lets us use segment-level covariates
- "Estimated abundance" lets us use either

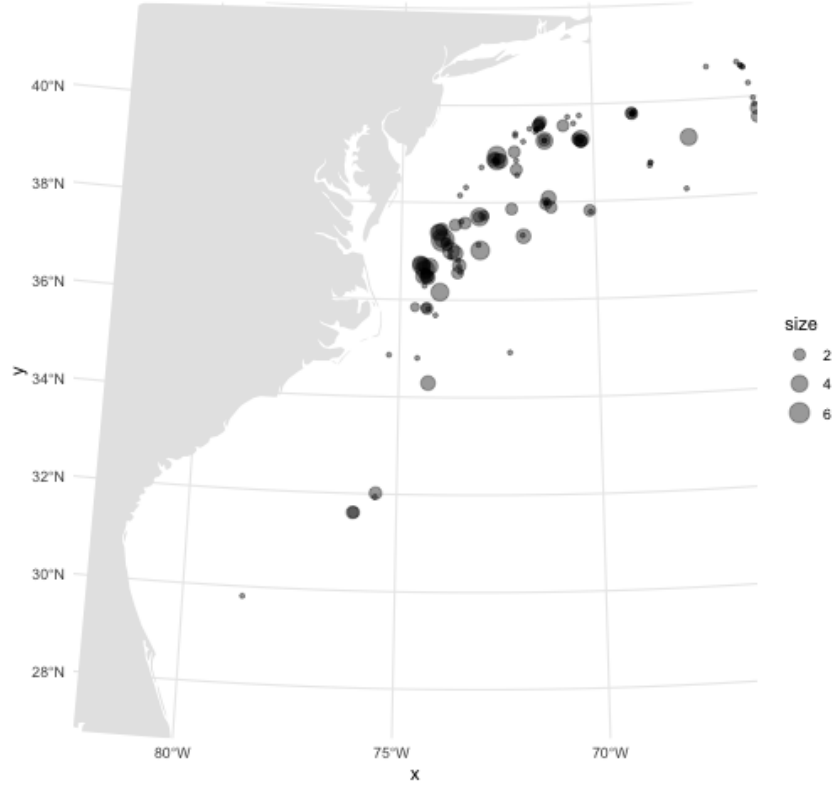
Sperm whale response example (either)

- Detection covariate: Beaufort
- Changes at segment level
- `count` or `abundance.est`



Sperm whale response example (`abundance.est`)

- Detection covariate: group size (`size`)
- Changes at observation level
- `abundance.est` only



Recap

Recap

- Adding smooths
- Path dependence
- Removing smooths
  - p-values
  - shrinkage
- Comparing models
- Comparing response distributions