

# Fitting GAMs in practice

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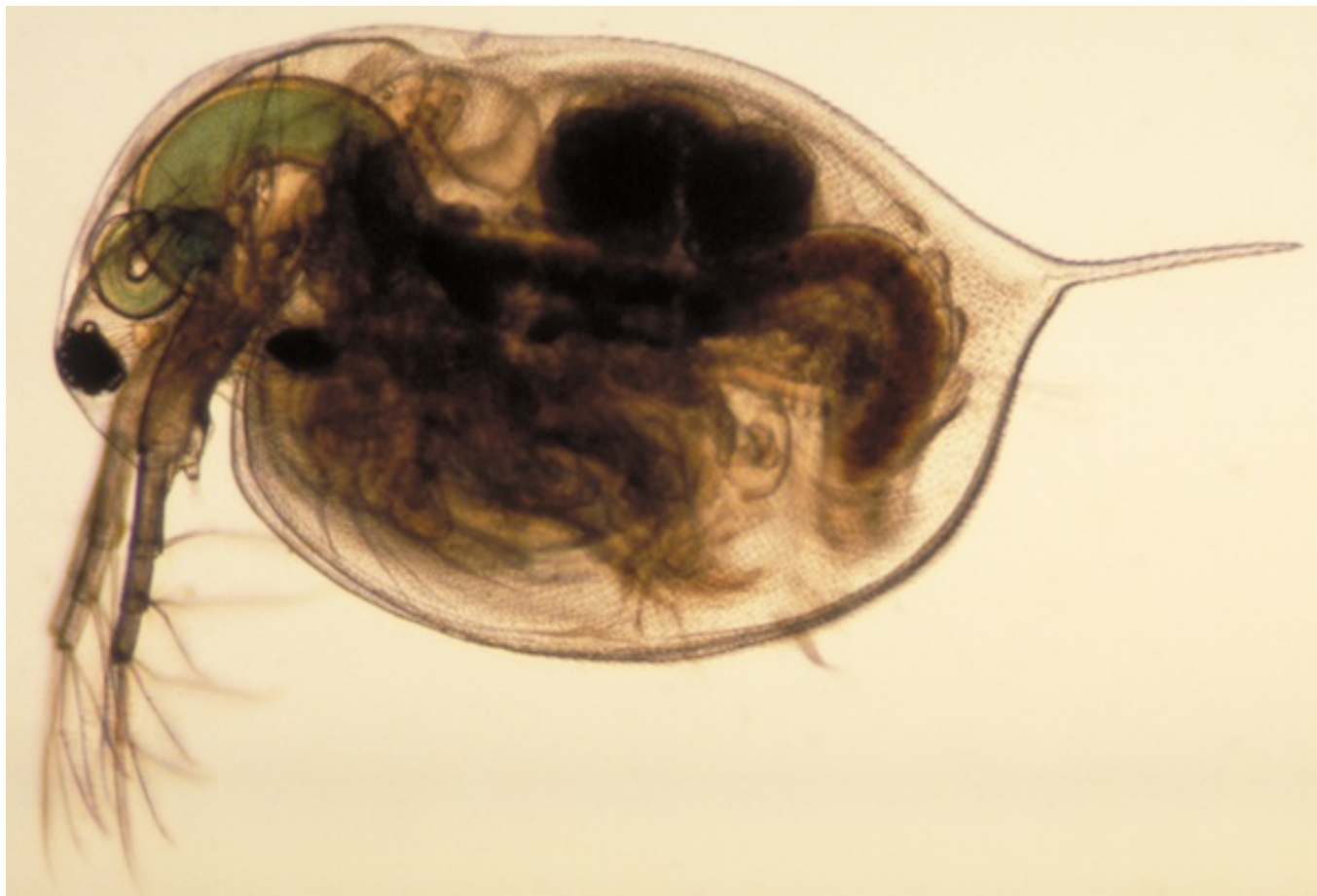
# Overview

- Introduction to some data
- Fitting simple models
- Plotting simple models

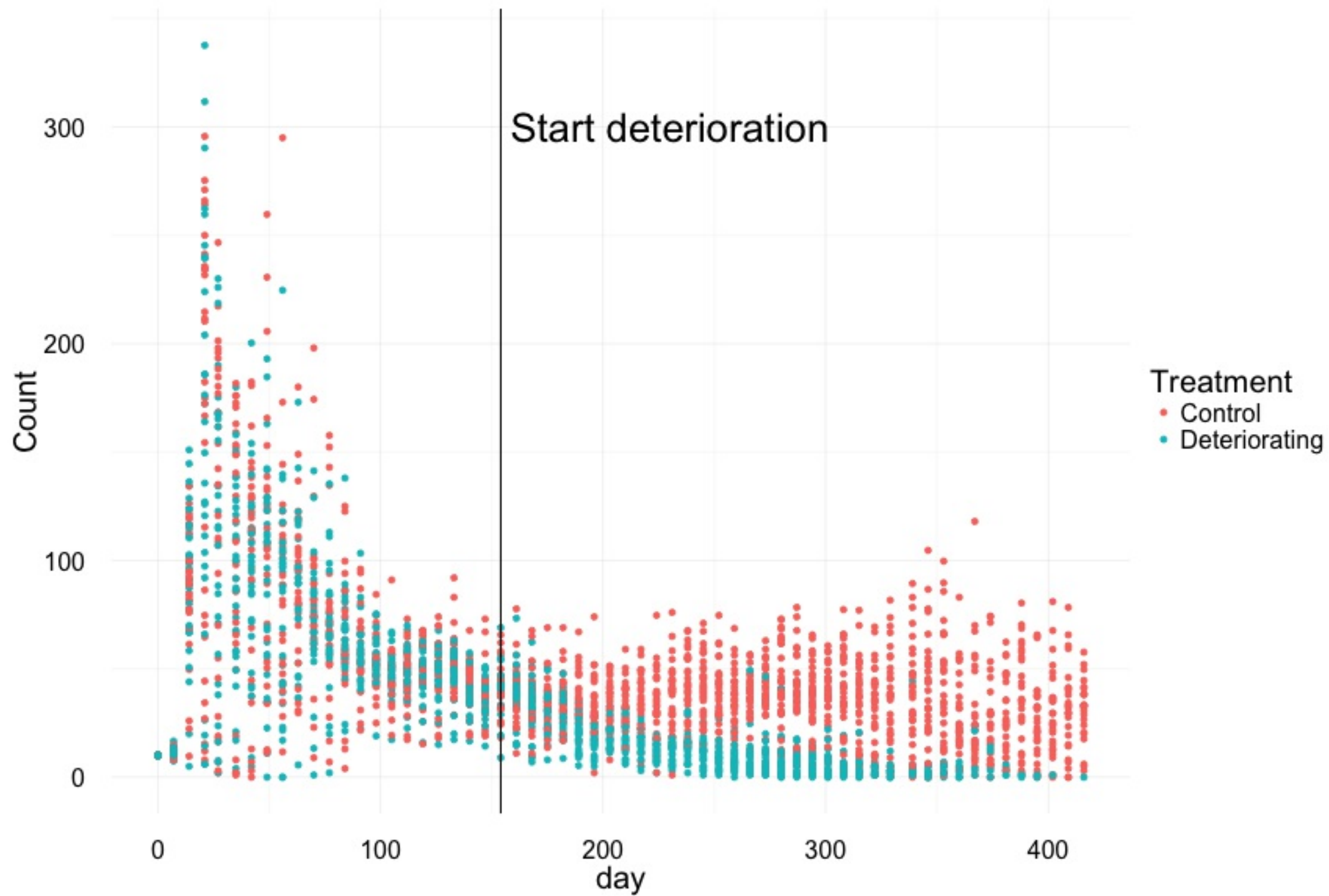
# Data

# Extinction experiment

- 60 populations of *Daphnia magna* in lab
- ½ in constant conditions, ½ in “deteriorating”
- Data from Drake & Griffen (Nature [doi:10.1038/nature09389](https://doi.org/10.1038/nature09389))



# Extinction experiment



# Inferential goals

- Make sense of all these dots!
- What are the “average” trends?
  - (What are non-average trends?)
- When do the deteriorating populations go extinct on average?

# Pantropical spotted dolphins

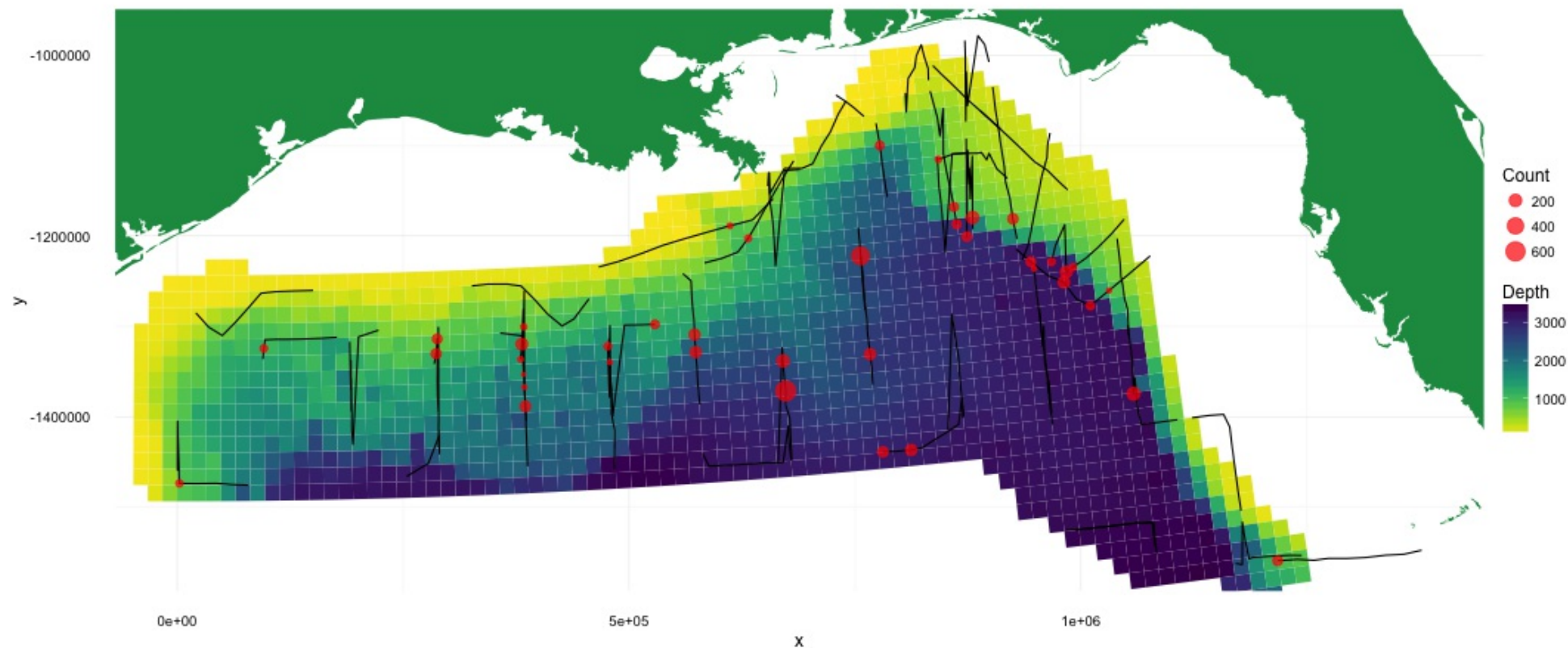
- Example taken from Miller et al (2013)
- [Paper appendix](#) has a better analysis
- Simple example here, ignoring all kinds of important stuff!





# Inferential aims

- How many dolphins are there?
- Where are the dolphins?
- What are they interested in?





# Translating maths into R

A simple example:

$$y_i = \beta_0 + s(x) + s(w) + \epsilon_i$$

where  $\epsilon_i \sim N(0, \sigma^2)$

Let's pretend that  $y_i \sim \text{Normal}$

- linear predictor: `formula = y ~ s(x) + s(w)`
- response distribution: `family=gaussian()`
- data: `data=some_data_frame`

# Putting that together

```
my_model <- gam(y ~ s(x) + s(w),  
               family = gaussian(),  
               data = some_data_frame,  
               method = "REML")
```

- `method="REML"` uses REML for smoothness selection (default is `"GCV.Cp"`)

What about a practical  
example?

# Simple extinction example

```
dmagna_happy <- gam(Nhat~s(day, k=50), data=pop_happy,  
method="REML")  
dmagna_unhappy <- gam(Nhat~s(day, k=50), data=pop_unhappy,  
method="REML")
```

- Fit 2 models, one to control group, one to experimental group
- Nhat is the count of *D. magna* (estimated from 3 censuses)
- Model as a function of day

# What did that do?

```
summary(dmagna_unhappy)
```

```
Family: gaussian  
Link function: identity
```

```
Formula:  
Nhat ~ s(day, k = 50)
```

```
Parametric coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	38.9173	0.6959	55.93	<2e-16 ***

```
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

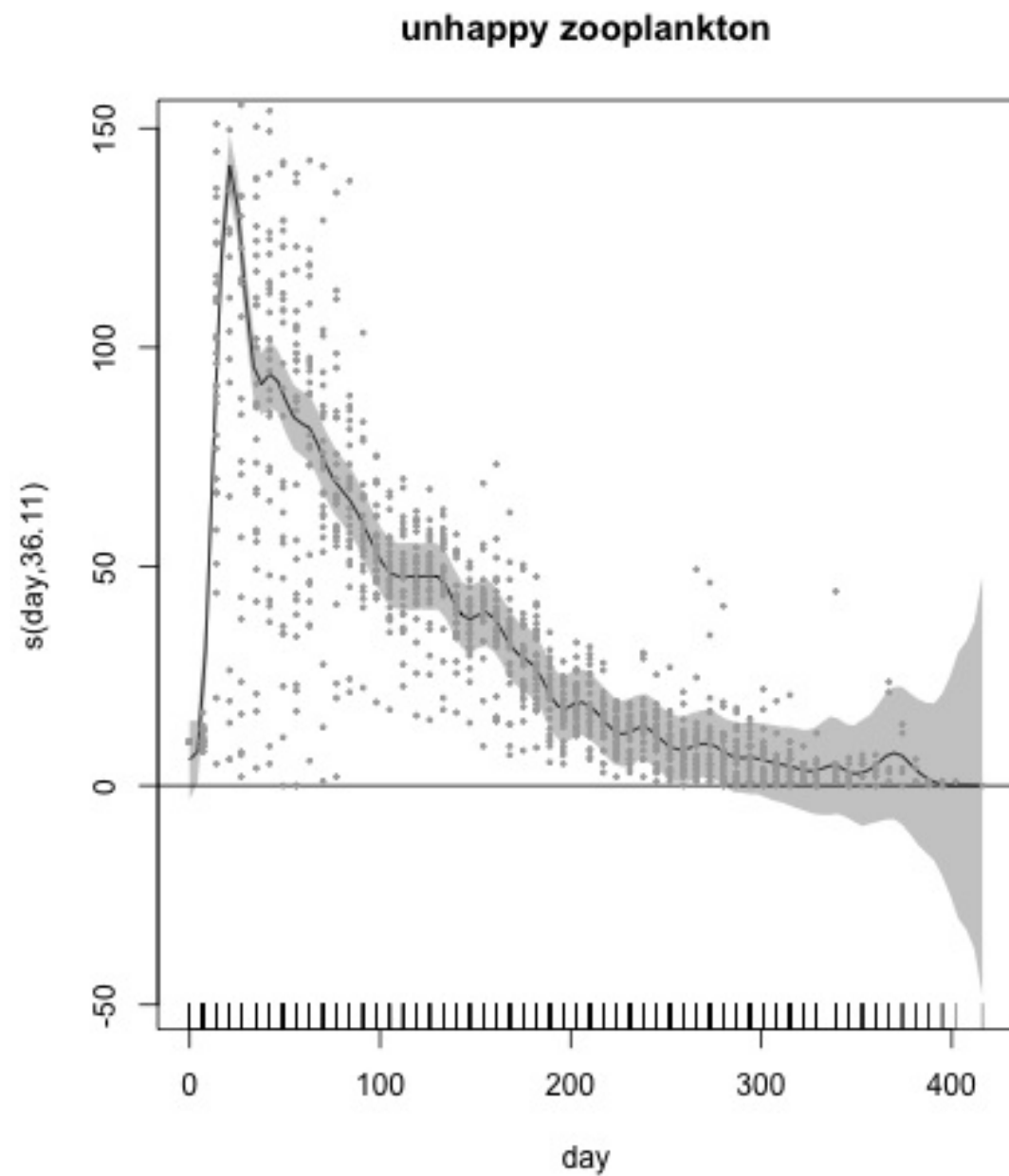
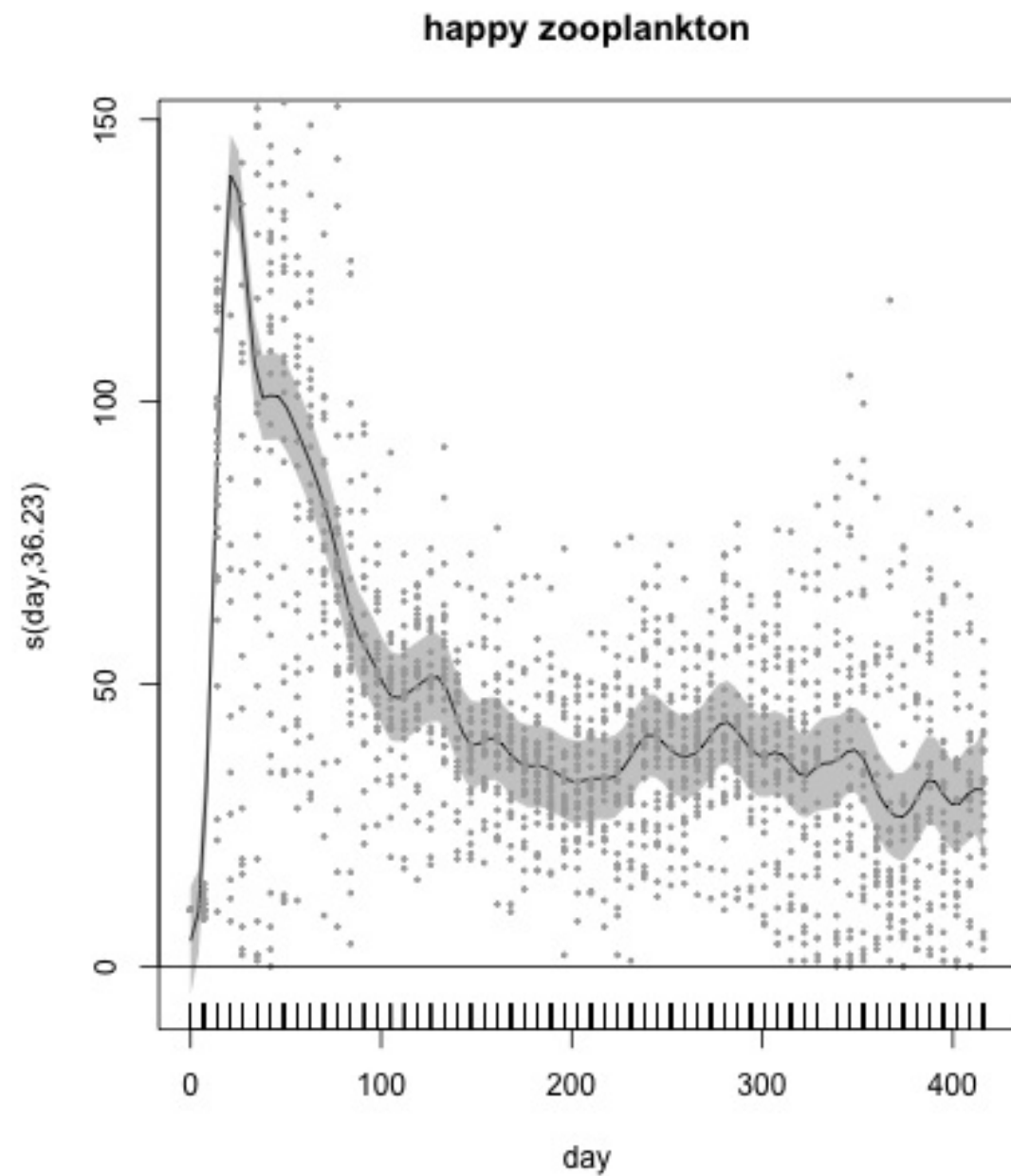
```
Approximate significance of smooth terms:
```

	edf	Ref.df	F	p-value
s(day)	36.11	42.04	60.94	<2e-16 ***

```
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
R-sq.(adj) = 0.657    Deviance explained = 66.6%  
-REML = 6296.6    Scale est. = 647.88    n = 1338
```

# Cool, but what about a plot?





# How did we do that?

```
plot(dmagna_unhappy, main="unhappy zooplankton",  
     shift=mean(pop_unhappy$Nhat), scale=0, shade=TRUE)  
abline(h=0)
```

- `scale=0` puts each term on it's own y axis
- Terms are centred, need `shift=` to re-centre (don't in models w/ > 1 term!)
- `shade=TRUE` makes +/-2 se into shaded area
- `main=` sets title, as usual

# A simple dolphin model

```
library(mgcv)
dolphins_depth <- gam(count ~ s(depth) + offset(off.set),
                      data = mexdolphins,
                      family = quasipoisson(),
                      method = "REML")
```

- count is a function of depth
- off.set is the effort expended
- we have count data, try quasi-Poisson distribution

# What did that do?

```
summary(dolphins_depth)
```

```
Family: quasipoisson  
Link function: log
```

```
Formula:  
count ~ s(depth) + offset(off.set)
```

```
Parametric coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-18.2344	0.8949	-20.38	<2e-16 ***

```
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

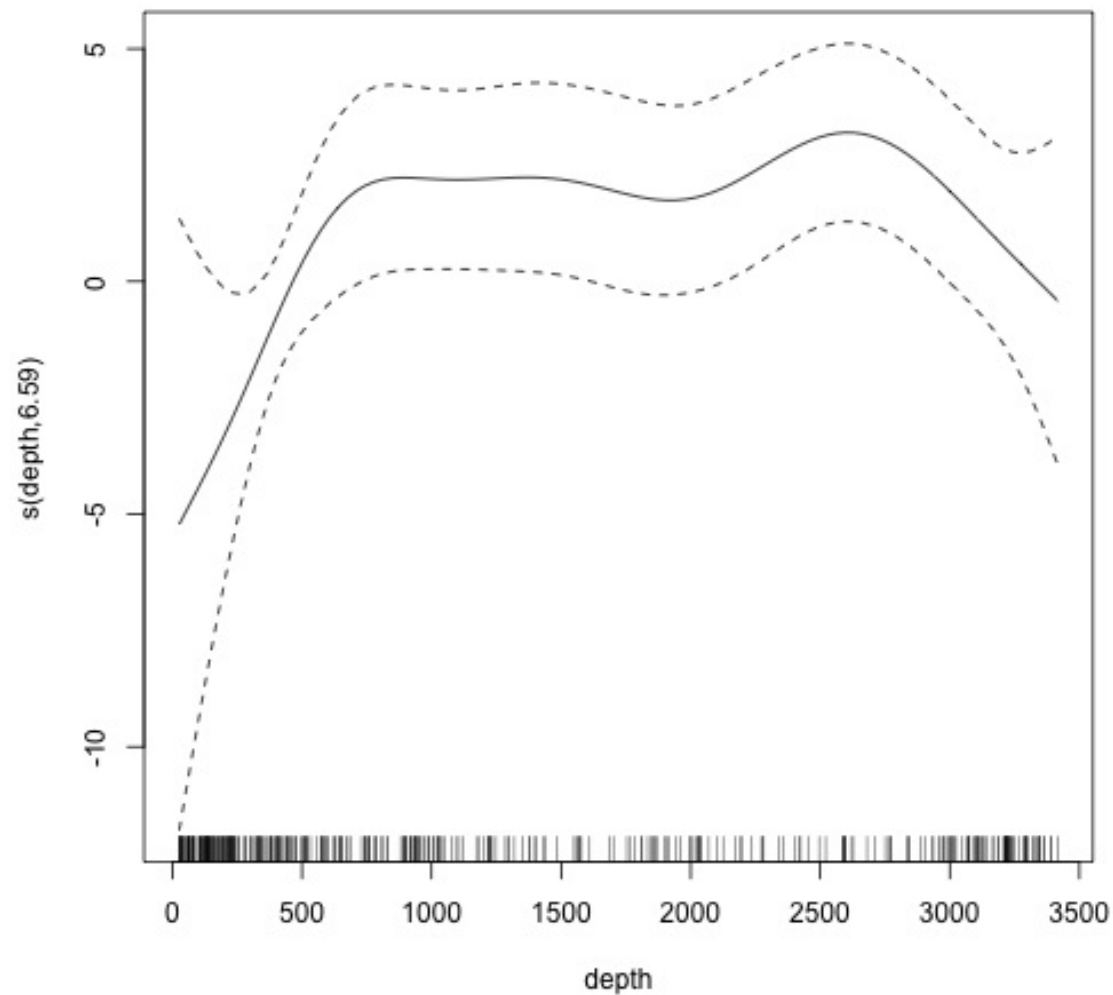
```
Approximate significance of smooth terms:
```

	edf	Ref.df	F	p-value
s(depth)	6.592	7.534	2.329	0.0224 *

```
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

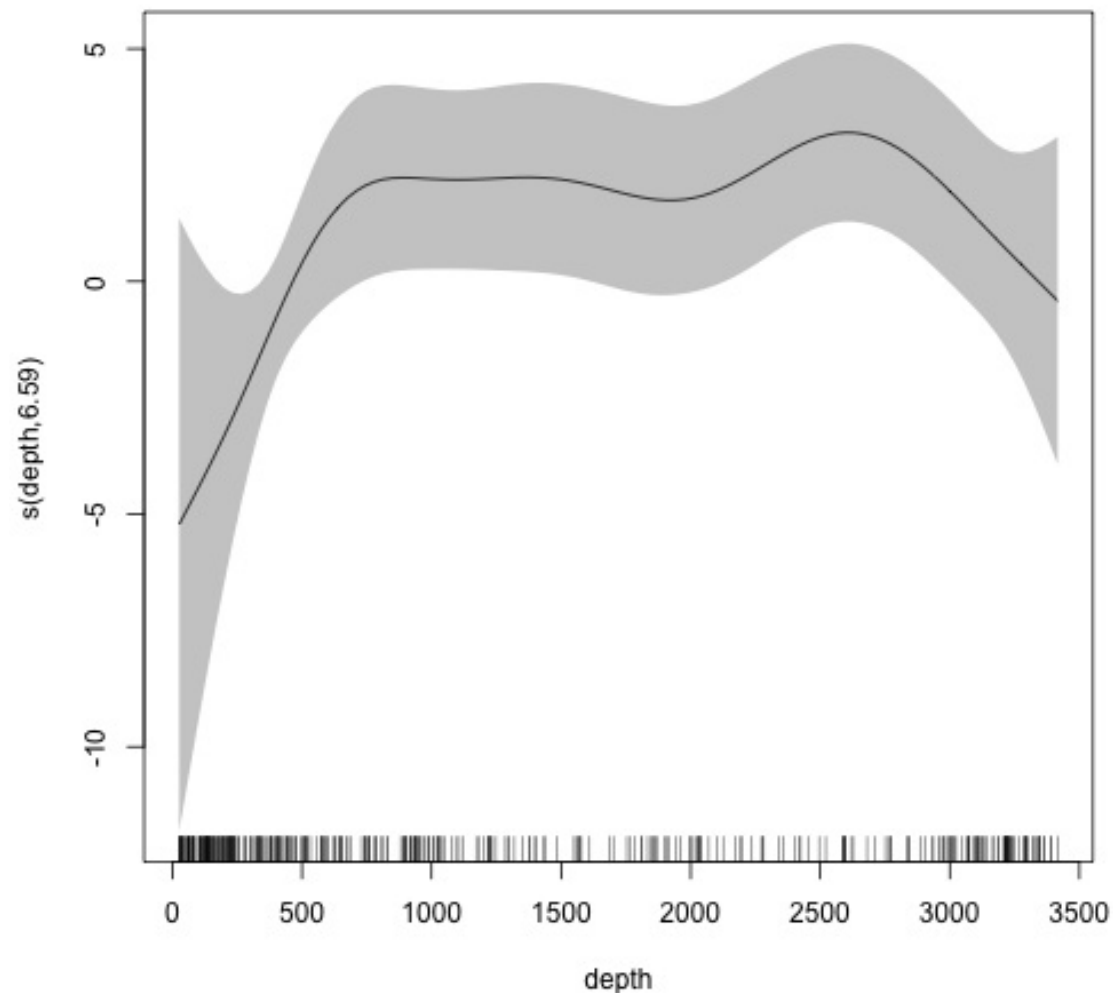
```
R-sq.(adj) = 0.0545    Deviance explained = 26.4%  
-REML = 948.28    Scale est. = 145.34    n = 387
```

# Plotting



- `plot(dolphins_depth)`
- Dashed lines indicate  $\pm 2$  standard errors
- Rug plot
- On the link scale
- EDF on y axis

# Plotting (shaded se)



- `plot(dolphins_depth, shade=TRUE)`
- `?plot` has a **lot** of options
- `plotdat <- plot(model)` gives you the data that generates the plot

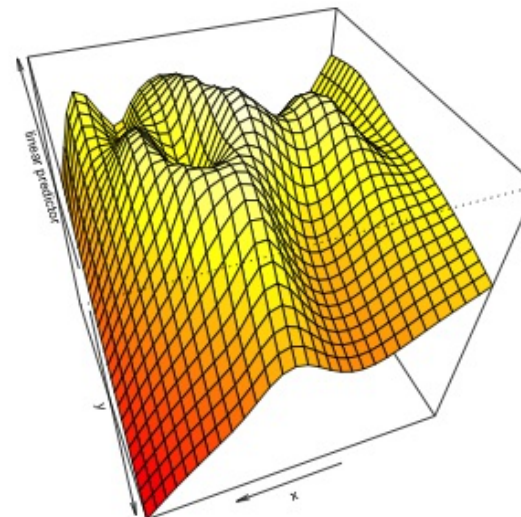
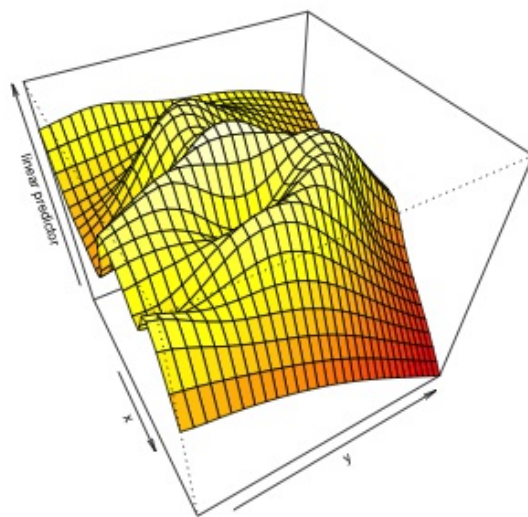
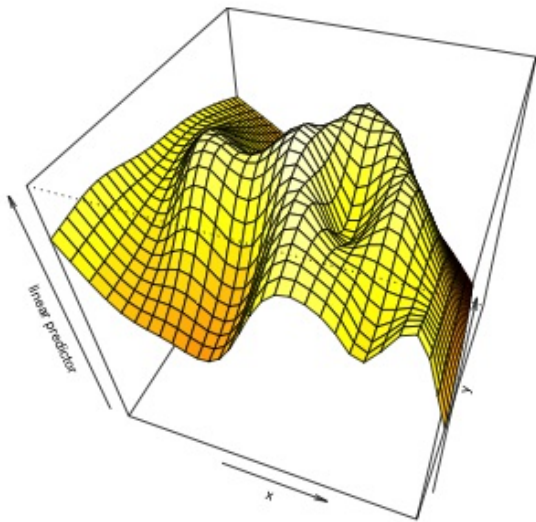
# Thin plate regression splines

- Default basis
- One basis function per data point
- Reduce # basis functions (eigendecomposition)
- Fitting on reduced problem
- Multidimensional
- Wood (2003)



# Bivariate terms

- Assumed an additive structure
- No interaction
- We can specify  $s(x, y)$  (and  $s(x, y, z, \dots)$ )
- (Assuming *isotropy* here...)



# Adding a term

- Add a **surface** for location (x and y)
- Just use + for an extra term

```
dolphins_depth_xy <- gam(count ~ s(depth) + s(x, y) +  
  offset(off.set),  
    data = mexdolphins,  
    family=quasipoisson(), method="REML")
```

# Summary

```
summary(dolphins_depth_xy)
```

Family: quasipoisson  
Link function: log

Formula:  
count ~ s(depth) + s(x, y) + offset(off.set)

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-19.1933	0.9468	-20.27	<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(depth)	6.804	7.669	1.461	0.191
s(x,y)	23.639	26.544	1.358	0.114

R-sq.(adj) = 0.22      Deviance explained = 49.9%  
-REML = 923.9      Scale est. = 79.474      n = 387

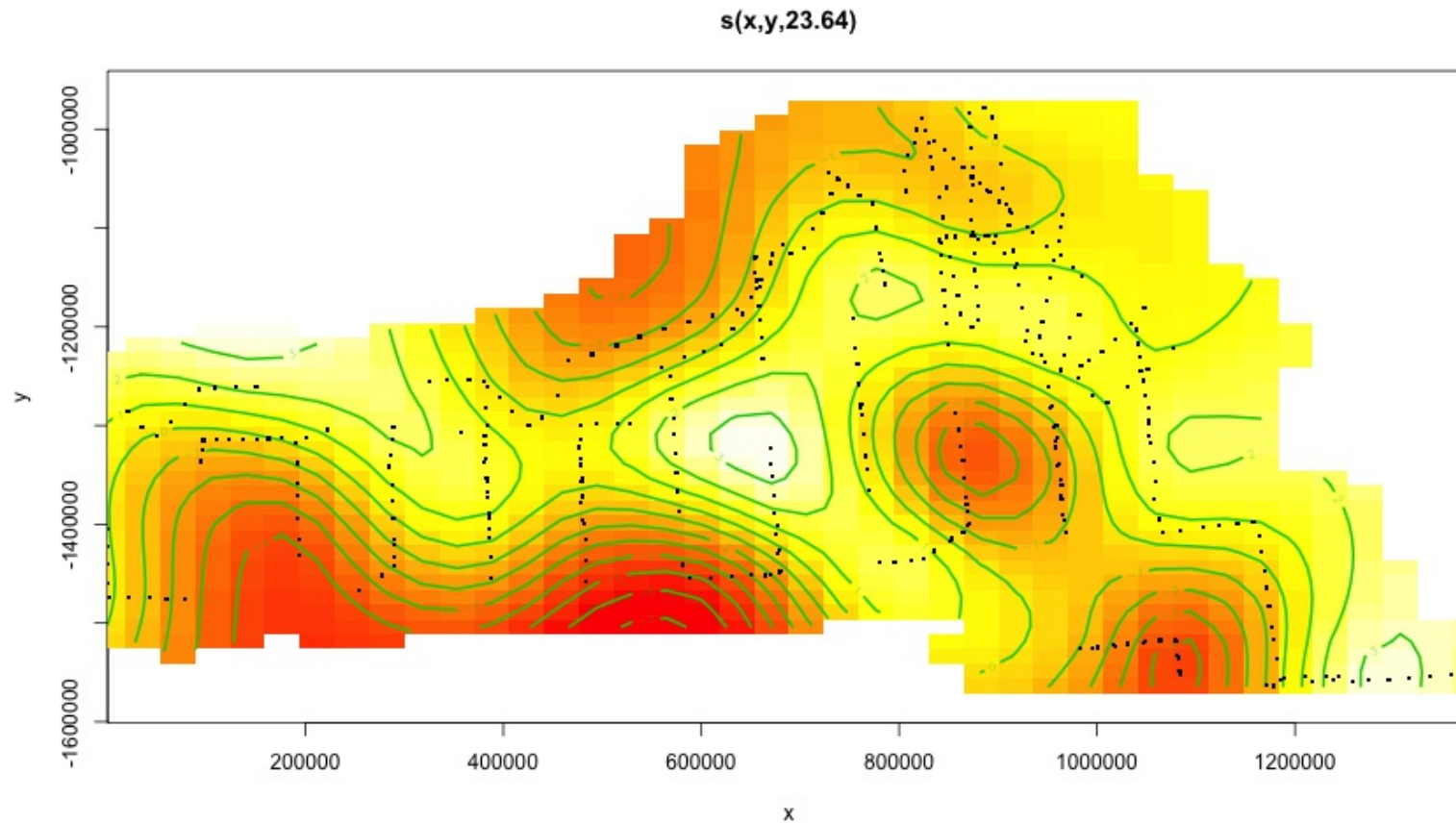
# Plot x,y term

```
plot(dolphins_depth_xy, select=2, cex=3, asp=1, lwd=2, scheme=2)
```

- `scale=0`: each plot on different scale
- `select=` picks which smooth to plot
- `scheme=2` much better for bivariate terms
- `vis.gam()` also useful

# Plot x,y term

```
plot(dolphins_depth_xy, select=2, cex=3, asp=1, lwd=2, scheme=2)
```



# Fitting/plotting GAMs summary

- `gam` does all the work
- very similar to `glm`
- `s` indicates a smooth term
- `summary`, `plot` methods