Data Exploration

2022-06-28

Packages

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.6     v purrr   0.3.4
## v tibble  3.1.7     v dplyr   1.0.9
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

## Loading required package: Rcpp

## Loading 'brms' package (version 2.17.0). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').

##
## Attaching package: 'brms'

## The following object is masked from 'package:stats':
##
##     ar

##
## Attaching package: 'tidybayes'

## The following objects are masked from 'package:brms':
##
##     dstudent_t, pstudent_t, qstudent_t, rstudent_t
```

Loading data

```
data <- read_csv('turf_prod_val.csv') |>
  filter(!is.na(depth))
```

```
## Rows: 214 Columns: 4
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (3): mean_prod (g C m-2 day-1), obs, Ref
## dbl (1): depth
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

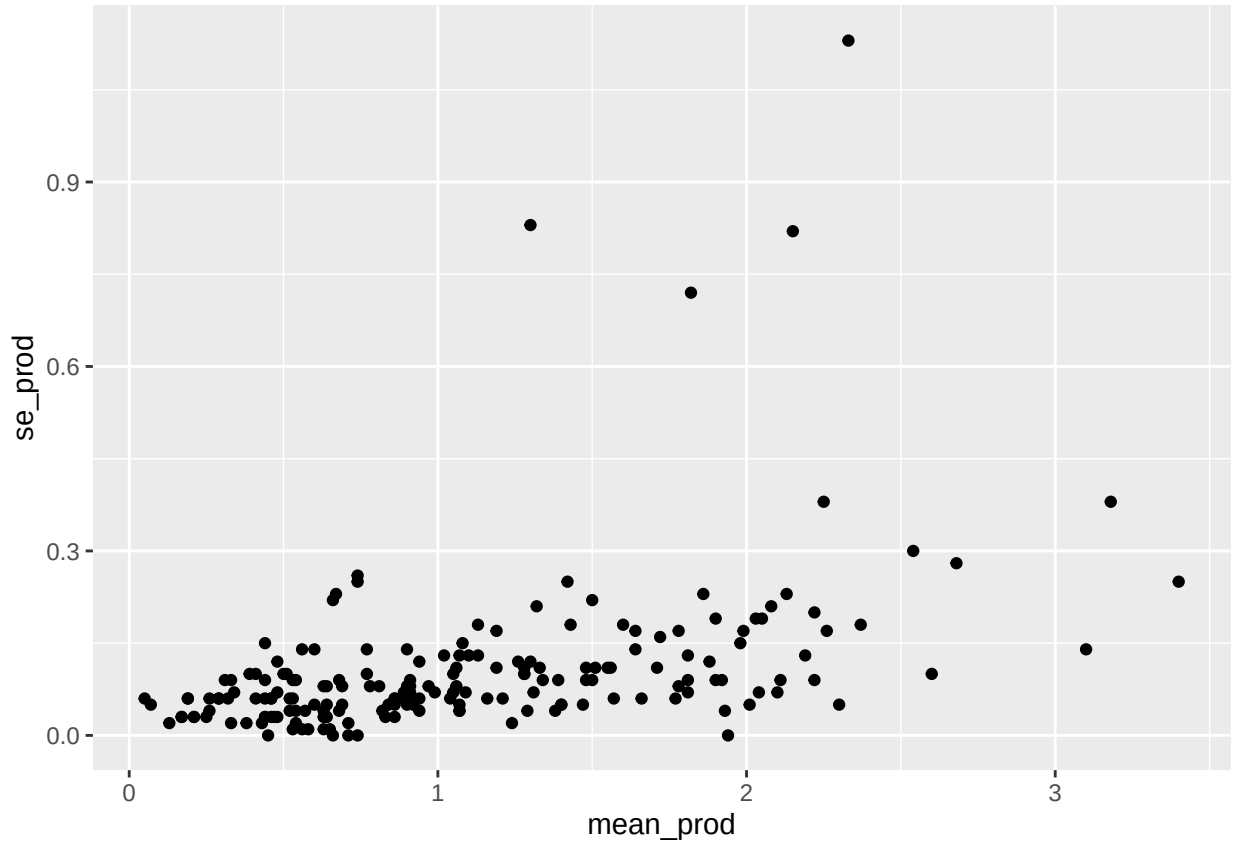
```
unit <- names(data)[1]
names(data)[1] <- 'prod'

x <- str_split(data$prod, '\xb1')
data$mean_prod <- as.numeric(substr(unlist(lapply(x, function(x)x[1])),1,4))
data$se_prod <- as.numeric(substr(unlist(lapply(x, function(x)x[2])),2,5))
```

```
## Warning: NAs introduced by coercion
```

```
data <- data %>% filter(mean_prod != 0)
```

Now, for the data points we do not have se, determine one from the relationship between mean and se:



Predicting variability using the mean for 14 points and also adjusting McClure 2019, ## which is a ci and not se, and also adding a small non zero value to all zero se

```r
mod_se <- lm(se_prod ~ mean_prod, data=data)

data[is.na(data$se_prod),'se_prod'] <- round(predict(mod_se, newdata=data[is.na(data$se_prod),]),2)

data[data$Ref == 'McClure 2019', 'se_prod'] <- data[data$Ref == 'McClure 2019', 'se_prod'] / 1.96

nzmin <- function(x) min(x[x>0])

data[data$se_prod == 0,'se_prod'] <- nzmin(data$se_prod)
```

And finally modelling

```
## Compiling Stan program...

## Trying to compile a simple C file

## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## clang -arch arm64 -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG   -I"/Library/Frame
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/StanHeade
## In file included from /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/RcppEigen
## In file included from /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/RcppEigen
## /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/RcppEigen/include/Eigen/src/Cor
## namespace Eigen {
## ^
## /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/RcppEigen/include/Eigen/src/Cor
## namespace Eigen {
##                 ^
##                 ;
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/StanHeade
## In file included from /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/RcppEigen
## /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/library/RcppEigen/include/Eigen/Core:96
## #include <complex>
##          ^~~~~~~~~
## 3 errors generated.
## make: *** [foo.o] Error 1

## Start sampling

##
## SAMPLING FOR MODEL '10f63a45fd17e5d9181b383b6c1bd659' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 5.2e-05 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.52 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 5000 [  0%]  (Warmup)
## Chain 1: Iteration:  500 / 5000 [ 10%]  (Warmup)
## Chain 1: Iteration: 1000 / 5000 [ 20%]  (Warmup)
```

```
## Chain 1: Iteration: 1500 / 5000 [ 30%]  (Warmup)
## Chain 1: Iteration: 2000 / 5000 [ 40%]  (Warmup)
## Chain 1: Iteration: 2500 / 5000 [ 50%]  (Warmup)
## Chain 1: Iteration: 2501 / 5000 [ 50%]  (Sampling)
## Chain 1: Iteration: 3000 / 5000 [ 60%]  (Sampling)
## Chain 1: Iteration: 3500 / 5000 [ 70%]  (Sampling)
## Chain 1: Iteration: 4000 / 5000 [ 80%]  (Sampling)
## Chain 1: Iteration: 4500 / 5000 [ 90%]  (Sampling)
## Chain 1: Iteration: 5000 / 5000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.638485 seconds (Warm-up)
## Chain 1:                0.633939 seconds (Sampling)
## Chain 1:                1.27242 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL '10f63a45fd17e5d9181b383b6c1bd659' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 2.9e-05 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.29 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 5000 [  0%]  (Warmup)
## Chain 2: Iteration:  500 / 5000 [ 10%]  (Warmup)
## Chain 2: Iteration: 1000 / 5000 [ 20%]  (Warmup)
## Chain 2: Iteration: 1500 / 5000 [ 30%]  (Warmup)
## Chain 2: Iteration: 2000 / 5000 [ 40%]  (Warmup)
## Chain 2: Iteration: 2500 / 5000 [ 50%]  (Warmup)
## Chain 2: Iteration: 2501 / 5000 [ 50%]  (Sampling)
## Chain 2: Iteration: 3000 / 5000 [ 60%]  (Sampling)
## Chain 2: Iteration: 3500 / 5000 [ 70%]  (Sampling)
## Chain 2: Iteration: 4000 / 5000 [ 80%]  (Sampling)
## Chain 2: Iteration: 4500 / 5000 [ 90%]  (Sampling)
## Chain 2: Iteration: 5000 / 5000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.632963 seconds (Warm-up)
## Chain 2:                0.640653 seconds (Sampling)
## Chain 2:                1.27362 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL '10f63a45fd17e5d9181b383b6c1bd659' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 3.2e-05 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.32 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 5000 [  0%]  (Warmup)
## Chain 3: Iteration:  500 / 5000 [ 10%]  (Warmup)
## Chain 3: Iteration: 1000 / 5000 [ 20%]  (Warmup)
## Chain 3: Iteration: 1500 / 5000 [ 30%]  (Warmup)
## Chain 3: Iteration: 2000 / 5000 [ 40%]  (Warmup)
## Chain 3: Iteration: 2500 / 5000 [ 50%]  (Warmup)
## Chain 3: Iteration: 2501 / 5000 [ 50%]  (Sampling)
```

```
## Chain 3: Iteration: 3000 / 5000 [ 60%]  (Sampling)
## Chain 3: Iteration: 3500 / 5000 [ 70%]  (Sampling)
## Chain 3: Iteration: 4000 / 5000 [ 80%]  (Sampling)
## Chain 3: Iteration: 4500 / 5000 [ 90%]  (Sampling)
## Chain 3: Iteration: 5000 / 5000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.647747 seconds (Warm-up)
## Chain 3:                0.672648 seconds (Sampling)
## Chain 3:                1.32039 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL '10f63a45fd17e5d9181b383b6c1bd659' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 3.2e-05 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.32 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 5000 [  0%]  (Warmup)
## Chain 4: Iteration:  500 / 5000 [ 10%]  (Warmup)
## Chain 4: Iteration: 1000 / 5000 [ 20%]  (Warmup)
## Chain 4: Iteration: 1500 / 5000 [ 30%]  (Warmup)
## Chain 4: Iteration: 2000 / 5000 [ 40%]  (Warmup)
## Chain 4: Iteration: 2500 / 5000 [ 50%]  (Warmup)
## Chain 4: Iteration: 2501 / 5000 [ 50%]  (Sampling)
## Chain 4: Iteration: 3000 / 5000 [ 60%]  (Sampling)
## Chain 4: Iteration: 3500 / 5000 [ 70%]  (Sampling)
## Chain 4: Iteration: 4000 / 5000 [ 80%]  (Sampling)
## Chain 4: Iteration: 4500 / 5000 [ 90%]  (Sampling)
## Chain 4: Iteration: 5000 / 5000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.646892 seconds (Warm-up)
## Chain 4:                0.670634 seconds (Sampling)
## Chain 4:                1.31753 seconds (Total)
## Chain 4:
```

Loading and tidying data to predict for

```
## Constrained max depth of site to 15m

pred_depth <- read.csv('moorea_depth.csv') %>%
  mutate(site=tolower(site)) %>%
  group_by(site) %>%
  mutate(depth=if_else(depth < -15,-15, depth)*-1) %>%
  slice_max(depth)

pred_data <- read.csv('moorea_benthos.csv') %>%
  mutate(site=gsub('\\s','_',tolower(site)))
```

Filtering and manipulating the time series for the correct categories

```
ts_data <- left_join(pred_data,pred_depth, by='site') %>%
  filter(Habitat=='Outer slope' & Season=='Mar') %>%
  mutate(subs_group=case_when(
      Substrate == 'Dead coral' ~ 'algal_turf',
      Substrate == 'Stegastes Turf' ~ 'algal_turf',
      Substrate == 'Rubble' ~ 'algal_turf',
      Substrate == 'Pavement' ~ 'algal_turf',
      Substrate == 'Macroalgae' ~ 'macroalgae',
      Substrate == 'Turbinaria' ~ 'macroalgae',
      TRUE ~ Substrate,
  )) %>%
  filter(subs_group %in% c('algal_turf','macroalgae')) %>%
  group_by(Year, site, Transect, lat, long, depth, subs_group) %>%
  summarise(prop=sum(proportion), .groups='drop_last') %>%
  pivot_wider(names_from=subs_group,values_from=prop,values_fill=0)
```

Now, how about trying to predict benthic reef productivity

by merging area specific turf productivity with turf cover

```
pred_val <- posterior_epred(brmod,
      newdata=ts_data %>% mutate(se_prod=0.1), ndraws=1000)


dim(ts_data)
```

```
## [1] 507   8
```

```
dim(pred_val)
```

```
## [1] 1000  507
```

```
tot_turf_prod <- (ts_data$algal_turf * t(pred_val)) * 10000
## in g C ha day-1


# aggregating

fts_data <- cbind(ts_data,
      turf_prod_mean=apply(tot_turf_prod,1,median),
      turf_prod_lhdi=apply(tot_turf_prod,1,function(x) median_hdci(x)$ymin),
      turf_prod_uhdi=apply(tot_turf_prod,1,function(x) median_hdci(x)$ymax))

## in g C ha-1 day-1
```

Now doing some plots

```
ggplot(data=fts_data) +
  geom_line(aes(x=Year,y=turf_prod_mean,group=interaction(Transect,site))) +
  geom_smooth(aes(x=Year,y=turf_prod_mean), colour='orange', alpha=0.8) +
  scale_x_continuous(breaks=c(2005,2009,2013,2017)) +
  ylab(expression(Algal~turf~productivity~'('*g~C~ha^-1*day^-1*')')) +
  theme_minimal()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```