Case Study 1

This case study was developed primarily by E. Wolkovich, D. Loughnan and X. Wang with the input of the full manuscript author team.

This code for the case study includes two sections. The first section explains how to simulate data that fits our needs. We aim to simulate population data where the population is declining, but the p-value remains greater than 0.05. The second section is on data visualization, comparing how the results differ when using Fisherian approaches and Bayesian approaches.

Data simulation

To simulate data that fits our needs, we use a simple linear function and add noise. We want the population data to exhibit either an increasing or decreasing trend, but some trends are not statistically significant (with a p-value greater than 0.05). After

Function

Function to simulate a population with linear growth and noise:

```
simulate_population <- function(a, b, t, noise_sd) {
   y <- numeric(t)
   time <- 1:t
   y <- a*time + b + rnorm(t, 0, noise_sd)
     # y is the population of certain time
     # a is the increasing/decreasing rate
     # b is the starting population size
     # time is the x variable
     # noise_sd
   model <- lm(y ~ time)
   # Extract the estimated slope (coefficient of time)
   estimated_slope <- coef(model)["time"]</pre>
```

```
pval <- coef(summary(lm(y ~ time)))[["time", "Pr(>|t|)"]]
return(c(estimated_slope, pval))
}
```

Simulate population data

Simulate population data with different increasing and decreasing rates as well as different noises

Select populations

Search for populations:

We want to search for cases were:

- (1) All the estimated slopes are pretty close to given slopes and
- (2) The bottom populations has a p-value between 0.05-0.15

After checking different seeds, we finally decided on seed 1546

```
givenslope noise estslope pval
time -2000 8600 -1708.306 0.146969632
time1 -1800 8200 -2121.081 0.031744531
time2 -1600 7800 -1494.864 0.190847601
```

```
time3 -1400 7400 -1330.010 0.164436645
time4 1400 7000 1499.433 0.035391410
time5 1600 6600 1260.549 0.116379852
time6 1800 6200 1600.972 0.005141529
time7 2000 5800 2212.688 0.004420759
```

We dropped the 2nd population with p-value smaller than 0.05.

Data analysis

The following code performs data analysis and visualization using both the traditional Fisherian approach and the Bayesian approach. For the Fisherian approach, we use an 1m model and plot the p-values for different populations, indicating whether the increase or decrease is statistically significant. For the Bayesian approach, we use Stan code with priors and plot the posterior distribution.

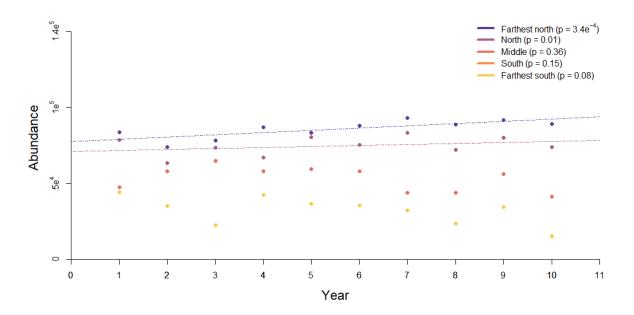
```
# Decided to run with 1546
set.seed(1546)
# Dropping -1600, 1600
a <- c(-2000, -1600, -1400, 600, 1400 , 1600, 2000)
t <- 10
time <- 1:t
b <- seq(40000, 101000, by=10000)
noise_sd <- c(7000, 6600, 6200, 5800, 5400, 5000, 4600)</pre>
```

Traditional Fisherian approach

With traditional Fisherian approach, we use lm model to plot

```
abund <- data.frame(reshape2::melt(t(abund)))
output$pred <- abund$value</pre>
```

Visualization



Bayesian approach

With Bayesian approach, we run the stan code:

```
data {
  int<lower=0> N; //No. obs
  int<lower=0> Ngrp; //No. in group---population or species
  int group[N]; // Group type
  vector[N] year;
  real ypred[N]; //response
}
```

```
parameters {
  real a[Ngrp] ;
  real b[Ngrp];
  real mu_a;
  real<lower=0> sigma_a;
  real mu_b;
 real<lower=0> sigma_b;
  real<lower=0> sigma_y;
}
model {
real mu_y[N];
for(i in 1:N){
     mu_y[i]=a[group[i]]+b[group[i]]*year[i];
a ~ normal(mu_a, sigma_a);
b ~ normal(mu_b, sigma_b);
    //Priors
mu_a ~normal(188, 50);
sigma_a ~normal(0,50);
mu_b \sim normal(0,10); //could also be centred at zero, 10
sigma_b ~normal(0,10); //sigma_b 0,10
sigma_y ~normal(0,10);
ypred ~ normal(mu_y, sigma_y);
'data.frame': 50 obs. of 4 variables:
 $ iter: int 1 2 3 4 5 6 7 8 9 10 ...
 $ pop : int 1 1 1 1 1 1 1 1 1 ...
 $ year: int 1 2 3 4 5 6 7 8 9 10 ...
 $ pred: num 43951 34961 22390 42250 36469 ...
mdlPop <- stan("partialPoolSimMdl.stan",</pre>
               data = datalistGrp)
```

```
sum <- summary(mdlPop)$summary

intercept <- sum[grep("a\\[", rownames(sum)), "mean"]

slopes <- sum[grep("b\\[", rownames(sum)), "mean"]

# Posterior distribution
post <- rstan::extract(mdlPop)</pre>
```

Visualization

