# Appendix S3 - Biomass analysis

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### **Background**

This is a modified subset of Appendix S3 from the article "Maintenance of community function through compensation breaks down over time in a desert rodent community" by Renata Diaz and S. K. Morgan Ernest, now published in *Ecology* (Diaz and Ernest 2022).

### Compensation

Compensation refers to the degree to which the remaining species on kangaroo rat removal plots absorb resources made available via kangaroo rat removal (Figure 1). We fit a generalized least squares (of the form compensation ~ timeperiod; note that "timeperiod" is coded as "oera" throughout) using the gls function from the R package nlme (Pinheiro, Bates, and R Core Team 2023). Because values from monthly censuses within each time period are subject to temporal autocorrelation, we included a continuous autoregressive temporal autocorrelation structure of order 1 (using the CORCAR1 function). We compared this model to models fit without the autocorrelation structure and without the time period term using AIC. The model with both the time period term and the autocorrelation structure was the best-fitting model via AIC (Table 1), and we used this model to calculate estimates and contrasts using the package emmeans (Lenth et al. 2023) (Table 2, Table 3).

## Data analysis

#### Data preparation

The following code downloads the data and prepares the compensation data frame for analysis.

If needed, install the soar package:

```
remotes::install_github('diazrenata/soar')
```

Data can be downloaded directly from the Portal data repository:

```
plotl <- get_plot_totals(currency = "biomass")

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Joining with `by = join_by(plot)`

plot_types <- list_plot_types() %>% filter(plot_type == "EE")

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Joining with `by = join_by(plot)`
```

For interpretability, translating the era and treatment "names" as RMD coded them for analysis to the corresponding dates:

```
oera_df <- data.frame(</pre>
  oera = c("a_pre_pb", "b_pre_reorg", "c_post_reorg"),
  `Timeperiod` = c("1988-1997", "1997-2010", "2010-2020")
oplot_df <- data.frame(oplottype = c("CC", "EE"),</pre>
                        `Treatment` = c("Control", "Exclosure"))
contrasts_df <- data.frame(</pre>
  contrast = c(
    "a_pre_pb - b_pre_reorg",
    "a_pre_pb - c_post_reorg",
    "b_pre_reorg - c_post_reorg"
  ),
 Comparison = c(
    "1988-1997 - 1997-2010",
    "1988-1997 - 2010-2020",
    "1997-2010 - 2010-2020"
  )
)
```

Because there are 5 exclosure plots and 4 control plots in these data, we remove 1 exclosure plot to achieve a balanced design. From the 5 possible exclosures to remove, we randomly select 1 using the seed 1977 (the year the Portal Project was initiated).

```
plot_types <- plot_types %>%
   filter(plot_type == "EE")

set.seed(1977)
remove_plot <- sample(plot_types$plot, 1, F) # results in removing plot 19

plotl <- plotl %>%
   filter(plot != remove_plot)
```

Finally, take treatment-level means and calculate the compensation variable:

Joining with `by = join\_by(period)`

#### GLS model

The following code fits the GLS models:

```
comp_mean_gls <-
  gls(smgran_comp ~ oera,
       correlation = corCAR1(form = ~ period),
       data = compensation)

comp_mean_gls_notime <-
  gls(smgran_comp ~ 1,
       correlation = corCAR1(form = ~ period),
       data = compensation)</pre>
```

```
comp_mean_gls_noautoc <-</pre>
    gls(smgran_comp ~ oera, data = compensation)
  comp_mean_null <- gls(smgran_comp ~ 1, data = compensation)</pre>
Model comparison via AIC:
  compensation_comparison <- data.frame(</pre>
    `Model specification` = c(
      "intercept + timeperiod + autocorrelation",
      "intercept + autocorrelation",
      "intercept + timeperiod",
      "intercept"
    ),
    AIC = c(
      AIC(comp_mean_gls),
      AIC(comp_mean_gls_notime),
      AIC(comp_mean_gls_noautoc),
      AIC(comp_mean_null)
    )
  )
Calculate estimates:
  comp_mean_gls_emmeans <- emmeans(comp_mean_gls, specs = ~ oera)</pre>
  compensation_estimates <- oera_df %>%
    left_join(as.data.frame(comp_mean_gls_emmeans)) %>%
    select(-oera)
Joining with `by = join_by(oera)`
Calculate contrasts:
  compensation_contrasts <-contrasts_df %>%
    left_join(as.data.frame(pairs(comp_mean_gls_emmeans))) %>%
    mutate(p.value = round(p.value, digits = 4)) %>%
    select(-contrast)
Joining with `by = join_by(contrast)`
```

# Results

#### **Tables**

Table 1: Comparisons for GLS on compensation.

Model.specification	AIC
intercept + timeperiod + autocorrelation	-17.623354
intercept + autocorrelation	-3.297103
intercept + timeperiod	92.184205
intercept	207.804481

knitr::kable(compensation\_estimates)

Table 2: Estimates for GLS on compensation.

Timeperiod	emmean	SE	df	lower.CL	upper.CL
1988-1997 1997-2010 2010-2020	0.5366915	$0.0511419 \\ 0.0452745 \\ 0.0517205$	41.90192	0.4453176	0.6280655

knitr::kable(compensation\_contrasts)

Table 3: Contrasts for GLS on compensation.

Comparison	estimate	SE	df	t.ratio	p.value
1988-1997 - 1997-2010	-0.3931253	0.0673811	43.21488	-5.834358	0.0000
1988-1997 - 2010-2020	-0.1006089	0.0727090	40.35555	-1.383719	0.3588
1997-2010 - 2010-2020	0.2925164	0.0678003	44.41615	4.314383	0.0003

## **Figures**

```
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Joining with `by = join_by(plot)`

Joining with `by = join_by(oera)`
```

# 

Figure 1: Dynamics of biomass and rodent community composition over time. Lines represent the 6-month moving averages of biomass compensation. Dotted vertical lines mark the boundaries between time periods used for statistical analysis. Horizontal lines are time-period estimates from generalized least squares models, and the semitransparent envelopes mark the 95% confidence or credible intervals.

## References

- Diaz, Renata M., and S. K. Morgan Ernest. 2022. "Maintenance of Community Function Through Compensation Breaks down over Time in a Desert Rodent Community." *Ecology* 103 (7): e3709. https://doi.org/10.1002/ecy.3709.
- Lenth, Russell V., Ben Bolker, Paul Buerkner, Iago Giné-Vázquez, Maxime Herve, Maarten Jung, Jonathon Love, Fernando Miguez, Hannes Riebl, and Henrik Singmann. 2023. "Emmeans: Estimated Marginal Means, Aka Least-Squares Means."
- Pinheiro, José, Douglas Bates, and R Core Team. 2023. Nlme: Linear and Nonlinear Mixed Effects Models.