Appendix S4 - Plot-level analysis

Supplemental information for Diaz and Ernest, "Maintenance of community function through compensation breaks down over time in a desert rodent community". In review at Ecology.

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In order to calculate energetic compensation and the total energy ratio, we require an estimate for the baseline values of total energy use, kangaroo rat energy use, and small granivore energy use on control plots. Estimating these baselines averages over between-plot variability among the control plots, and for consistency, in the main analysis, we also aggregate across the exclosure plots and focus on treatment-level means. However, we can explore some degree of plot-level variability in our analyses by examining the effect of plot as a random factor within exclosure plots (for total energy and compensation) and across all plots involved in analyses of proportional energy use (controls and exclosures for *C. baileyi*, and only controls for *Dipodomys*).

Calculations of compensation and the total energy ratio

```
compensation_dat <- filter(plotl_vars, oplottype == "EE")
total_e_dat <- filter(plotl_vars, oplottype == "EE")
pb_dat <- filter(plotl_vars, as.numeric(oera) > 1)
dipo_c_dat <- filter(plotl_vars, oplottype == "CC")</pre>
```

Compensation

```
comp_plot_gls <- lme(compensation ~ oera , random = ~1|fplot, correlation = corCAR1(form = ~ period |
comp_plot_gls_noautoc <- lme(compensation ~ oera , random = ~1|fplot, data = compensation_dat)</pre>
comp_plot_gls_norandom <- gls(compensation ~ oera , correlation = corCAR1(form = ~ period | fplot), dat
comp_plot_gls_notime <- lme(compensation ~ 1 , random = ~1 | fplot, correlation = corCAR1(form = ~ perior
comp_plot_gls_notime_nocor <- lme(compensation ~ 1 , random = ~1|fplot, data = compensation_dat)</pre>
comp_plot_gls_notime_nocor_norand <- gls(compensation ~ 1 , data = compensation_dat)</pre>
AIC(comp_plot_gls)
## [1] 1360.207
AIC(comp_plot_gls_noautoc)
## [1] 1680.916
AIC(comp_plot_gls_norandom)
## [1] 1409.83
AIC(comp_plot_gls_notime)
## [1] 1408.362
AIC(comp_plot_gls_notime_nocor)
## [1] 1879.126
AIC(comp_plot_gls_notime_nocor_norand)
## [1] 2036.371
comp_mean_gls_emmeans <- emmeans(comp_plot_gls, specs = ~ oera)</pre>
```

Table S1. Coefficients from GLS for compensation

	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.3451282	0.1048354	1362	3.292096	0.0010199
oera.L	0.0653090	0.0373313	1362	1.749446	0.0804392
oera.Q	-0.2845830	0.0341063	1362	-8.343990	0.0000000

Table S2. Estimates from GLS for compensation

oera	emmean	SE	df	lower.CL	upper.CL
a_pre_pb	0.1827673	0.1091842	3	-0.1647055	0.5302400
b_pre_reorg	0.5774892	0.1078860	3	0.2341478	0.9208306
c_post_reorg	0.2751282	0.1093969	3	-0.0730215	0.6232779

Table S3. Contrasts from GLS for compensation

contrast	estimate	SE	df	t.ratio	p.value
a_pre_pb - b_pre_reorg a_pre_pb - c_post_reorg b_pre_reorg - c_post_reorg	-0.0923609	$\begin{array}{c} 0.0491845 \\ 0.0527944 \\ 0.0496411 \end{array}$	1362	-1.749446	

Total energy use

[1] 474.8558

[1] 924.183

[1] 507.7842

[1] 543.5425

[1] 1266.21

[1] 1382.747

Table S4. Coefficients from GLS on total energy ratio

	Value	Std.Error	DF	t-value	p-value
(Intercept) oera.L oera.Q	0.1454309	0.0709701 0.0301324 0.0273660	1362	7.070865 4.826392 -9.302977	0.0e+00 1.5e-06 0.0e+00

Table S5. Estimates from GLS on total energy ratio

oera	emmean	SE	df	lower.CL	upper.CL
a_pre_pb	0.2950508	0.0751321	3	0.0559470	0.5341547
b_pre_reorg	0.7096879	0.0738511	3	0.4746606	0.9447151
c_post_reorg	0.5007212	0.0752881	3	0.2611207	0.7403216

Table S6. Contrasts from GLS on total energy ratio

contrast	estimate	SE	df	t.ratio	p.value
a_pre_pb - b_pre_reorg	-0.4146370	0.0395736	1362	-10.477622	0
a_pre_pb - c_post_reorg	-0.2056703	0.0426137	1362	-4.826392	0
$b_pre_reorg - c_post_reorg$	0.2089667	0.0398571	1362	5.242901	0

Kangaroo rat proportional energy use

[1] 1040.861

[1] 1108.49

Table S7. Coefficients from GLM on Dipodomys energy use.

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	2.181163	0.1305753	16.704251	0
oera.L	-1.946096	0.2664545	-7.303670	0
oera.Q	1.124620	0.1769225	6.356572	0

Table S8. Estimates from GLM on Dipodomys energy use.

oera	prob	SE	df	asymp.LCL	asymp.UCL
a_pre_pb b_pre_reorg c_post_reorg	0.7795273	0.0062020 0.0183934 0.0208516		0.9701452 0.7434769 0.7388780	$\begin{array}{c} 0.9944566 \\ 0.8155777 \\ 0.8206149 \end{array}$

Table S9. Contrasts from GLMER on Dipodomys energy use.

contrast	estimate	SE	df	z.ratio	p.value
a_pre_pb - b_pre_reorg	0.2027736	0.0194108	Inf	10.4464200	0
$a_pre_pb - c_post_reorg$	0.2025545	0.0217545	Inf	9.3109407	0
$b_pre_reorg - c_post_reorg$	-0.0002191	0.0278048	Inf	-0.0078811	1

C. baileyi proportional energy use

[1] 1021.318

[1] 1020.263

[1] 1042.758

[1] 1321.149

[1] 1166.653

[1] 1162.901

[1] 1869.097

[1] 2036.489

Table S10. Coefficients from GLM on C. baileyi energy use

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-2.443643	0.2067789	-11.81766	0
oera.L	-1.866286	0.1530068	-12.19740	0
oplottype.L	3.265183	0.2913472	11.20719	0

Table S11. Estimates from GLM on C. baileyi energy use

oera	prob	SE	df	asymp.LCL	asymp.UCL
b_pre_reorg c_post_reorg				0.1602961 0.0125784	$0.3302516 \\ 0.0327827$

Table S12. Contrasts from GLM on C. baileyi energy use.

contrast	estimate	SE	df	z.ratio	p.value
b_pre_reorg - c_post_reorg	0.2225933	0.0406393	Inf	5.477298	0