2021_MARSSModel_Condense

```
library(MARSS)

## Warning: package 'MARSS' was built under R version 4.0.5

library(xtable)

## Warning: package 'xtable' was built under R version 4.0.5

library(tidyverse)

## Warning: package 'tidyverse' was built under R version 4.0.5

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

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.5     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.0.2     v forcats 0.5.1

## Warning: package 'ggplot2' was built under R version 4.0.5

## Warning: package 'tibble' was built under R version 4.0.5

## Warning: package 'tidyr' was built under R version 4.0.5

## Warning: package 'readr' was built under R version 4.0.5

## Warning: package 'purrr' was built under R version 4.0.5

## Warning: package 'dplyr' was built under R version 4.0.5

## Warning: package 'forcats' was built under R version 4.0.5

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

#Read in data

```
#Matrix Klamath + pond dataset
daily_means_long_klamath <- readRDS('daily_means_long_klamath.rds')
transformed_dat_klamath <- readRDS('transformed_dat_klamath.rds')
transformed_dat_klamath_df <- as.data.frame(t(transformed_dat_klamath))
str(transformed_dat_klamath)

#Matrix Airtemp dataset
```

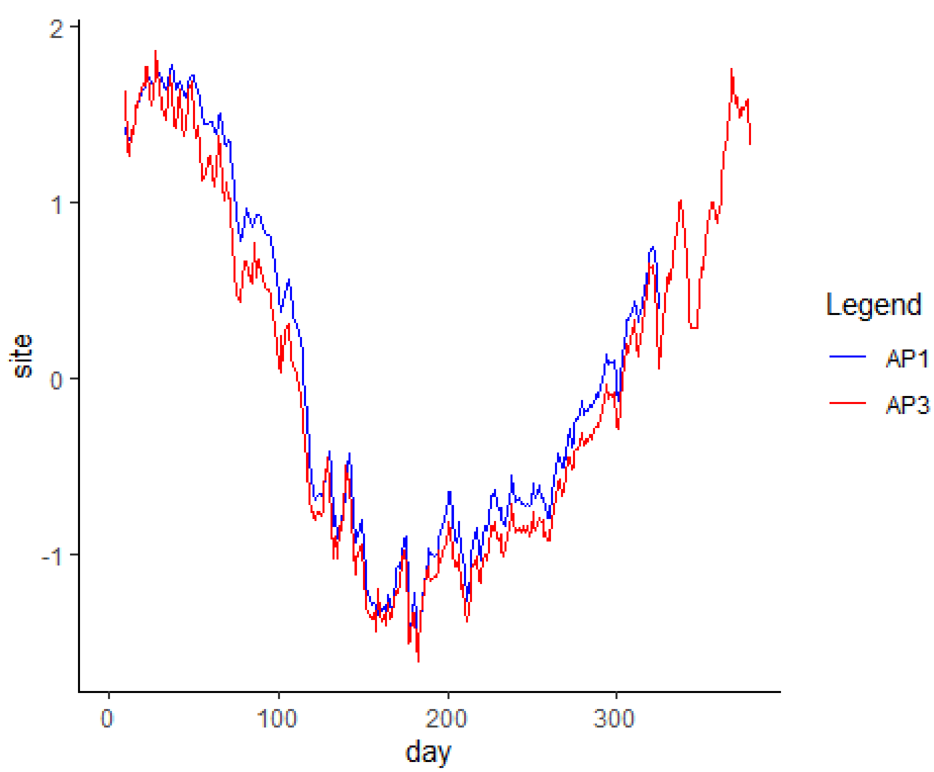
```
covariate_klamath <- readRDS('covariate.rds')
transformed_covariate_klamath <- zscore(covariate_klamath)
```

Steps:

1) Among sensor replicates, drop time series with (many) gaps.

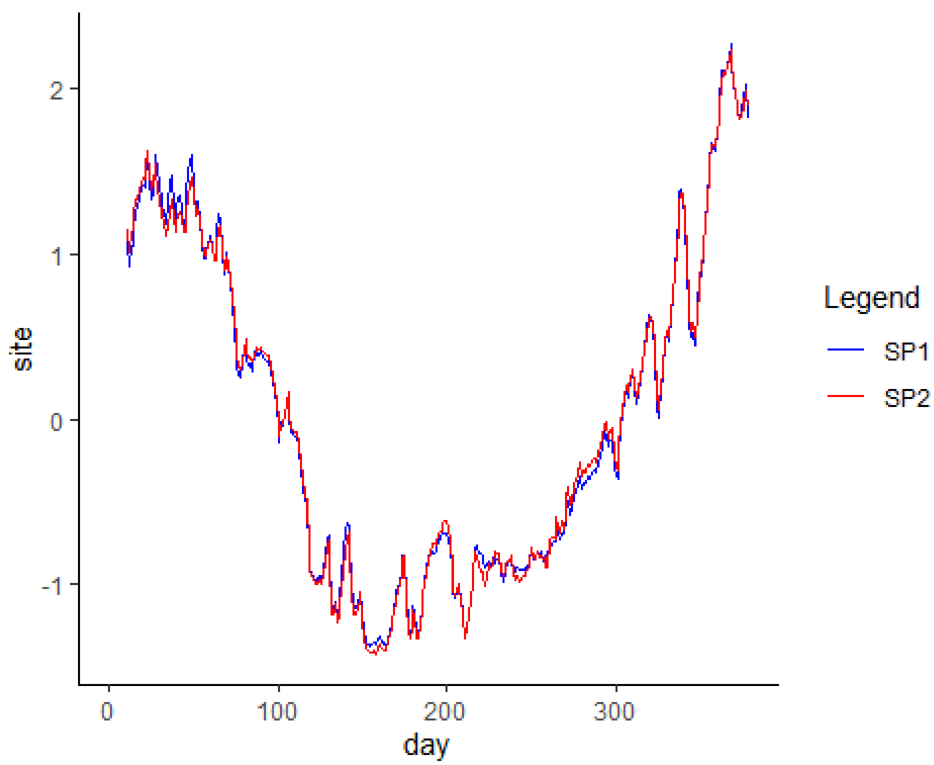
2) Then take mean across replicate sensors, so that we end up with 1 time series per habitat, 2+9+1 (12 x 378)

```
#AP
color <- c("AP1" = "blue", "AP3" = "red")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = AP1, color = "AP1")) +
  geom_line(aes(x = day, y = AP3, color = "AP3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("AP1","AP3"))

## Warning: Removed 63 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).
```



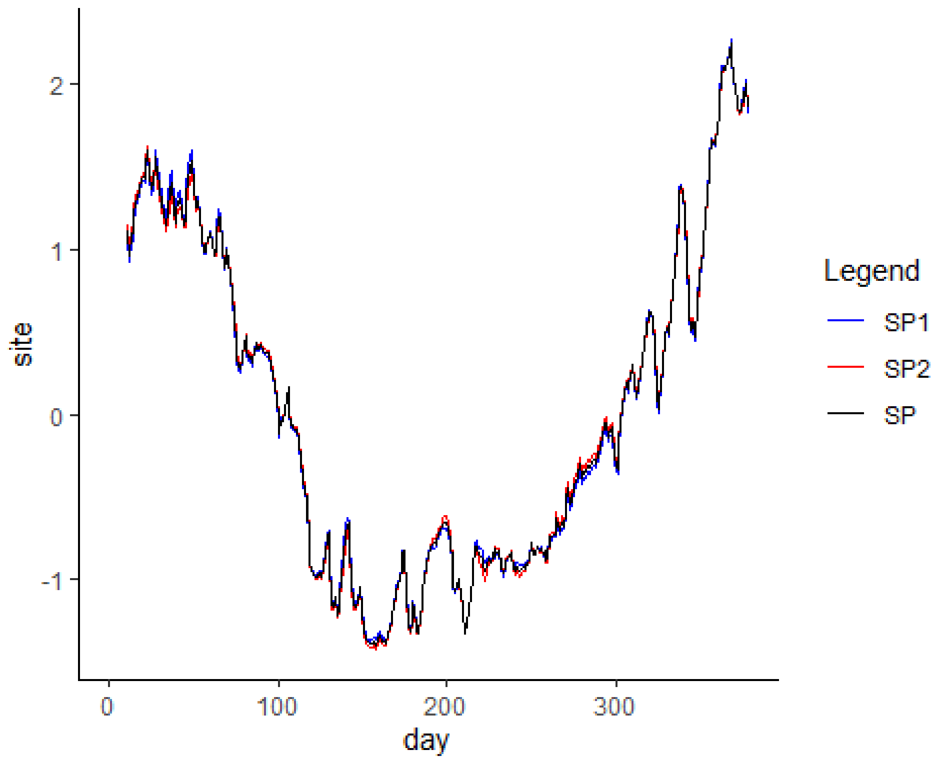

```
#need to remove AP1
```

```r
#SP
color <- c("SP1" = "blue", "SP2" = "red")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = SP1, color = "SP1")) +
  geom_line(aes(x = day, y = SP2, color = "SP2"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("SP1","SP2"))

## Warning: Removed 10 row(s) containing missing values (geom_path).

## Warning: Removed 10 row(s) containing missing values (geom_path).
```

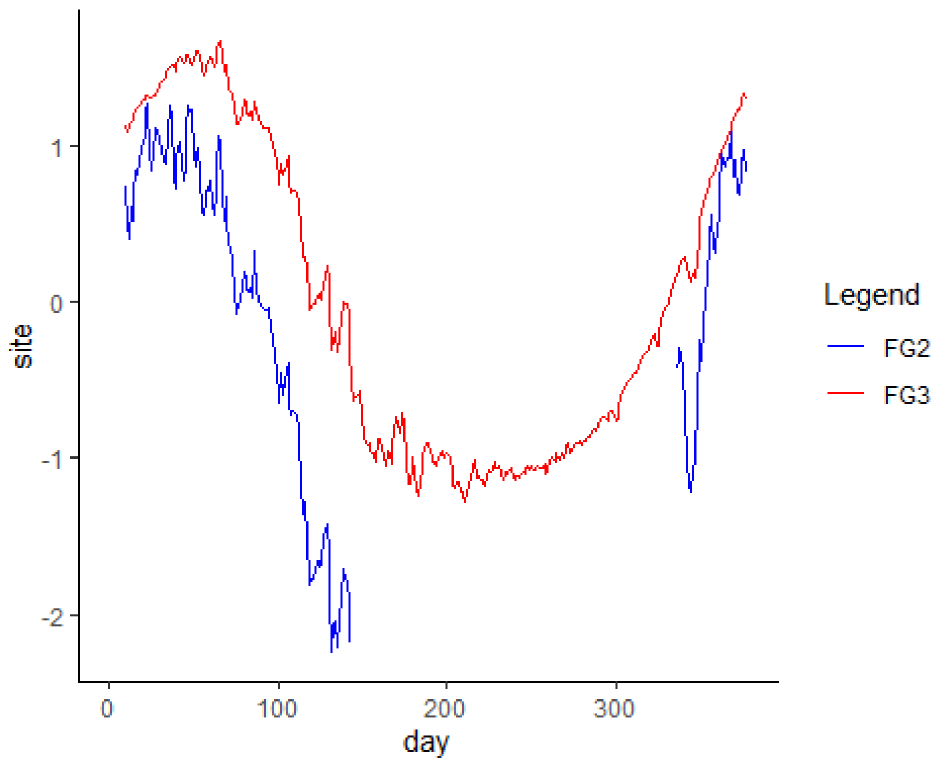



```r
#both good, need to take average
transformed_dat_klamath_df$SP <-
rowMeans(transformed_dat_klamath_df[,c('SP1', 'SP2')], na.rm=TRUE)

color <- c("SP1" = "blue", "SP2" = "red", SP = "black")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = SP1, color = "SP1")) +
  geom_line(aes(x = day, y = SP2, color = "SP2"))+
  geom_line(aes(x = day, y = SP, color = "SP"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("SP1","SP2", "SP"))
```

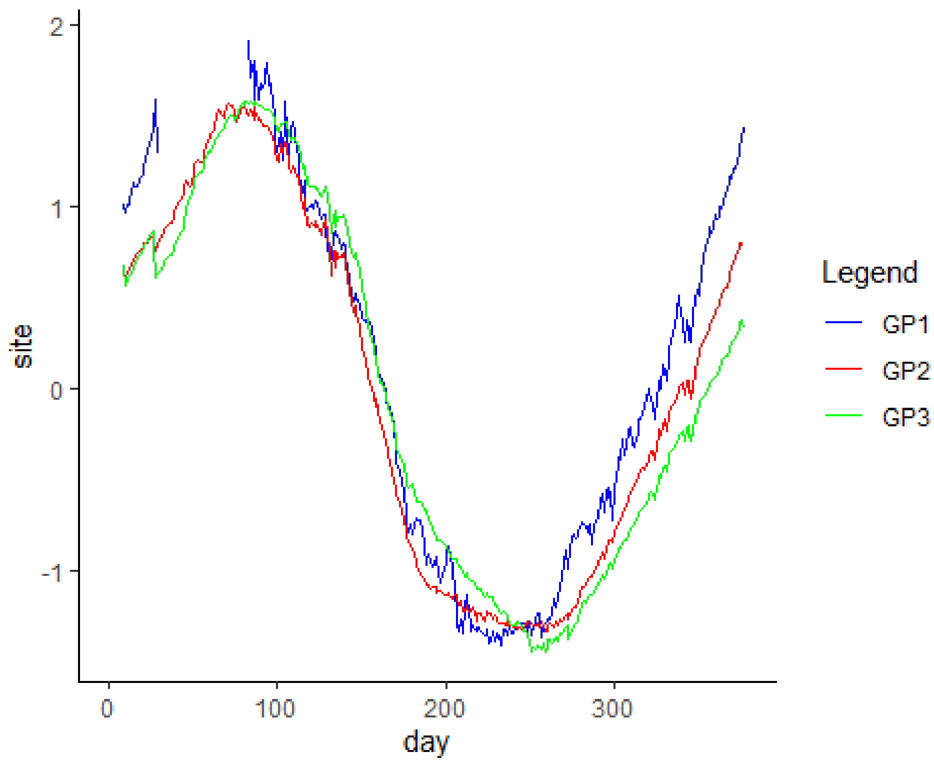
```
## Warning: Removed 10 row(s) containing missing values (geom_path).

## Warning: Removed 10 row(s) containing missing values (geom_path).

## Warning: Removed 10 row(s) containing missing values (geom_path).
```



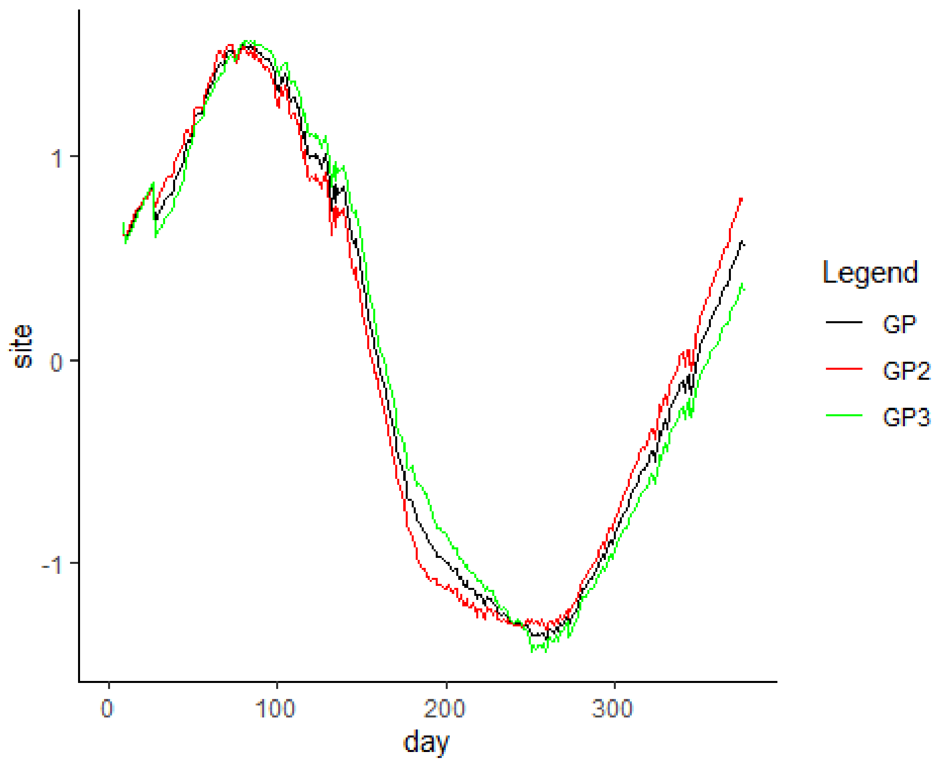

```
#FG
color <- c("FG2" = "blue", "FG3" = "red")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = FG2, color = "FG2")) +
  geom_line(aes(x = day, y = FG3, color = "FG3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("FG2","FG3"))

## Warning: Removed 10 row(s) containing missing values (geom_path).

## Warning: Removed 10 row(s) containing missing values (geom_path).
```



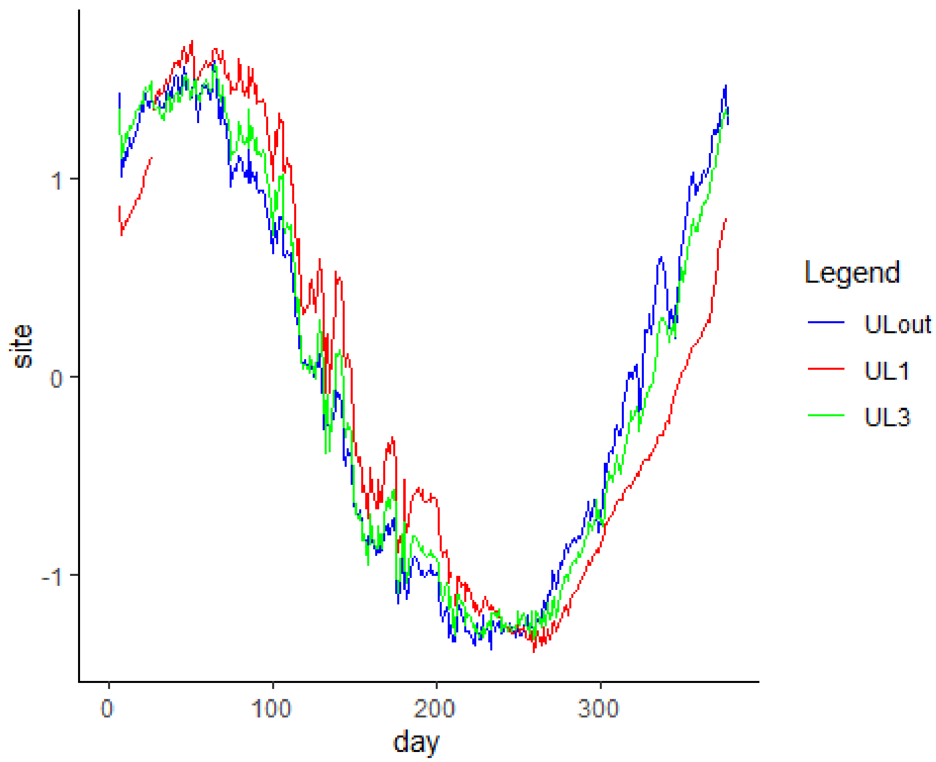

```r
#need to remove FG2

#GP
color <- c("GP1" = "blue", "GP2" = "red", "GP3" = "green")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = GP1, color = "GP1")) +
  geom_line(aes(x = day, y = GP2, color = "GP2"))+
  geom_line(aes(x = day, y = GP3, color = "GP3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("GP1","GP2","GP3"))

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).
```



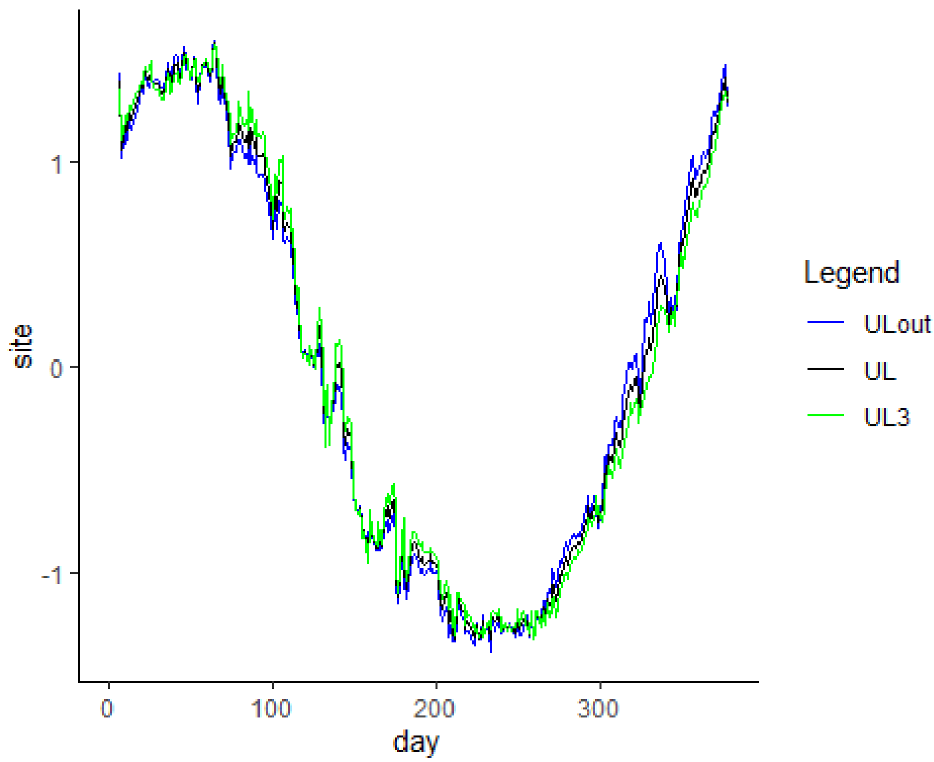

```r
#need to remove GP1
transformed_dat_klamath_df$GP <-
rowMeans(transformed_dat_klamath_df[,c('GP2', 'GP3')], na.rm=TRUE)

color <- c("GP" = "black", "GP2" = "red", "GP3" = "green")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = GP, color = "GP")) +
  geom_line(aes(x = day, y = GP2, color = "GP2"))+
  geom_line(aes(x = day, y = GP3, color = "GP3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("GP","GP2","GP3"))

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).
```



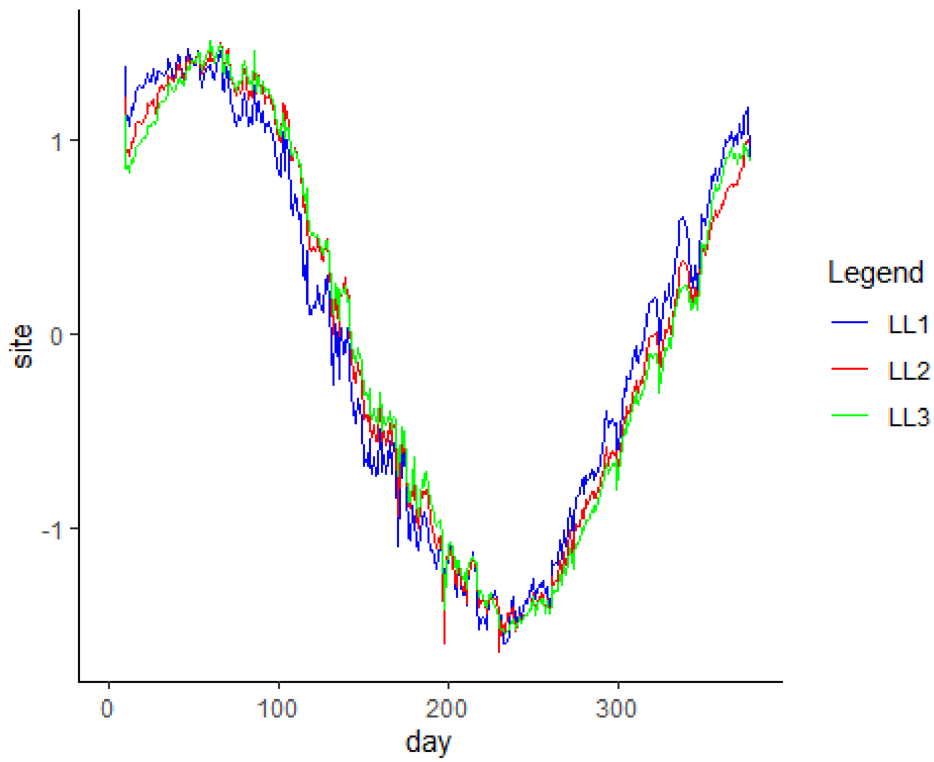

```
#UL
color <- c("ULout" = "blue", "UL1" = "red", "UL3" = "green")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = ULout, color = "ULout")) +
  geom_line(aes(x = day, y = UL1, color = "UL1"))+
  geom_line(aes(x = day, y = UL3, color = "UL3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("ULout","UL1","UL3"))

## Warning: Removed 7 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).
```



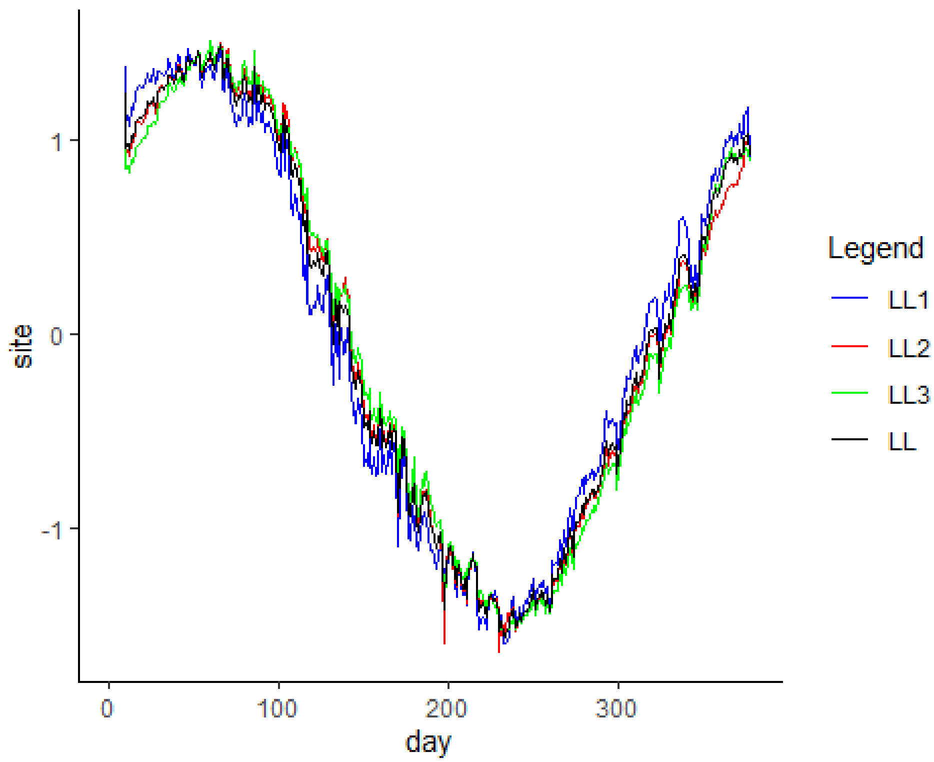

```
#need to remove UL1
transformed_dat_klamath_df$UL <-
rowMeans(transformed_dat_klamath_df[,c('ULout', 'UL3')], na.rm=TRUE)

color <- c("ULout" = "blue", "UL" = "black", "UL3" = "green")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = ULout, color = "ULout")) +
  geom_line(aes(x = day, y = UL, color = "UL"))+
  geom_line(aes(x = day, y = UL3, color = "UL3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("ULout","UL","UL3"))

## Warning: Removed 7 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).
```



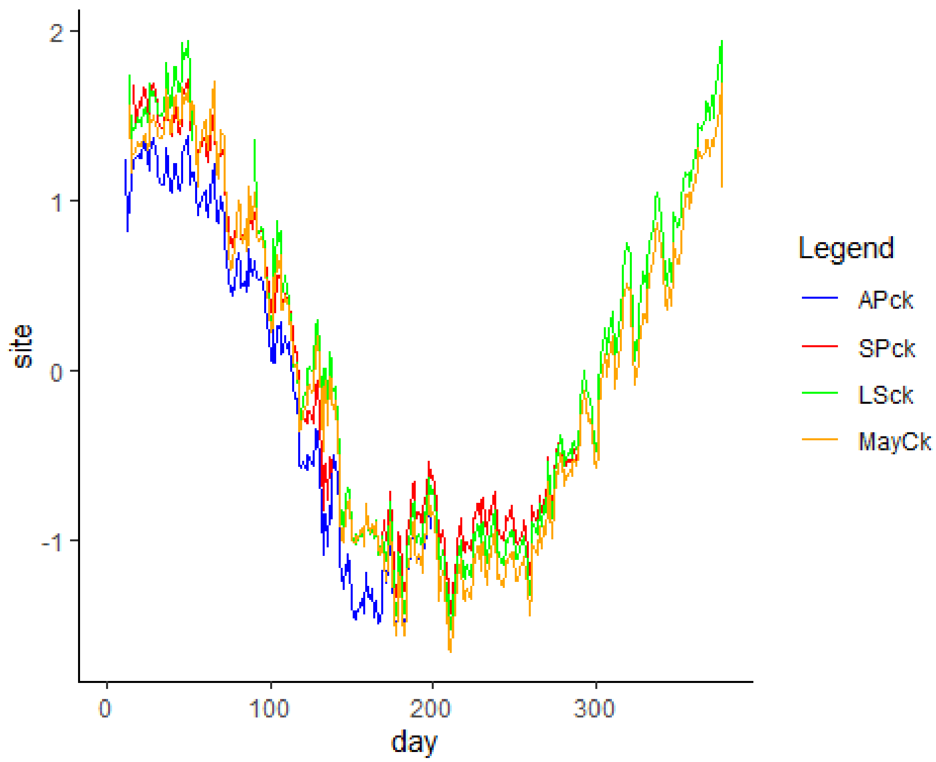

```
#LL
color <- c("LL1" = "blue", "LL2" = "red", "LL3" = "green")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = LL1, color = "LL1")) +
  geom_line(aes(x = day, y = LL2, color = "LL2"))+
  geom_line(aes(x = day, y = LL3, color = "LL3"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("LL1","LL2","LL3"))

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).
```



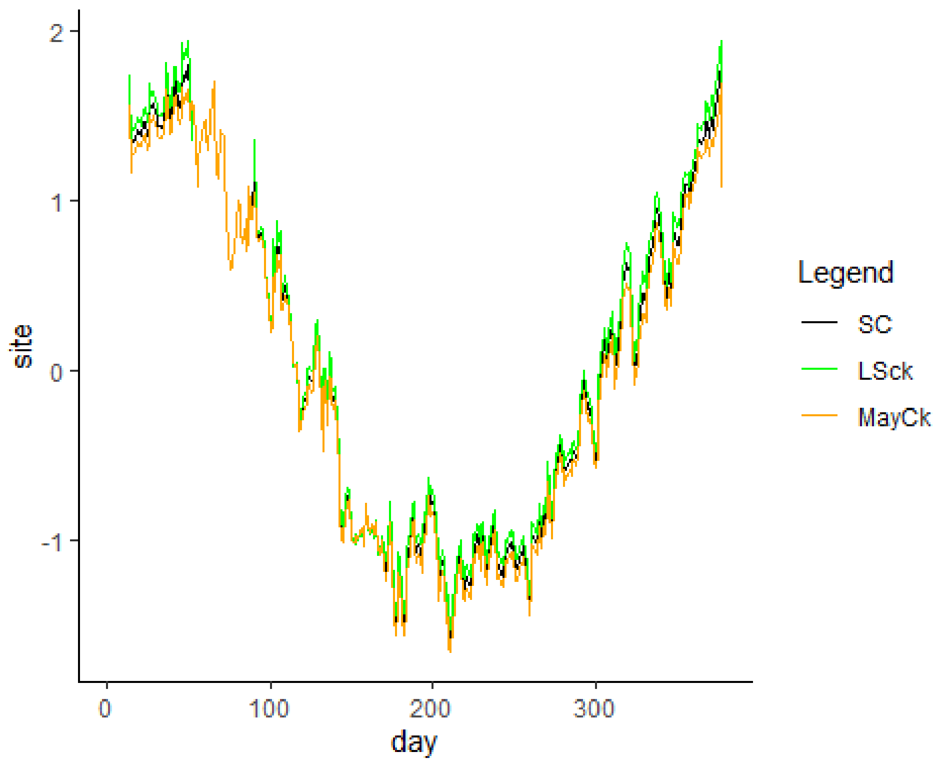

```
#all ok
transformed_dat_klamath_df$LL <-
rowMeans(transformed_dat_klamath_df[,c('LL1','LL2', 'LL3')], na.rm=TRUE)

color <- c("LL1" = "blue", "LL2" = "red", "LL3" = "green", 'LL' = "black")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = LL1, color = "LL1")) +
  geom_line(aes(x = day, y = LL2, color = "LL2"))+
  geom_line(aes(x = day, y = LL3, color = "LL3"))+
   geom_line(aes(x = day, y = LL, color = "LL"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("LL1","LL2","LL3", "LL"))

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).

## Warning: Removed 9 row(s) containing missing values (geom_path).
```



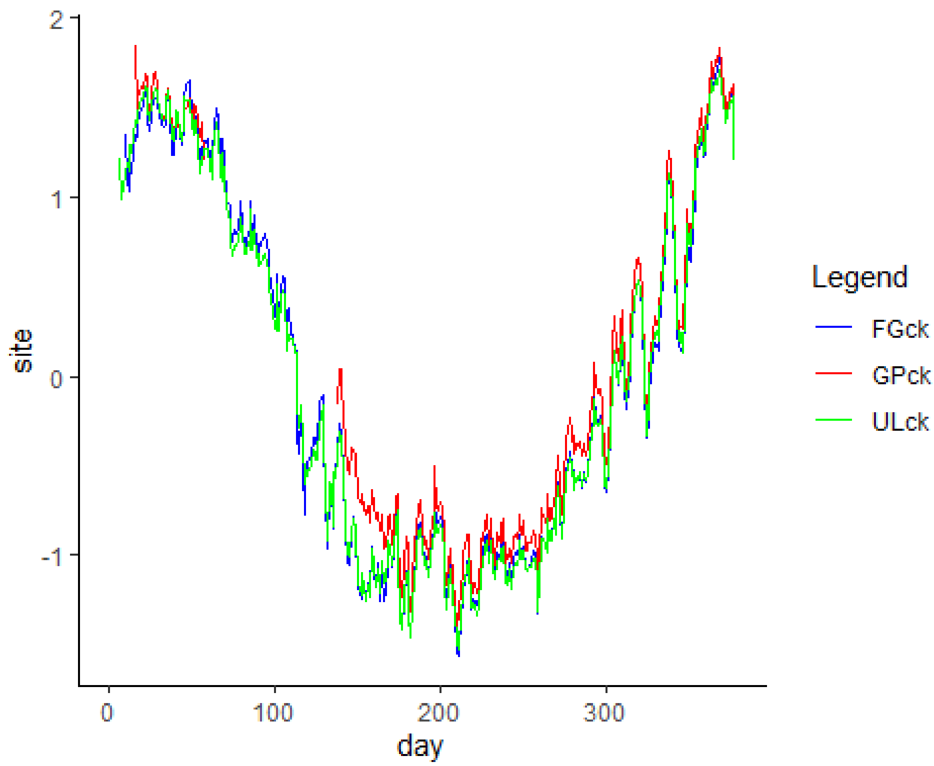

```
#SC
color <- c("APck" = "blue", "SPck" = "red", "LSck" = "green",
"MayCk"="orange")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = APck, color = "APck")) +
  geom_line(aes(x = day, y = SPck, color = "SPck"))+
  geom_line(aes(x = day, y = LSck, color = "LSck"))+
  geom_line(aes(x = day, y = MayCk, color = "MayCk"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels =
c("APck","SPck","LSck","MayCk"))

## Warning: Removed 189 row(s) containing missing values (geom_path).

## Warning: Removed 104 row(s) containing missing values (geom_path).

## Warning: Removed 12 row(s) containing missing values (geom_path).

## Warning: Removed 12 row(s) containing missing values (geom_path).
```



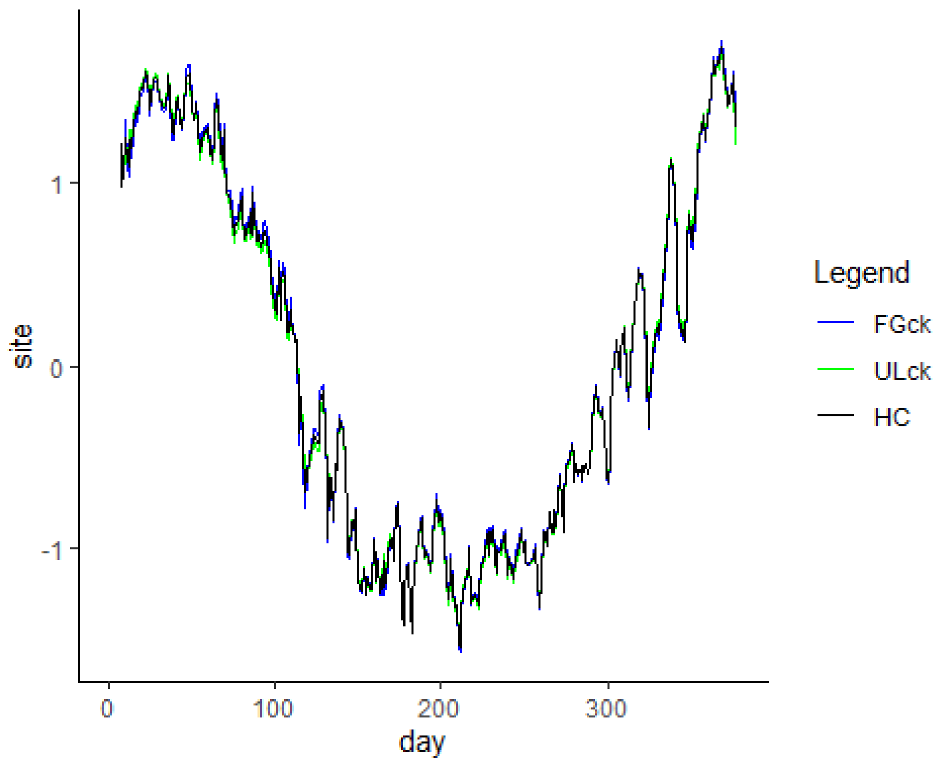

```
#need to remove APck and SPck
transformed_dat_klamath_df$SC <-
rowMeans(transformed_dat_klamath_df[,c('LSck','MayCk')], na.rm=TRUE)

color <- c("SC" = "black","LSck" = "green", "MayCk"="orange")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = SC, color = "SC"))+
  geom_line(aes(x = day, y = LSck, color = "LSck"))+
  geom_line(aes(x = day, y = MayCk, color = "MayCk"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("SC","LSck","MayCk"))

## Warning: Removed 12 row(s) containing missing values (geom_path).

## Warning: Removed 12 row(s) containing missing values (geom_path).

## Warning: Removed 12 row(s) containing missing values (geom_path).
```




```
#HC
color <- c("FGck" = "blue", "GPck" = "red", "ULck" = "green")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = FGck, color = "FGck")) +
  geom_line(aes(x = day, y = GPck, color = "GPck"))+
  geom_line(aes(x = day, y = ULck, color = "ULck"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("FGck","GPck","ULck"))

## Warning: Removed 10 row(s) containing missing values (geom_path).

## Warning: Removed 16 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).
```




```
#need to remove GPck
transformed_dat_klamath_df$HC <-
rowMeans(transformed_dat_klamath_df[,c('ULck','FGck')], na.rm=TRUE)

color <- c("FGck" = "blue", "ULck" = "green", "HC" = "black")
transformed_dat_klamath_df %>% rowid_to_column(var = "day") %>% ggplot()+
  geom_line(aes(x = day, y = FGck, color = "FGck")) +
  geom_line(aes(x = day, y = ULck, color = "ULck"))+
   geom_line(aes(x = day, y = HC, color = "HC"))+
  labs(x = "day", y = "site", color = "Legend")+
  theme_classic()+
  scale_color_manual(values = color, labels = c("FGck","ULck", "HC"))

## Warning: Removed 10 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).

## Warning: Removed 7 row(s) containing missing values (geom_path).
```



#Matrix of transformed data with 12 sites (condensed_transdat)

```
condensed_transdat_df <- cbind(AP = transformed_dat_klamath_df$AP3, SP =
transformed_dat_klamath_df$SP, Durazo = transformed_dat_klamath_df$Durazo, LS
= transformed_dat_klamath_df$LS, May = transformed_dat_klamath_df$May, FG =
transformed_dat_klamath_df$FG3, GP = transformed_dat_klamath_df$GP, UL =
transformed_dat_klamath_df$UL, LL = transformed_dat_klamath_df$LL, SC =
transformed_dat_klamath_df$SC, HC = transformed_dat_klamath_df$HC, KSV =
transformed_dat_klamath_df$KSV)
condensed_transdat <- as.matrix(t(condensed_transdat_df))
str(condensed_transdat)
```

```
##  num [1:12, 1:378] NA NaN NA NA NA NA NaN NaN NaN NaN ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : chr [1:12] "AP" "SP" "Durazo" "LS" ...
##   ..$ : NULL
```

```
saveRDS(condensed_transdat, "condensed_transdat.rds")
```

Hypothesis 1: all states have different levels of stochastic (Q) and deterministic (C) variability

AICc -9599.906

```
mod1_condense = list()
mod1_condense$A = "zero"
mod1_condense$Z = "identity"
```

```
mod1_condense$R = "zero" #all the sensors are same, so observation error
should be same
mod1_condense$Q = "diagonal and unequal"
mod1_condense$B = "diagonal and unequal" #assuming no species interactions
mod1_condense$U = "zero"
mod1_condense$C = "unequal"
mod1_condense$c = transformed_covariate_klamath
mod1_condense.fit = MARSS(condensed_transdat, model=mod1_condense)
```

```
## MARSS: NaNs in data are being replaced with NAs.  There might be a problem
if NaNs shouldn't be in the data.
## NA is the normal missing value designation.
## Success! abstol and log-log tests passed at 153 iterations.
## Alert: conv.test.slope.tol is 0.5.
## Test with smaller values (<0.1) to ensure convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 153 iterations.
## Log-likelihood: 4857.285
## AIC: -9618.57   AICc: -9617.484
##
##                          Estimate
## B.(X.AP,X.AP)            0.942858
## B.(X.SP,X.SP)            0.968046
## B.(X.Durazo,X.Durazo)    0.967180
## B.(X.LS,X.LS)            0.987704
## B.(X.May,X.May)          0.966777
## B.(X.FG,X.FG)            0.972812
## B.(X.GP,X.GP)            0.987907
## B.(X.UL,X.UL)            0.965388
## B.(X.LL,X.LL)            0.965301
## B.(X.SC,X.SC)            0.911952
## B.(X.HC,X.HC)            0.890677
## B.(X.KSV,X.KSV)          0.945554
## Q.(X.AP,X.AP)            0.008070
## Q.(X.SP,X.SP)            0.006837
## Q.(X.Durazo,X.Durazo)    0.008850
## Q.(X.LS,X.LS)            0.005552
## Q.(X.May,X.May)          0.024014
## Q.(X.FG,X.FG)            0.003015
## Q.(X.GP,X.GP)            0.000809
## Q.(X.UL,X.UL)            0.004623
## Q.(X.LL,X.LL)            0.005431
## Q.(X.SC,X.SC)            0.015851
## Q.(X.HC,X.HC)            0.013369
## Q.(X.KSV,X.KSV)          0.005327
## x0.X.AP                  2.471342
## x0.X.SP                  1.288391
```

```
## x0.X.Durazo           1.695049
## x0.X.LS               1.695107
## x0.X.May              1.933986
## x0.X.FG               1.296982
## x0.X.GP               0.632370
## x0.X.UL               1.631588
## x0.X.LL               1.487285
## x0.X.SC               3.612499
## x0.X.HC               2.116309
## x0.X.KSV              1.106298
## C.X.AP                0.057603
## C.X.SP                0.035406
## C.X.Durazo            0.033553
## C.X.LS                0.010417
## C.X.May               0.028579
## C.X.FG                0.030953
## C.X.GP                0.018791
## C.X.UL                0.037363
## C.X.LL                0.037844
## C.X.SC                0.088024
## C.X.HC                0.113147
## C.X.KSV               0.057921
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```
mod1_condense.params =MARSSparamCIs(mod1_condense.fit)
MARSSparamCIs(mod1_condense.fit)
```

```
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 153 iterations.
## Log-likelihood: 4857.285
## AIC: -9618.57   AICc: -9617.484
##
##                           ML.Est  Std.Err    low.CI    up.CI
## B.(X.AP,X.AP)           0.942858 9.98e-03  0.923290 0.962425
## B.(X.SP,X.SP)           0.968046 8.89e-03  0.950627 0.985464
## B.(X.Durazo,X.Durazo) 0.967180 1.01e-02  0.947471 0.986889
## B.(X.LS,X.LS)           0.987704 7.41e-03  0.973183 1.002224
## B.(X.May,X.May)         0.966777 1.29e-02  0.941399 0.992155
## B.(X.FG,X.FG)           0.972812 5.22e-03  0.962583 0.983041
## B.(X.GP,X.GP)           0.987907 1.86e-03  0.984254 0.991560
## B.(X.UL,X.UL)           0.965388 6.54e-03  0.952573 0.978204
## B.(X.LL,X.LL)           0.965301 6.46e-03  0.952634 0.977969
## B.(X.SC,X.SC)           0.911952 1.37e-02  0.885028 0.938876
## B.(X.HC,X.HC)           0.890677 1.33e-02  0.864686 0.916667
```

```
## B.(X.KSV,X.KSV)       0.945554 8.96e-03  0.927994 0.963113
## Q.(X.AP,X.AP)         0.008070 5.94e-04  0.006906 0.009235
## Q.(X.SP,X.SP)         0.006837 5.04e-04  0.005849 0.007825
## Q.(X.Durazo,X.Durazo) 0.008850 6.54e-04  0.007567 0.010132
## Q.(X.LS,X.LS)         0.005552 4.10e-04  0.004748 0.006357
## Q.(X.May,X.May)       0.024014 1.84e-03  0.020409 0.027618
## Q.(X.FG,X.FG)         0.003015 2.22e-04  0.002579 0.003450
## Q.(X.GP,X.GP)         0.000809 5.96e-05  0.000692 0.000926
## Q.(X.UL,X.UL)         0.004623 3.39e-04  0.003958 0.005289
## Q.(X.LL,X.LL)         0.005431 4.00e-04  0.004648 0.006215
## Q.(X.SC,X.SC)         0.015851 1.17e-03  0.013554 0.018148
## Q.(X.HC,X.HC)         0.013369 9.82e-04  0.011445 0.015293
## Q.(X.KSV,X.KSV)       0.005327 4.00e-04  0.004544 0.006111
## x0.X.AP               2.471342 4.56e-01  1.577050 3.365633
## x0.X.SP               1.288391 3.47e-01  0.607769 1.969013
## x0.X.Durazo           1.695049 4.64e-01  0.785959 2.604138
## x0.X.LS               1.695107 3.16e-01  1.075835 2.314380
## x0.X.May              1.933986 7.65e-01  0.434243 3.433728
## x0.X.FG               1.296982 2.09e-01  0.887063 1.706901
## x0.X.GP               0.632370 9.13e-02  0.453480 0.811259
## x0.X.UL               1.631588 2.17e-01  1.206646 2.056529
## x0.X.LL               1.487285 2.75e-01  0.948641 2.025929
## x0.X.SC               3.612499 1.14e+00  1.385920 5.839078
## x0.X.HC               2.116309 5.45e-01  1.048644 3.183974
## x0.X.KSV              1.106298 7.76e-02  0.954217 1.258379
## C.X.AP                0.057603 9.89e-03  0.038220 0.076985
## C.X.SP                0.035406 8.78e-03  0.018195 0.052618
## C.X.Durazo            0.033553 9.94e-03  0.014065 0.053040
## C.X.LS                0.010417 7.33e-03 -0.003956 0.024789
## C.X.May               0.028579 1.35e-02  0.002126 0.055033
## C.X.FG                0.030953 5.18e-03  0.020806 0.041101
## C.X.GP                0.018791 1.84e-03  0.015179 0.022403
## C.X.UL                0.037363 6.48e-03  0.024652 0.050073
## C.X.LL                0.037844 6.40e-03  0.025305 0.050383
## C.X.SC                0.088024 1.37e-02  0.061163 0.114884
## C.X.HC                0.113147 1.32e-02  0.087314 0.138981
## C.X.KSV               0.057921 8.88e-03  0.040523 0.075318
## Initial states (x0) defined at t=0
##
## CIs calculated at alpha = 0.05 via method=hessian
```

Hypothesis 2: all states have save levels of stochastic (Q) and deterministic (C) variability

AICc -8356.184

```
mod2_condense = list()
mod2_condense$A = "zero"
mod2_condense$Z = "identity"
```

```
mod2_condense$R = "zero" #all the sensors are same, so observation error should be same
mod2_condense$Q = "diagonal and equal"
mod2_condense$B = "diagonal and equal" #assuming no species interactions
mod2_condense$U = "zero"
mod2_condense$C = "equal"
mod2_condense$c = transformed_covariate_klamath
mod2_condense.fit = MARSS(condensed_transdat, model=mod2_condense)
```

```
## MARSS: NaNs in data are being replaced with NAs.  There might be a problem if NaNs shouldn't be in the data.
## NA is the normal missing value designation.
## Success! abstol and log-log tests passed at 91 iterations.
## Alert: conv.test.slope.tol is 0.5.
## Test with smaller values (<0.1) to ensure convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 91 iterations.
## Log-likelihood: 4179.008
## AIC: -8328.017   AICc: -8327.907
##
##              Estimate
## B.diag        0.96268
## Q.diag        0.00862
## x0.X.AP       2.10294
## x0.X.SP       1.33729
## x0.X.Durazo   1.72025
## x0.X.LS       2.02143
## x0.X.May      1.90140
## x0.X.FG       1.38748
## x0.X.GP       0.69061
## x0.X.UL       1.65739
## x0.X.LL       1.51656
## x0.X.SC       2.21232
## x0.X.HC       1.42914
## x0.X.KSV      1.09279
## C.1           0.03920
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```
mod2_condense.params =MARSSparamCIs(mod2_condense.fit)
MARSSparamCIs(mod2_condense.fit)
```

```
##
## MARSS fit is
## Estimation method: kem
```

```
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 91 iterations.
## Log-likelihood: 4179.008
## AIC: -8328.017   AICc: -8327.907
##
##                ML.Est  Std.Err  low.CI   up.CI
## B.diag        0.96268 0.002541 0.95770 0.96766
## Q.diag        0.00862 0.000184 0.00826 0.00898
## x0.X.AP       2.10294 0.368852 1.38001 2.82588
## x0.X.SP       1.33729 0.393307 0.56642 2.10815
## x0.X.Durazo 1.72025 0.447742 0.84269 2.59781
## x0.X.LS       2.02143 0.448790 1.14182 2.90104
## x0.X.May      1.90140 0.448344 1.02266 2.78014
## x0.X.FG       1.38748 0.367109 0.66796 2.10700
## x0.X.GP       0.69061 0.340206 0.02382 1.35740
## x0.X.UL       1.65739 0.288615 1.09172 2.22307
## x0.X.LL       1.51656 0.341139 0.84794 2.18518
## x0.X.SC       2.21232 0.449576 1.33117 3.09347
## x0.X.HC       1.42914 0.288301 0.86408 1.99420
## x0.X.KSV      1.09279 0.096448 0.90375 1.28182
## C.1           0.03920 0.002528 0.03424 0.04415
## Initial states (x0) defined at t=0
##
## CIs calculated at alpha = 0.05 via method=hessian
```

Hypothesis 3: Habitat type: Creeks vs ponds vs Klamath

AICc: -8586.263

```
mod3_condense = list()
## Modify matrices
# 1st: group time series into categories
hypothesis = c("pond","pond","pond","pond",
               "pond","pond","pond","pond",
               "pond","creek","creek","Klamath")

# 2nd: build C matrix (12 x 1)
mod3_condense$C = matrix(hypothesis)
mod3_condense$c = transformed_covariate_klamath

# 3rd: build Q matrix (12 x 12, with "C vector" in its diagonal)
Q <-  matrix(list("pond",0,0,0,0,0,0,0,0,0,0,0,
                  0,"pond",0,0,0,0,0,0,0,0,0,0,
                  0,0,"pond",0,0,0,0,0,0,0,0,0,
                  0,0,0,"pond",0,0,0,0,0,0,0,0,
                  0,0,0,0,"pond",0,0,0,0,0,0,0,
                  0,0,0,0,0,"pond",0,0,0,0,0,0,
                  0,0,0,0,0,0,"pond",0,0,0,0,0,
                  0,0,0,0,0,0,0,"pond",0,0,0,0,
```

```r
                  0,0,0,0,0,0,0,0,"pond",0,0,0,
                  0,0,0,0,0,0,0,0,0,"creek",0,0,
                  0,0,0,0,0,0,0,0,0,0,"creek",0,
                  0,0,0,0,0,0,0,0,0,0,0,"Klamath"),12,12)

# 4th: B, identical as Q
B <- Q

mod3_condense$A = "zero"
mod3_condense$Z = "identity"
mod3_condense$R = "zero" #all the sensors are same, so observation error
should be same
mod3_condense$Q = Q
mod3_condense$B = Q
mod3_condense$U = "zero"
mod3_condense$C = matrix(hypothesis)
mod3_condense$c = transformed_covariate_klamath
mod3_condense.fit = MARSS(condensed_transdat, model=mod3_condense)

## MARSS: NaNs in data are being replaced with NAs.  There might be a problem
if NaNs shouldn't be in the data.
## NA is the normal missing value designation.
## Success! abstol and log-log tests passed at 174 iterations.
## Alert: conv.test.slope.tol is 0.5.
## Test with smaller values (<0.1) to ensure convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 174 iterations.
## Log-likelihood: 4322.357
## AIC: -8602.714   AICc: -8602.502
##
##              Estimate
## B.pond        0.97214
## B.creek       0.90200
## B.Klamath     0.94555
## Q.pond        0.00739
## Q.creek       0.01463
## Q.Klamath     0.00533
## x0.X.AP       1.96679
## x0.X.SP       1.27285
## x0.X.Durazo   1.62143
## x0.X.LS       1.89098
## x0.X.May      1.78356
## x0.X.FG       1.31606
## x0.X.GP       0.67854
## x0.X.UL       1.58070
## x0.X.LL       1.43608
## x0.X.SC       3.99633
```

```
## x0.X.HC      1.98203
## x0.X.KSV     1.10630
## C.pond       0.02952
## C.creek      0.09995
## C.Klamath    0.05792
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```
mod3_condense.params =MARSSparamCIs(mod3_condense.fit)
MARSSparamCIs(mod3_condense.fit)
```

```
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 174 iterations.
## Log-likelihood: 4322.357
## AIC: -8602.714   AICc: -8602.502
##
##               ML.Est  Std.Err  low.CI   up.CI
## B.pond      0.97214 0.002588 0.96706 0.97721
## B.creek     0.90200 0.009564 0.88325 0.92074
## B.Klamath   0.94555 0.008959 0.92799 0.96311
## Q.pond      0.00739 0.000182 0.00703 0.00774
## Q.creek     0.01463 0.000762 0.01314 0.01613
## Q.Klamath   0.00533 0.000400 0.00454 0.00611
## x0.X.AP     1.96679 0.322298 1.33510 2.59848
## x0.X.SP     1.27285 0.341415 0.60369 1.94201
## x0.X.Durazo 1.62143 0.384107 0.86859 2.37426
## x0.X.LS     1.89098 0.385139 1.13612 2.64583
## x0.X.May    1.78356 0.384701 1.02956 2.53756
## x0.X.FG     1.31606 0.320583 0.68773 1.94439
## x0.X.GP     0.67854 0.298741 0.09302 1.26407
## x0.X.UL     1.58070 0.256472 1.07803 2.08338
## x0.X.LL     1.43608 0.299678 0.84872 2.02343
## x0.X.SC     3.99633 1.134910 1.77195 6.22072
## x0.X.HC     1.98203 0.518557 0.96568 2.99838
## x0.X.KSV    1.10630 0.077594 0.95422 1.25838
## C.pond      0.02952 0.002575 0.02447 0.03457
## C.creek     0.09995 0.009524 0.08129 0.11862
## C.Klamath   0.05792 0.008876 0.04052 0.07532
## Initial states (x0) defined at t=0
##
## CIs calculated at alpha = 0.05 via method=hessian
```

Hypothesis 4: By watershed

AICc: -8597.364

```
mod4_condense = list()
## Modify matrices
# 1st: group time series into categories
rownames(condensed_transdat)

##  [1] "AP"     "SP"     "Durazo" "LS"     "May"    "FG"     "GP"     "UL"
##  [9] "LL"     "SC"     "HC"     "KSV"

hypothesis2 = c("SC","SC","SC","SC",
               "SC","HC","HC","HC",
               "HC","SC","HC","Klamath")

# 2nd: build C matrix (12 x 1)
mod4_condense$C = matrix(hypothesis2)
mod4_condense$c = transformed_covariate_klamath

# 3rd: build Q matrix (12 x 12, with "C vector" in its diagonal)
Q <-  matrix(list("SC",0,0,0,0,0,0,0,0,0,0,0,
                  0,"SC",0,0,0,0,0,0,0,0,0,0,
                  0,0,"SC",0,0,0,0,0,0,0,0,0,
                  0,0,0,"SC",0,0,0,0,0,0,0,0,
                  0,0,0,0,"SC",0,0,0,0,0,0,0,
                  0,0,0,0,0,"HC",0,0,0,0,0,0,
                  0,0,0,0,0,0,"HC",0,0,0,0,0,
                  0,0,0,0,0,0,0,"HC",0,0,0,0,
                  0,0,0,0,0,0,0,0,"HC",0,0,0,
                  0,0,0,0,0,0,0,0,0,"SC",0,0,
                  0,0,0,0,0,0,0,0,0,0,"HC",0,
                  0,0,0,0,0,0,0,0,0,0,0,"Klamath"),12,12)

# 4th: B, identical as Q
B <- Q

mod4_condense$A = "zero"
mod4_condense$Z = "identity"
mod4_condense$R = "zero" #all the sensors are same, so observation error 
should be same
mod4_condense$Q = Q
mod4_condense$B = Q
mod4_condense$U = "zero"
mod4_condense$C = matrix(hypothesis2)
mod4_condense$c = transformed_covariate_klamath
mod4_condense.fit = MARSS(condensed_transdat, model=mod4_condense)

## MARSS: NaNs in data are being replaced with NAs.  There might be a problem 
if NaNs shouldn't be in the data.
```

```
## NA is the normal missing value designation.
## Success! abstol and log-log tests passed at 94 iterations.
## Alert: conv.test.slope.tol is 0.5.
## Test with smaller values (<0.1) to ensure convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 94 iterations.
## Log-likelihood: 4316.005
## AIC: -8590.01   AICc: -8589.798
##
##              Estimate
## B.SC          0.95981
## B.HC          0.96701
## B.Klamath     0.94555
## Q.SC          0.01154
## Q.HC          0.00577
## Q.Klamath     0.00533
## x0.X.AP       2.16128
## x0.X.SP       1.37678
## x0.X.Durazo   1.78037
## x0.X.LS       2.09239
## x0.X.May      1.96804
## x0.X.FG       1.33906
## x0.X.GP       0.67251
## x0.X.UL       1.61312
## x0.X.LL       1.46665
## x0.X.SC       2.29015
## x0.X.HC       1.39184
## x0.X.KSV      1.10630
## C.SC          0.04004
## C.HC          0.03700
## C.Klamath     0.05792
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```
mod4_condense.params =MARSSparamCIs(mod4_condense.fit)
MARSSparamCIs(mod4_condense.fit)
```

```
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 94 iterations.
## Log-likelihood: 4316.005
## AIC: -8590.01   AICc: -8589.798
##
```

```
##              ML.Est Std.Err  low.CI   up.CI
## B.SC        0.95981 0.00444 0.95110 0.96851
## B.HC        0.96701 0.00292 0.96129 0.97273
## B.Klamath   0.94555 0.00896 0.92799 0.96311
## Q.SC        0.01154 0.00035 0.01086 0.01223
## Q.HC        0.00577 0.00019 0.00540 0.00615
## Q.Klamath   0.00533 0.00040 0.00454 0.00611
## x0.X.AP     2.16128 0.43895 1.30095 3.02160
## x0.X.SP     1.37678 0.46591 0.46361 2.28995
## x0.X.Durazo 1.78037 0.53408 0.73360 2.82713
## x0.X.LS     2.09239 0.53694 1.04000 3.14477
## x0.X.May    1.96804 0.53572 0.91804 3.01804
## x0.X.FG     1.33906 0.29324 0.76433 1.91380
## x0.X.GP     0.67251 0.27192 0.13956 1.20547
## x0.X.UL     1.61312 0.23258 1.15727 2.06897
## x0.X.LL     1.46665 0.27338 0.93083 2.00246
## x0.X.SC     2.29015 0.53909 1.23355 3.34674
## x0.X.HC     1.39184 0.23209 0.93694 1.84674
## x0.X.KSV    1.10630 0.07759 0.95422 1.25838
## C.SC        0.04004 0.00444 0.03134 0.04873
## C.HC        0.03700 0.00290 0.03133 0.04268
## C.Klamath   0.05792 0.00888 0.04052 0.07532
## Initial states (x0) defined at t=0
##
## CIs calculated at alpha = 0.05 via method=hessian
```

#Plot Covariates

```
mod1_condense.fit = MARSS(condensed_transdat, model=mod1_condense)
```

```
## MARSS: NaNs in data are being replaced with NAs.  There might be a problem
if NaNs shouldn't be in the data.
## NA is the normal missing value designation.
## Success! abstol and log-log tests passed at 153 iterations.
## Alert: conv.test.slope.tol is 0.5.
## Test with smaller values (<0.1) to ensure convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 153 iterations.
## Log-likelihood: 4857.285
## AIC: -9618.57   AICc: -9617.484
##
##                         Estimate
## B.(X.AP,X.AP)           0.942858
## B.(X.SP,X.SP)           0.968046
## B.(X.Durazo,X.Durazo) 0.967180
## B.(X.LS,X.LS)           0.987704
## B.(X.May,X.May)         0.966777
```

```
## B.(X.FG,X.FG)         0.972812
## B.(X.GP,X.GP)         0.987907
## B.(X.UL,X.UL)         0.965388
## B.(X.LL,X.LL)         0.965301
## B.(X.SC,X.SC)         0.911952
## B.(X.HC,X.HC)         0.890677
## B.(X.KSV,X.KSV)       0.945554
## Q.(X.AP,X.AP)         0.008070
## Q.(X.SP,X.SP)         0.006837
## Q.(X.Durazo,X.Durazo) 0.008850
## Q.(X.LS,X.LS)         0.005552
## Q.(X.May,X.May)       0.024014
## Q.(X.FG,X.FG)         0.003015
## Q.(X.GP,X.GP)         0.000809
## Q.(X.UL,X.UL)         0.004623
## Q.(X.LL,X.LL)         0.005431
## Q.(X.SC,X.SC)         0.015851
## Q.(X.HC,X.HC)         0.013369
## Q.(X.KSV,X.KSV)       0.005327
## x0.X.AP               2.471342
## x0.X.SP               1.288391
## x0.X.Durazo           1.695049
## x0.X.LS               1.695107
## x0.X.May              1.933986
## x0.X.FG               1.296982
## x0.X.GP               0.632370
## x0.X.UL               1.631588
## x0.X.LL               1.487285
## x0.X.SC               3.612499
## x0.X.HC               2.116309
## x0.X.KSV              1.106298
## C.X.AP                0.057603
## C.X.SP                0.035406
## C.X.Durazo            0.033553
## C.X.LS                0.010417
## C.X.May               0.028579
## C.X.FG                0.030953
## C.X.GP                0.018791
## C.X.UL                0.037363
## C.X.LL                0.037844
## C.X.SC                0.088024
## C.X.HC                0.113147
## C.X.KSV               0.057921
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```
mod1_condense.params =MARSSparamCIs(mod1_condense.fit)
MARSSparamCIs(mod1_condense.fit)
```

```
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 153 iterations.
## Log-likelihood: 4857.285
## AIC: -9618.57   AICc: -9617.484
##
##                            ML.Est  Std.Err    low.CI    up.CI
## B.(X.AP,X.AP)            0.942858 9.98e-03  0.923290 0.962425
## B.(X.SP,X.SP)            0.968046 8.89e-03  0.950627 0.985464
## B.(X.Durazo,X.Durazo)    0.967180 1.01e-02  0.947471 0.986889
## B.(X.LS,X.LS)            0.987704 7.41e-03  0.973183 1.002224
## B.(X.May,X.May)          0.966777 1.29e-02  0.941399 0.992155
## B.(X.FG,X.FG)            0.972812 5.22e-03  0.962583 0.983041
## B.(X.GP,X.GP)            0.987907 1.86e-03  0.984254 0.991560
## B.(X.UL,X.UL)            0.965388 6.54e-03  0.952573 0.978204
## B.(X.LL,X.LL)            0.965301 6.46e-03  0.952634 0.977969
## B.(X.SC,X.SC)            0.911952 1.37e-02  0.885028 0.938876
## B.(X.HC,X.HC)            0.890677 1.33e-02  0.864686 0.916667
## B.(X.KSV,X.KSV)          0.945554 8.96e-03  0.927994 0.963113
## Q.(X.AP,X.AP)            0.008070 5.94e-04  0.006906 0.009235
## Q.(X.SP,X.SP)            0.006837 5.04e-04  0.005849 0.007825
## Q.(X.Durazo,X.Durazo)    0.008850 6.54e-04  0.007567 0.010132
## Q.(X.LS,X.LS)            0.005552 4.10e-04  0.004748 0.006357
## Q.(X.May,X.May)          0.024014 1.84e-03  0.020409 0.027618
## Q.(X.FG,X.FG)            0.003015 2.22e-04  0.002579 0.003450
## Q.(X.GP,X.GP)            0.000809 5.96e-05  0.000692 0.000926
## Q.(X.UL,X.UL)            0.004623 3.39e-04  0.003958 0.005289
## Q.(X.LL,X.LL)            0.005431 4.00e-04  0.004648 0.006215
## Q.(X.SC,X.SC)            0.015851 1.17e-03  0.013554 0.018148
## Q.(X.HC,X.HC)            0.013369 9.82e-04  0.011445 0.015293
## Q.(X.KSV,X.KSV)          0.005327 4.00e-04  0.004544 0.006111
## x0.X.AP                  2.471342 4.56e-01  1.577050 3.365633
## x0.X.SP                  1.288391 3.47e-01  0.607769 1.969013
## x0.X.Durazo              1.695049 4.64e-01  0.785959 2.604138
## x0.X.LS                  1.695107 3.16e-01  1.075835 2.314380
## x0.X.May                 1.933986 7.65e-01  0.434243 3.433728
## x0.X.FG                  1.296982 2.09e-01  0.887063 1.706901
## x0.X.GP                  0.632370 9.13e-02  0.453480 0.811259
## x0.X.UL                  1.631588 2.17e-01  1.206646 2.056529
## x0.X.LL                  1.487285 2.75e-01  0.948641 2.025929
## x0.X.SC                  3.612499 1.14e+00  1.385920 5.839078
## x0.X.HC                  2.116309 5.45e-01  1.048644 3.183974
## x0.X.KSV                 1.106298 7.76e-02  0.954217 1.258379
## C.X.AP                   0.057603 9.89e-03  0.038220 0.076985
## C.X.SP                   0.035406 8.78e-03  0.018195 0.052618
## C.X.Durazo               0.033553 9.94e-03  0.014065 0.053040
## C.X.LS                   0.010417 7.33e-03 -0.003956 0.024789
## C.X.May                  0.028579 1.35e-02  0.002126 0.055033
```

```
## C.X.FG                 0.030953 5.18e-03  0.020806 0.041101
## C.X.GP                 0.018791 1.84e-03  0.015179 0.022403
## C.X.UL                 0.037363 6.48e-03  0.024652 0.050073
## C.X.LL                 0.037844 6.40e-03  0.025305 0.050383
## C.X.SC                 0.088024 1.37e-02  0.061163 0.114884
## C.X.HC                 0.113147 1.32e-02  0.087314 0.138981
## C.X.KSV                0.057921 8.88e-03  0.040523 0.075318
## Initial states (x0) defined at t=0
##
## CIs calculated at alpha = 0.05 via method=hessian
```

```
mod1_condense.params
```

```
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## Estimation converged in 153 iterations.
## Log-likelihood: 4857.285
## AIC: -9618.57   AICc: -9617.484
##
##                          ML.Est  Std.Err    low.CI    up.CI
## B.(X.AP,X.AP)          0.942858 9.98e-03  0.923290 0.962425
## B.(X.SP,X.SP)          0.968046 8.89e-03  0.950627 0.985464
## B.(X.Durazo,X.Durazo) 0.967180 1.01e-02  0.947471 0.986889
## B.(X.LS,X.LS)          0.987704 7.41e-03  0.973183 1.002224
## B.(X.May,X.May)        0.966777 1.29e-02  0.941399 0.992155
## B.(X.FG,X.FG)          0.972812 5.22e-03  0.962583 0.983041
## B.(X.GP,X.GP)          0.987907 1.86e-03  0.984254 0.991560
## B.(X.UL,X.UL)          0.965388 6.54e-03  0.952573 0.978204
## B.(X.LL,X.LL)          0.965301 6.46e-03  0.952634 0.977969
## B.(X.SC,X.SC)          0.911952 1.37e-02  0.885028 0.938876
## B.(X.HC,X.HC)          0.890677 1.33e-02  0.864686 0.916667
## B.(X.KSV,X.KSV)        0.945554 8.96e-03  0.927994 0.963113
## Q.(X.AP,X.AP)          0.008070 5.94e-04  0.006906 0.009235
## Q.(X.SP,X.SP)          0.006837 5.04e-04  0.005849 0.007825
## Q.(X.Durazo,X.Durazo) 0.008850 6.54e-04  0.007567 0.010132
## Q.(X.LS,X.LS)          0.005552 4.10e-04  0.004748 0.006357
## Q.(X.May,X.May)        0.024014 1.84e-03  0.020409 0.027618
## Q.(X.FG,X.FG)          0.003015 2.22e-04  0.002579 0.003450
## Q.(X.GP,X.GP)          0.000809 5.96e-05  0.000692 0.000926
## Q.(X.UL,X.UL)          0.004623 3.39e-04  0.003958 0.005289
## Q.(X.LL,X.LL)          0.005431 4.00e-04  0.004648 0.006215
## Q.(X.SC,X.SC)          0.015851 1.17e-03  0.013554 0.018148
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## x0.X.AP                2.471342 4.56e-01  1.577050 3.365633
## x0.X.SP                1.288391 3.47e-01  0.607769 1.969013
## x0.X.Durazo            1.695049 4.64e-01  0.785959 2.604138
## x0.X.LS                1.695107 3.16e-01  1.075835 2.314380
```
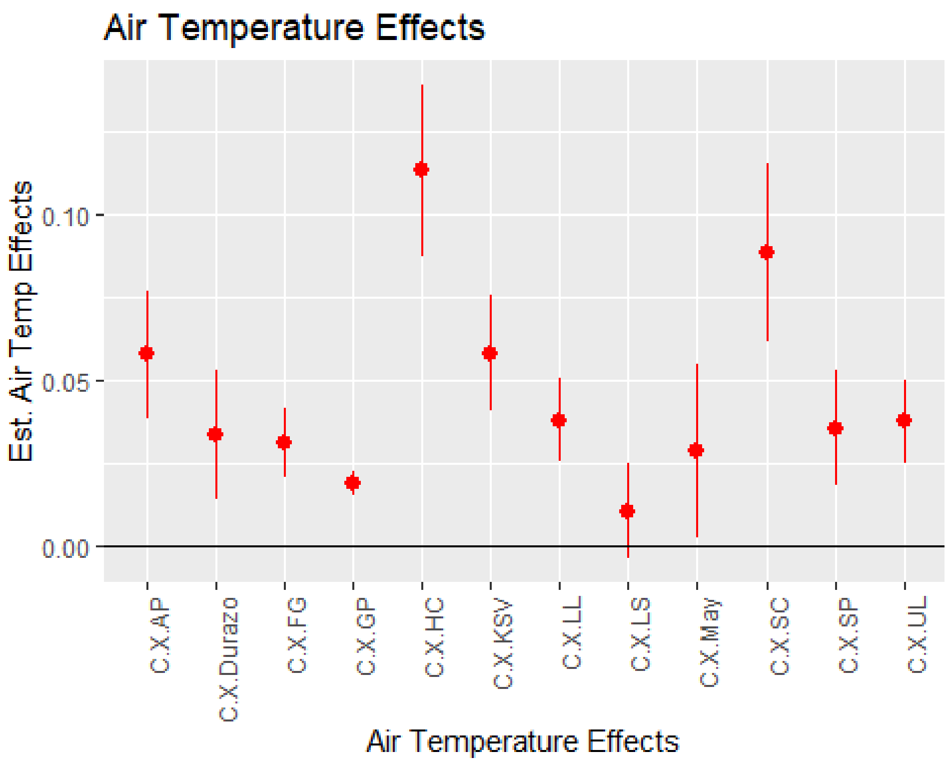

```
## x0.X.May              1.933986 7.65e-01  0.434243 3.433728
## x0.X.FG               1.296982 2.09e-01  0.887063 1.706901
## x0.X.GP               0.632370 9.13e-02  0.453480 0.811259
## x0.X.UL               1.631588 2.17e-01  1.206646 2.056529
## x0.X.LL               1.487285 2.75e-01  0.948641 2.025929
## x0.X.SC               3.612499 1.14e+00  1.385920 5.839078
## x0.X.HC               2.116309 5.45e-01  1.048644 3.183974
## x0.X.KSV              1.106298 7.76e-02  0.954217 1.258379
## C.X.AP                0.057603 9.89e-03  0.038220 0.076985
## C.X.SP                0.035406 8.78e-03  0.018195 0.052618
## C.X.Durazo            0.033553 9.94e-03  0.014065 0.053040
## C.X.LS                0.010417 7.33e-03 -0.003956 0.024789
## C.X.May               0.028579 1.35e-02  0.002126 0.055033
## C.X.FG                0.030953 5.18e-03  0.020806 0.041101
## C.X.GP                0.018791 1.84e-03  0.015179 0.022403
## C.X.UL                0.037363 6.48e-03  0.024652 0.050073
## C.X.LL                0.037844 6.40e-03  0.025305 0.050383
## C.X.SC                0.088024 1.37e-02  0.061163 0.114884
## C.X.HC                0.113147 1.32e-02  0.087314 0.138981
## C.X.KSV               0.057921 8.88e-03  0.040523 0.075318
## Initial states (x0) defined at t=0
##
## CIs calculated at alpha = 0.05 via method=hessian
```

```
mod1_condense_df <- broom::tidy(mod1_condense.fit)

ggplot(data = mod1_condense_df) +
  geom_pointrange(data = mod1_condense_df[c(37:48),], aes(x = term, y =
estimate, ymin = conf.low, ymax = conf.up), color = "red") +
  geom_hline(yintercept = 0) +
  labs(x = "Air Temperature Effects",
       y = "Est. Air Temp Effects") +
  ggtitle("Air Temperature Effects") +
  theme(axis.text.x=element_text(angle = 90, hjust = 1))
```


Air Temperature Effects
Est. Air Temp Effects
0.10
0.05
0.00
C.X.AP
C.X.Durazo
C.X.FG
C.X.GP
C.X.HC
C.X.KSV
C.X.LL
C.X.LS
C.X.May
C.X.SC
C.X.SP
C.X.UL
Air Temperature Effects