2021_MARSSModel

##Read in data

```
KSV_meantemps <- readRDS('KSV_meantemps.rds')
daily_means_long_klamath <- readRDS('daily_means_long.rds')
covariate_klamath <- readRDS('covariate.rds')

daily_means_long_klamath <-rbind(daily_means_long_klamath, KSV =
KSV_meantemps)
str(daily_means_long_klamath)
```

##Data Matrix

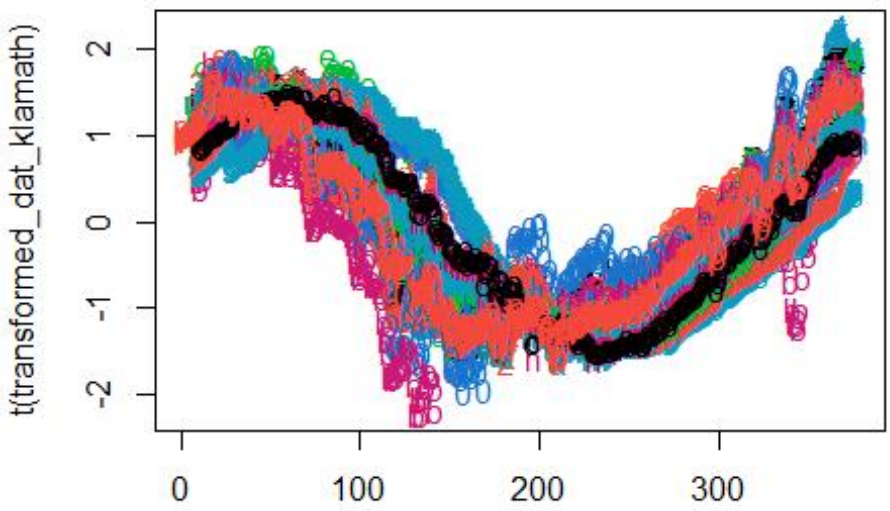
```
#Convert data to matrix
daily_means_long_klamath <- as.matrix(daily_means_long_klamath)
saveRDS(daily_means_long_klamath,"daily_means_long_klamath.rds")

#z score
transformed_dat_klamath <- as.matrix(daily_means_long_klamath)
transformed_dat_klamath <- zscore(transformed_dat_klamath)
saveRDS(transformed_dat_klamath,"transformed_dat_klamath.rds")
```

##Covariates

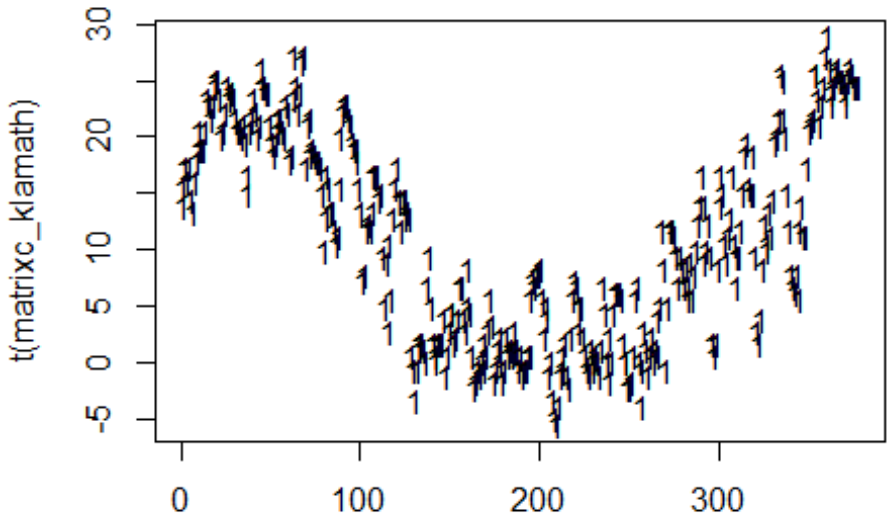
```
#Build the little c matrix, call it matrixc
matrixc_klamath <- matrix(nrow=1,ncol=378)
matrixc_klamath <- (as.matrix(covariate_klamath))
saveRDS(matrixc_klamath,"matrixc_klamath.rds")
```

###Check data and covariates

```
matplot(t(transformed_dat_klamath))
```




```
matplot(t(matrixc_klamath))
```




```
#looks okay, we removed AP2 in the visualization .rmd file
```

##Z-Matrices ###matrix2_klamath

```
#Hypothesis 1: All ponds and creeks and mainstem are separate
matrix2_klamath <- matrix(nrow=26,ncol=12)
matrix2_klamath[c(1:2),1] <- 1 #Alexander
matrix2_klamath[c(1:2),c(2:12)] <- 0
matrix2_klamath[c(4:5),2] <- 1 #Stender
matrix2_klamath[c(4:5),c(1,3:12)] <- 0
matrix2_klamath[c(3,6,9,11,12),3] <- 1 #Seiad Creek
matrix2_klamath[c(3,6,9,11,12),c(1,2,4:12)] <- 0
matrix2_klamath[7,4] <- 1 #Durazo
matrix2_klamath[7,c(1:3,5:12)] <- 0
matrix2_klamath[8,5] <- 1 #Lower Seiad
matrix2_klamath[8,c(1:4,6:12)] <- 0
matrix2_klamath[10,6] <- 1 #May
matrix2_klamath[10,c(1:5,7:12)] <- 0
matrix2_klamath[c(12:13),7] <- 1 #Fish Gulch
matrix2_klamath[c(12:13),c(1:6,8:12)] <- 0
matrix2_klamath[c(15:17),8] <- 1 #Goodman
matrix2_klamath[c(15:17),c(1:7,9:12)] <- 0
matrix2_klamath[c(19:21),9] <- 1 #Upper Lawrence
matrix2_klamath[c(19:21),c(1:8,10:12)] <- 0
matrix2_klamath[c(23:25),10] <- 1 #Lower Lawrence
matrix2_klamath[c(23:25),c(1:9,11:12)] <- 0
matrix2_klamath[c(14,18,22),11] <- 1 #Horse Creek
matrix2_klamath[c(14,18,22),c(1:10,12)] <- 0
matrix2_klamath[26,12] <- 1 #Klamath
matrix2_klamath[26,c(1:11)] <- 0
matrix2_klamath
```

```
##       [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12]
##  [1,]    1    0    0    0    0    0    0    0    0     0     0     0
##  [2,]    1    0    0    0    0    0    0    0    0     0     0     0
##  [3,]    0    0    1    0    0    0    0    0    0     0     0     0
##  [4,]    0    1    0    0    0    0    0    0    0     0     0     0
##  [5,]    0    1    0    0    0    0    0    0    0     0     0     0
##  [6,]    0    0    1    0    0    0    0    0    0     0     0     0
##  [7,]    0    0    0    1    0    0    0    0    0     0     0     0
##  [8,]    0    0    0    0    1    0    0    0    0     0     0     0
##  [9,]    0    0    1    0    0    0    0    0    0     0     0     0
## [10,]    0    0    0    0    0    1    0    0    0     0     0     0
## [11,]    0    0    1    0    0    0    0    0    0     0     0     0
## [12,]    0    0    0    0    0    0    1    0    0     0     0     0
## [13,]    0    0    0    0    0    0    1    0    0     0     0     0
## [14,]    0    0    0    0    0    0    0    0    0     0     1     0
## [15,]    0    0    0    0    0    0    0    1    0     0     0     0
## [16,]    0    0    0    0    0    0    0    1    0     0     0     0
## [17,]    0    0    0    0    0    0    0    1    0     0     0     0
## [18,]    0    0    0    0    0    0    0    0    0     0     1     0
## [19,]    0    0    0    0    0    0    0    0    1     0     0     0
```

```
## [20,]    0    0    0    0    0    0    0    0    1     0     0     0
## [21,]    0    0    0    0    0    0    0    0    1     0     0     0
## [22,]    0    0    0    0    0    0    0    0    0     0     1     0
## [23,]    0    0    0    0    0    0    0    0    0     1     0     0
## [24,]    0    0    0    0    0    0    0    0    0     1     0     0
## [25,]    0    0    0    0    0    0    0    0    0     1     0     0
## [26,]    0    0    0    0    0    0    0    0    0     0     0     1
```

###matrix3_klamath

```
#Hypothesis 2: ponds versus creeks versus Klamath
matrix3_klamath <- matrix(nrow=26, ncol=3)
matrix3_klamath[c(1:2,4:5,7:8,10,12:13,15:17,19:21,23:25),1] <- 1 #All ponds
matrix3_klamath[c(1:2,4:5,7:8,10,12:13,15:17,19:21,23:25),c(2:3)] <- 0
matrix3_klamath[c(3,6,9,11,14,18,22),c(1,3)] <- 0 #All creeks
matrix3_klamath[c(3,6,9,11,14,18,22),2] <- 1
matrix3_klamath[26,3] <- 1 #Klamath
matrix3_klamath[26,c(1:2)] <- 0
matrix3_klamath
```

```
##       [,1] [,2] [,3]
##  [1,]    1    0    0
##  [2,]    1    0    0
##  [3,]    0    1    0
##  [4,]    1    0    0
##  [5,]    1    0    0
##  [6,]    0    1    0
##  [7,]    1    0    0
##  [8,]    1    0    0
##  [9,]    0    1    0
## [10,]    1    0    0
## [11,]    0    1    0
## [12,]    1    0    0
## [13,]    1    0    0
## [14,]    0    1    0
## [15,]    1    0    0
## [16,]    1    0    0
## [17,]    1    0    0
## [18,]    0    1    0
## [19,]    1    0    0
## [20,]    1    0    0
## [21,]    1    0    0
## [22,]    0    1    0
## [23,]    1    0    0
## [24,]    1    0    0
## [25,]    1    0    0
## [26,]    0    0    1
```

###matrix4_klamath

```
#Hypothesis 3: tributary versus tributary versus Klamath
matrix4_klamath <-matrix(nrow=26,ncol=5)
matrix4_klamath[c(1:2,4:5,7:8,10),1] <- 1  #Seiad Creek Ponds
matrix4_klamath[c(1:2,4:5,7:8,10),c(2:5)] <- 0
matrix4_klamath[c(3,6,9,11),2] <- 1 #Seiad Creek
matrix4_klamath[c(3,6,9,11),c(1,3:5)] <- 0
matrix4_klamath[c(12:13,15:17,19:21,23:25),3] <- 1 #Horse Creek Ponds
matrix4_klamath[c(12:13,15:17,19:21,23:25),c(1,2,4,5)] <- 0
matrix4_klamath[c(14,18,22),4] <- 1 #Horse Creek
matrix4_klamath[c(14,18,22),c(1:3,5)] <- 0
matrix4_klamath[26,5] <- 1 #Klamath
matrix4_klamath[c(26),c(1:4)] <- 0
matrix4_klamath
```

```
##       [,1] [,2] [,3] [,4] [,5]
##  [1,]    1    0    0    0    0
##  [2,]    1    0    0    0    0
##  [3,]    0    1    0    0    0
##  [4,]    1    0    0    0    0
##  [5,]    1    0    0    0    0
##  [6,]    0    1    0    0    0
##  [7,]    1    0    0    0    0
##  [8,]    1    0    0    0    0
##  [9,]    0    1    0    0    0
## [10,]    1    0    0    0    0
## [11,]    0    1    0    0    0
## [12,]    0    0    1    0    0
## [13,]    0    0    1    0    0
## [14,]    0    0    0    1    0
## [15,]    0    0    1    0    0
## [16,]    0    0    1    0    0
## [17,]    0    0    1    0    0
## [18,]    0    0    0    1    0
## [19,]    0    0    1    0    0
## [20,]    0    0    1    0    0
## [21,]    0    0    1    0    0
## [22,]    0    0    0    1    0
## [23,]    0    0    1    0    0
## [24,]    0    0    1    0    0
## [25,]    0    0    1    0    0
## [26,]    0    0    0    0    1
```

###matrix5_klamath

```
#Hypothesis 4: All sensors are the same
matrix5_klamath <-  matrix(nrow=26, ncol=1)
matrix5_klamath[,] <- 1
matrix5_klamath
```

```
##       [,1]
##  [1,]    1
```

```
##  [2,]    1
##  [3,]    1
##  [4,]    1
##  [5,]    1
##  [6,]    1
##  [7,]    1
##  [8,]    1
##  [9,]    1
## [10,]    1
## [11,]    1
## [12,]    1
## [13,]    1
## [14,]    1
## [15,]    1
## [16,]    1
## [17,]    1
## [18,]    1
## [19,]    1
## [20,]    1
## [21,]    1
## [22,]    1
## [23,]    1
## [24,]    1
## [25,]    1
## [26,]    1
```

```
saveRDS(matrix2_klamath,"matrix2_klamath.rds")
saveRDS(matrix3_klamath,"matrix3_klamath.rds")
saveRDS(matrix4_klamath,"matrix4_klamath.rds")
saveRDS(matrix5_klamath,"matrix5_klamath.rds")
```

##MARSS models ###Create a FT for seasonality and combine with AirTemp

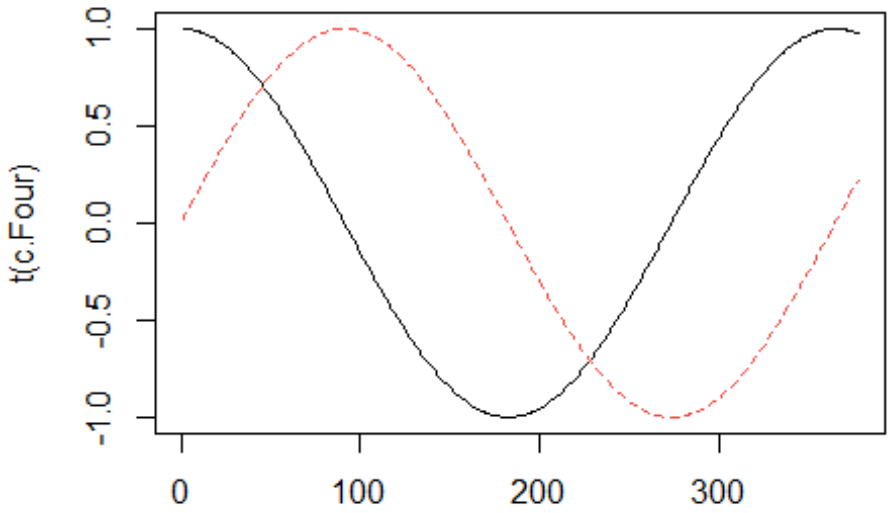
```
#Correct for seasonality using Fourier Series
TT = ncol(transformed_dat_klamath) # number of time periods/samples
period = 365 # number of "seasons" (e.g., 12 months per year)
per.1st = 182 # first "season" (e.g., Jan = 1, July = 7)
c = diag(period) # create factors for seasons
for(i in 2:(ceiling(TT/period))) {c = cbind(c,diag(period))}
dim(c)
```

```
## [1] 365 730
```

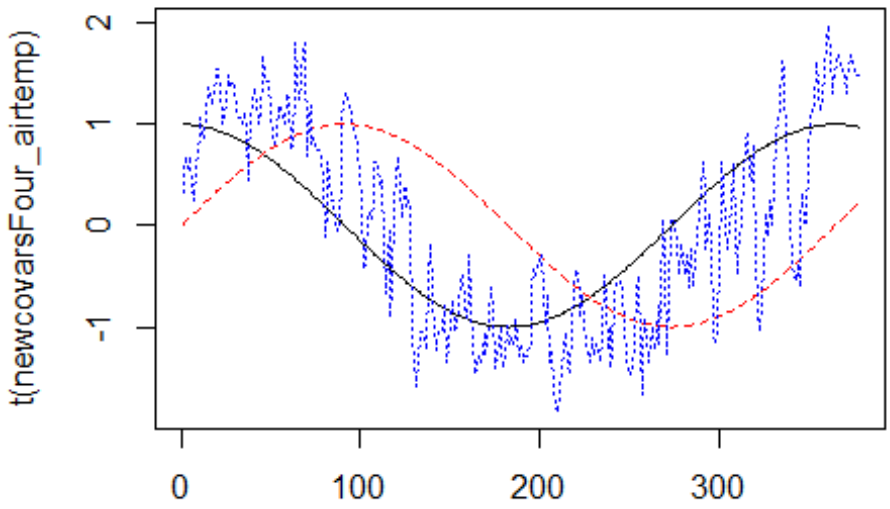
```
#Create Fourier Series
cos.t = cos(2 * pi * seq(TT) / period)
sin.t = sin(2 * pi * seq(TT) / period)
c.Four = rbind(cos.t,sin.t)
cor(c.Four[1,],c.Four[2,]) # not correlated!
```

```
## [1] 0.007872561
```

```
matplot(t(c.Four), type="l")
```




```
#Now fit model with seasonality AND an additional covariate (airtemp from
above)
matrixc_klamath_z <- zscore(matrixc_klamath)
newcovarsFour_airtemp <-rbind(c.Four, "airtemp"=matrixc_klamath_z)
matplot(t(newcovarsFour_airtemp), type="l", col=c("black","red","blue"))
```



####Things I tried: 1) zscore data + covar; 2) no zscore; 3) zscore covar; 4) zscore data; 5) no covar at all; 6) zscore covar + FT; 6) just FT

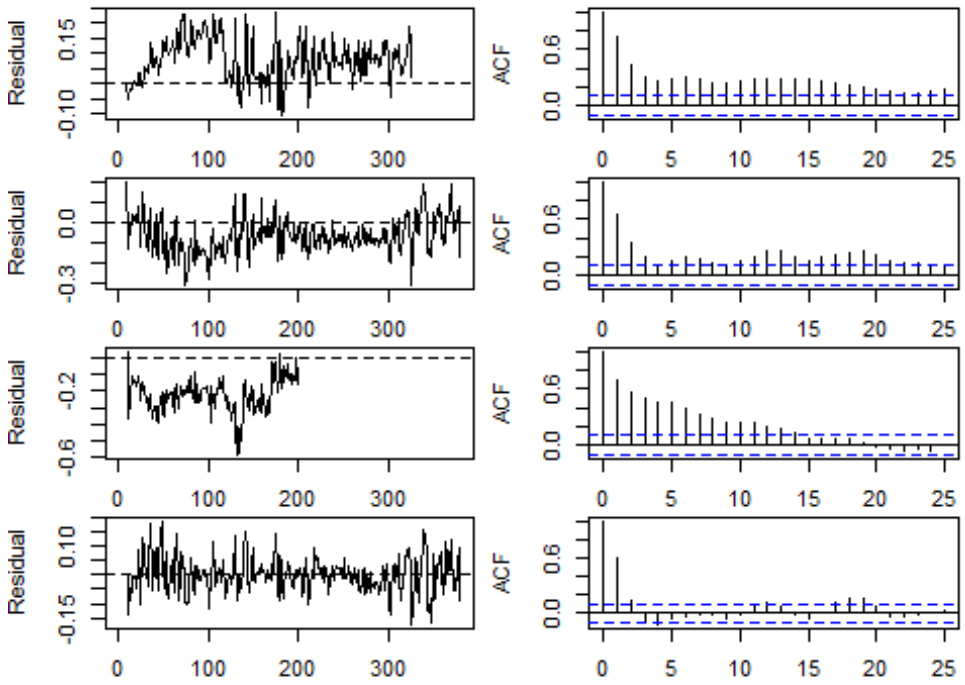
###model 1

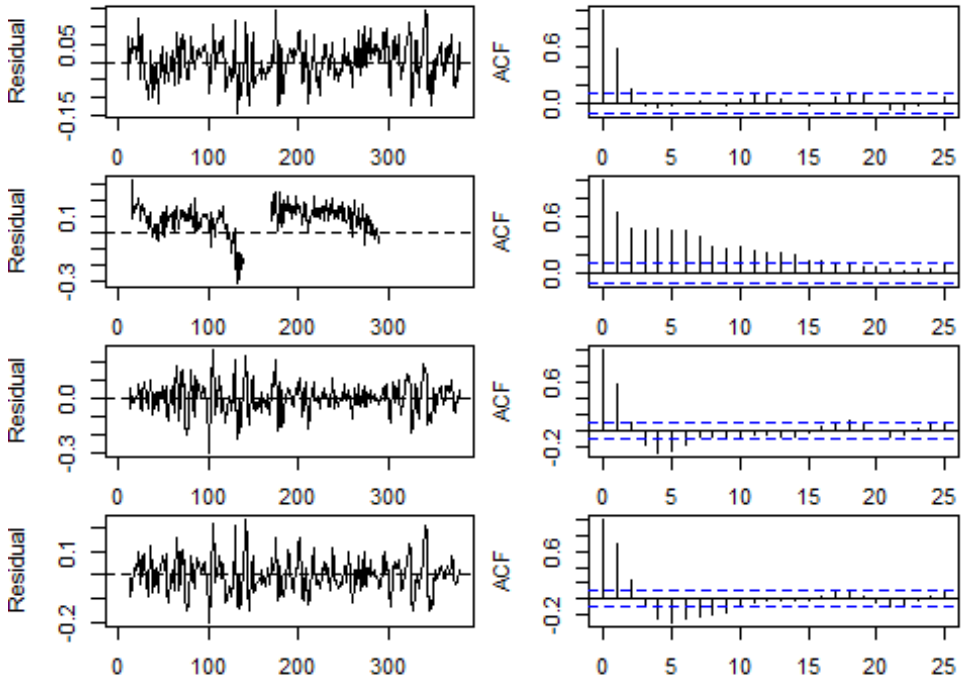
```
#Hypothesis 1, Model 1: all separate
mod11_klamath = list()
mod11_klamath$A = "zero" #no trend because we z scored
mod11_klamath$Z = matrix2_klamath
mod11_klamath$R = "diagonal and equal" #all the sensors are same, so
observation error should be same
mod11_klamath$Q = "diagonal and unequal"
mod11_klamath$B = "identity" #assuming no species interactions
mod11_klamath$U = "zero" #no trend because we z scored
mod11_klamath$C = "unequal" #Can set C to unequal because it is going off the
Z matrix where I have already indicated how to split up the sites.
mod11_klamath$c = matrixc_klamath
mod11_klamath.fit = MARSS(transformed_dat_klamath, model=mod11_klamath,
control=list(maxit=10000))

## Success! abstol and log-log tests passed at 65 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
```

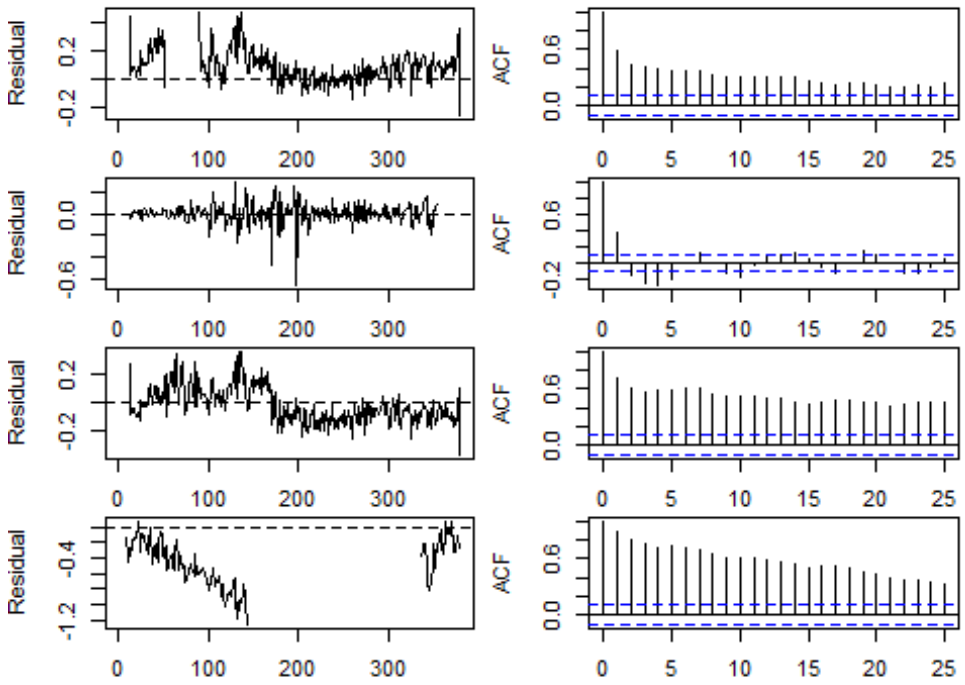
```
## Estimation converged in 65 iterations.
## Log-likelihood: 1566.017
## AIC: -3058.035   AICc: -3057.714
##
##              Estimate
## R.diag       3.09e-02
## Q.(X1,X1)    5.35e-03
## Q.(X2,X2)    7.28e-03
## Q.(X3,X3)    7.68e-03
## Q.(X4,X4)    6.63e-03
## Q.(X5,X5)    5.44e-03
## Q.(X6,X6)    1.62e-02
## Q.(X7,X7)    4.93e-03
## Q.(X8,X8)    1.77e-03
## Q.(X9,X9)    2.59e-03
## Q.(X10,X10)  2.21e-03
## Q.(X11,X11)  1.00e-02
## Q.(X12,X12)  5.10e-03
## x0.X1        1.39e+00
## x0.X2        9.89e-01
## x0.X3        1.10e+00
## x0.X4        1.22e+00
## x0.X5        1.54e+00
## x0.X6        1.42e+00
## x0.X7        8.31e-01
## x0.X8        6.65e-01
## x0.X9        1.03e+00
## x0.X10       1.01e+00
## x0.X11       1.05e+00
## x0.X12       9.96e-01
## C.X1         2.05e-04
## C.X2         4.26e-04
## C.X3         4.58e-04
## C.X4         2.04e-04
## C.X5        -9.02e-05
## C.X6         9.00e-05
## C.X7         2.43e-04
## C.X8         5.48e-04
## C.X9         3.73e-04
## C.X10        3.66e-04
## C.X11        6.39e-04
## C.X12        2.62e-04
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.

mod11_klamath.params = MARSSparamCIs(mod11_klamath.fit)
saveRDS(mod11_klamath.fit,"mod11_klamath.fit.rds")
saveRDS(mod11_klamath.params,"mod11_klamath.params.rds")
```

####Messing with Residuals

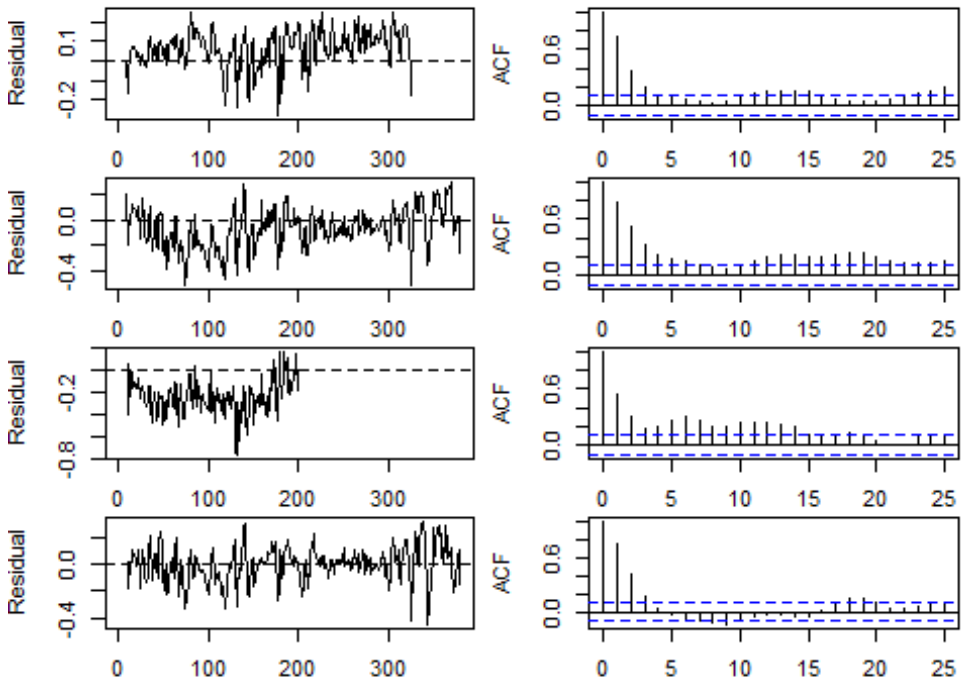
```
mod11_klamath.fit <- readRDS("mod11_klamath.fit.rds")
mod11_klamath.params <- readRDS("mod11_klamath.params.rds")

#model.residuals = the model residuals (data minus model predicted values) as
a n x T matrix

#tT: smoothed residuals conditioned on all the data t=1 to T, aka smoothation
residuals *Smoothed residuals are autocorrelated so an ACF test would not
reveal model inadequacy
par(mfrow=c(4,2), mai=c(0.1,0.5,0.2,0.1),omi=c(0.5,0,0,0))
for (j in 1:12) {
  plot.ts(residuals<-MARSSresiduals(mod11_klamath.fit, type =
"tT")$model.residuals[j, ],
            ylab = "Residual")
    abline(h = 0, lty = "dashed")
    acf(residuals,na.action = na.pass)
}
```

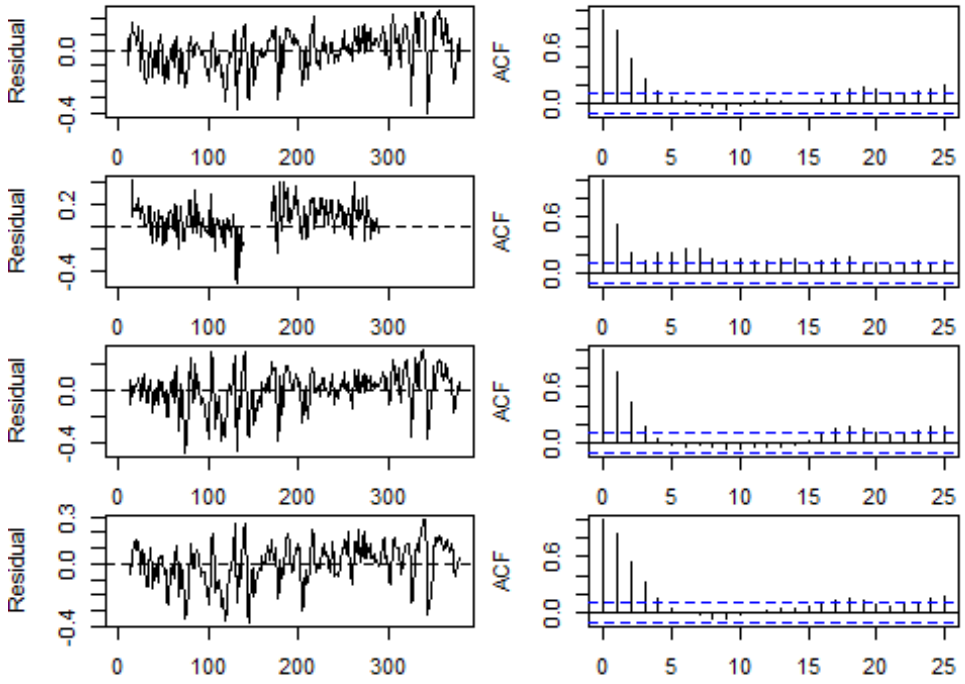

Residual
ACF
0
100
200
300
0
5
10
15
20
25

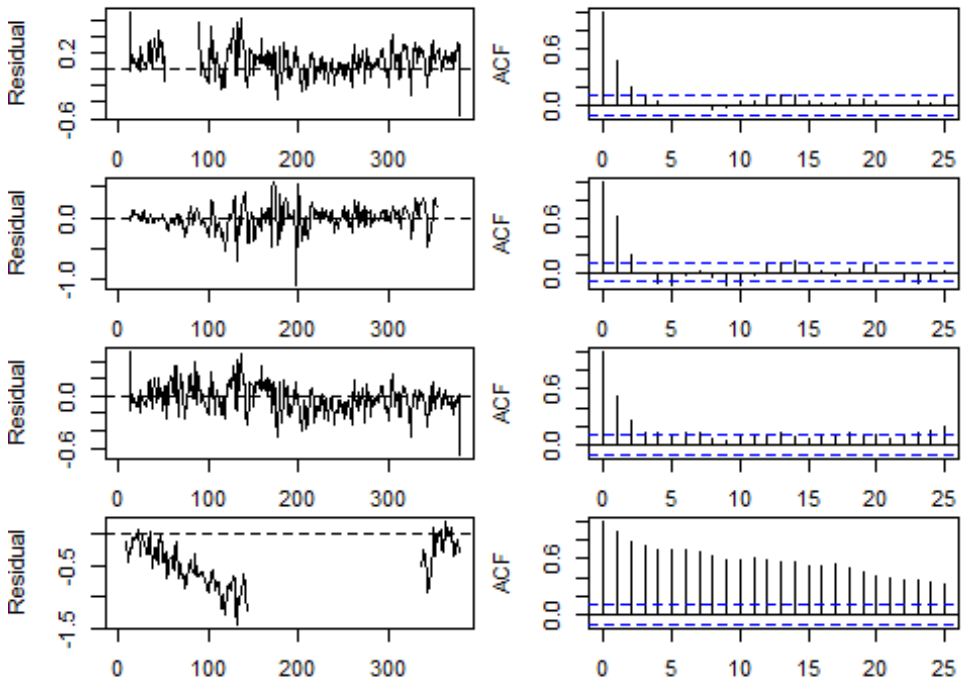

Residual
ACF
0
100
200
300
0
5
10
15
20
25



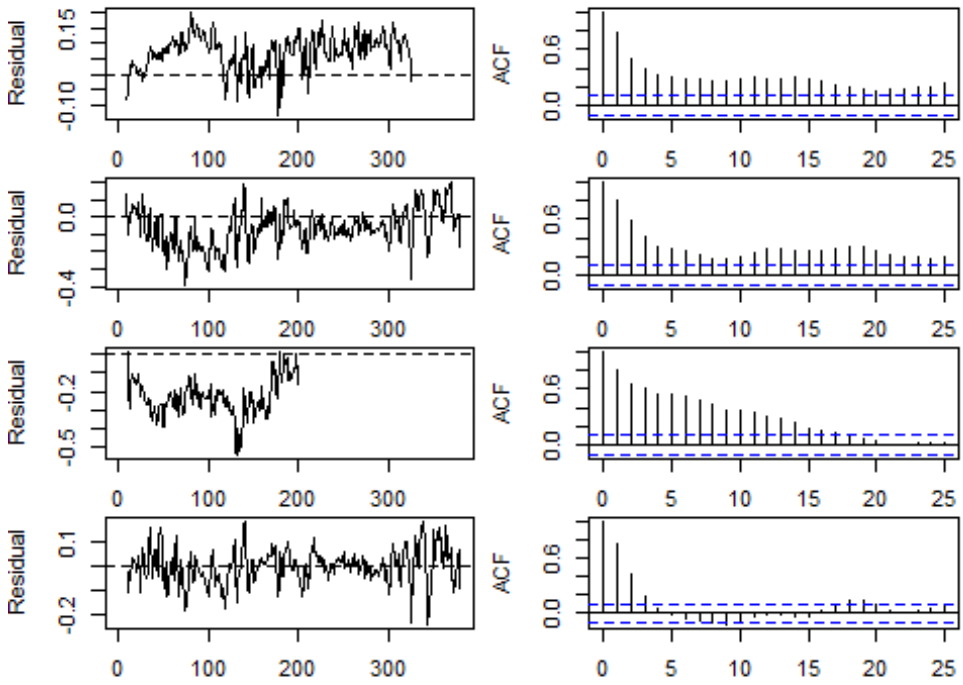

```
#tt1: one-step-ahead residuals, aka innovations residuals
par(mfrow=c(4,2), mai=c(0.1,0.5,0.2,0.1),omi=c(0.5,0,0,0))
for (j in 1:12) {
  plot.ts(residuals<-MARSSresiduals(mod11_klamath.fit, type =
"tt1")$model.residuals[j, ],
             ylab = "Residual")
    abline(h = 0, lty = "dashed")
    acf(residuals,na.action = na.pass)
}
```

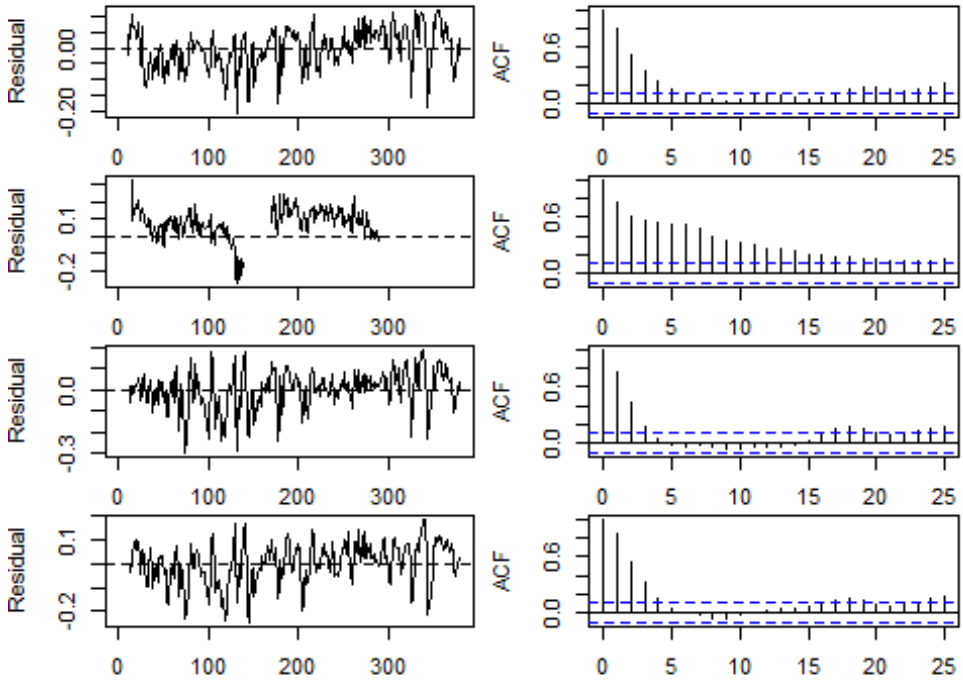

Residual
ACF
0
100
200
300
0
5
10
15
20
25

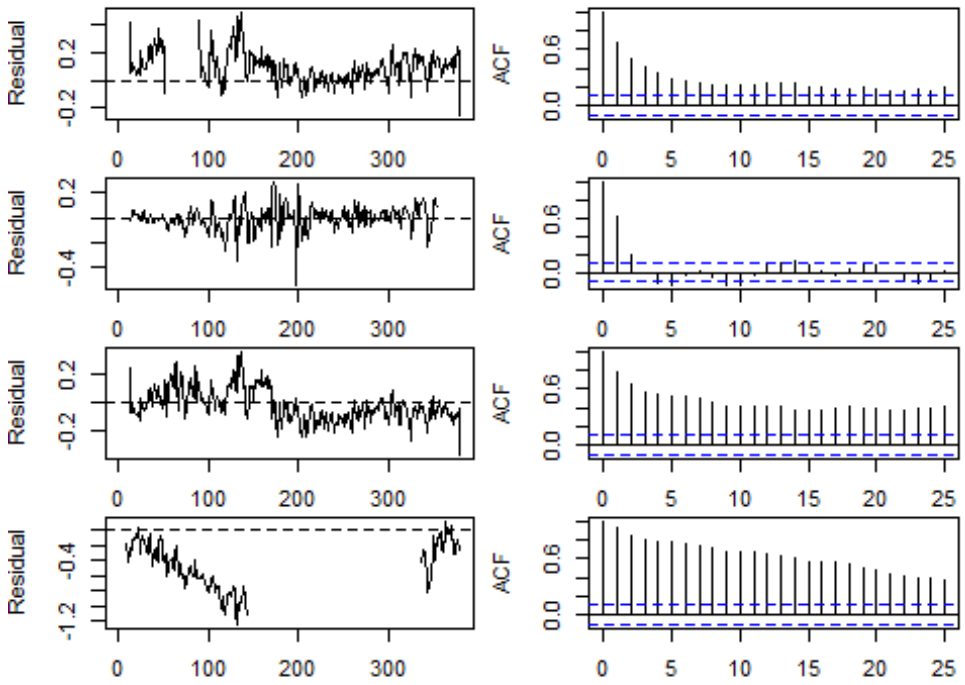

Residual
ACF
0
100
200
300
0
5
10
15
20
25




```
#tt: contemporaneous residuals, only for the observations
par(mfrow=c(4,2), mai=c(0.1,0.5,0.2,0.1),omi=c(0.5,0,0,0))
for (j in 1:12) {
  plot.ts(residuals<-MARSSresiduals(mod11_klamath.fit, type =
"tt")$model.residuals[j, ],
             ylab = "Residual")
    abline(h = 0, lty = "dashed")
    acf(residuals,na.action = na.pass)
}
```


Residual
ACF
0
100
200
300
0
5
10
15
20
25


Residual
ACF
0
100
200
300
0
5
10
15
20
25

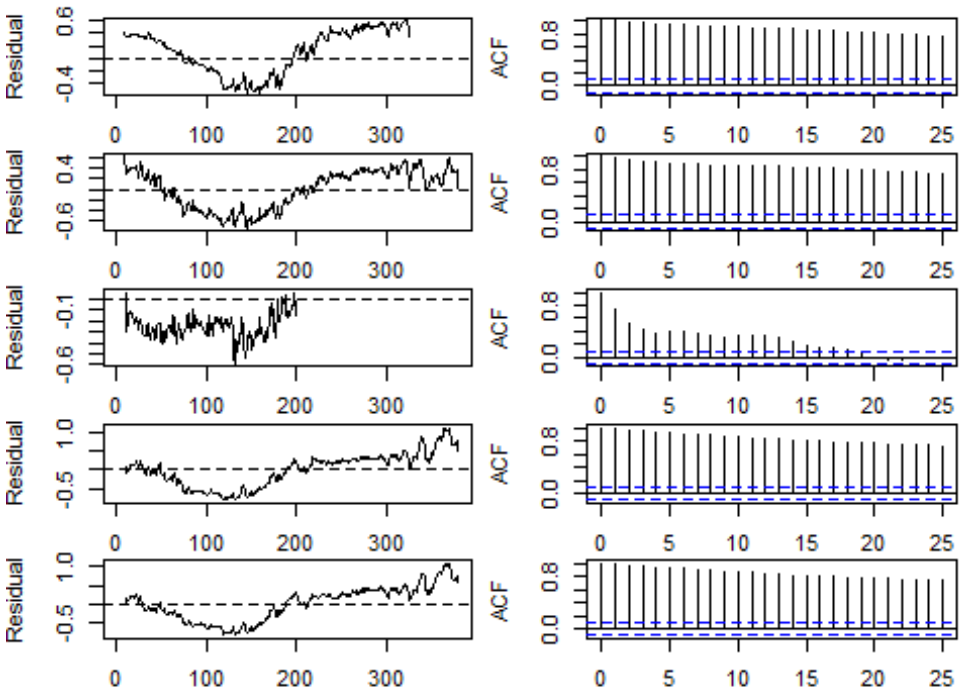


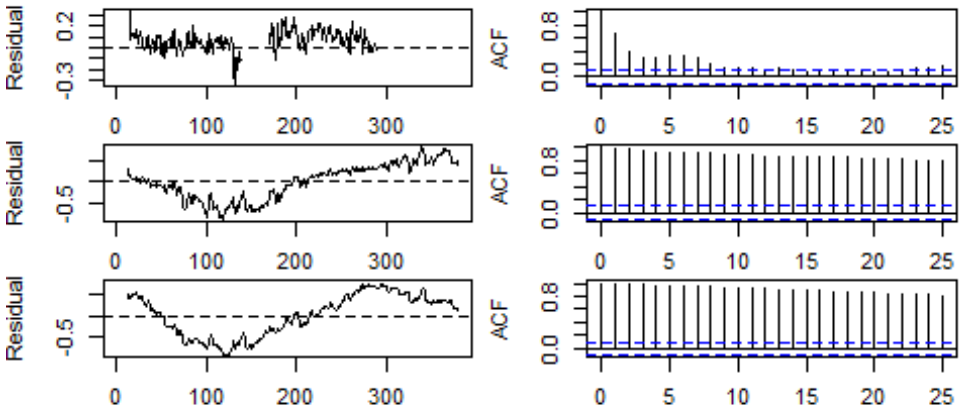
###model 2

```
#Hypothesis 2, Model 3: ponds vs. creeks
mod12_klamath <- mod11_klamath
mod12_klamath$Z <- matrix3_klamath
mod12_klamath$c <- matrixc_klamath
mod12_klamath.fit = MARSS(transformed_dat_klamath, model=mod12_klamath,
control=list(maxit=10000))
```

```
## Success! abstol and log-log tests passed at 48 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 48 iterations.
## Log-likelihood: -4126.332
## AIC: 8272.665   AICc: 8272.69
##
##           Estimate
## R.diag    0.141571
## Q.(X1,X1) 0.002861
## Q.(X2,X2) 0.006578
## Q.(X3,X3) 0.004944
## x0.X1     0.972943
## x0.X2     1.090202
```

```
## x0.X3     1.034314
## C.X1      0.000368
## C.X2      0.000429
## C.X3      0.000158
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.

mod12_klamath.params = MARSSparamCIs(mod12_klamath.fit)
saveRDS(mod12_klamath.fit,"mod12_klamath.fit.rds")
saveRDS(mod12_klamath.params,"mod12_klamath.params.rds")

par(mfrow=c(5,2), mai=c(0.1,0.5,0.2,0.1), omi=c(0.5,0,0,0))
  for (j in 1:8) {
    plot.ts(residuals<-MARSSresiduals(mod12_klamath.fit, type =
"tt")$model.residuals[j, ],
            ylab = "Residual")
    abline(h = 0, lty = "dashed")
    acf(residuals,na.action = na.pass)
  }
```

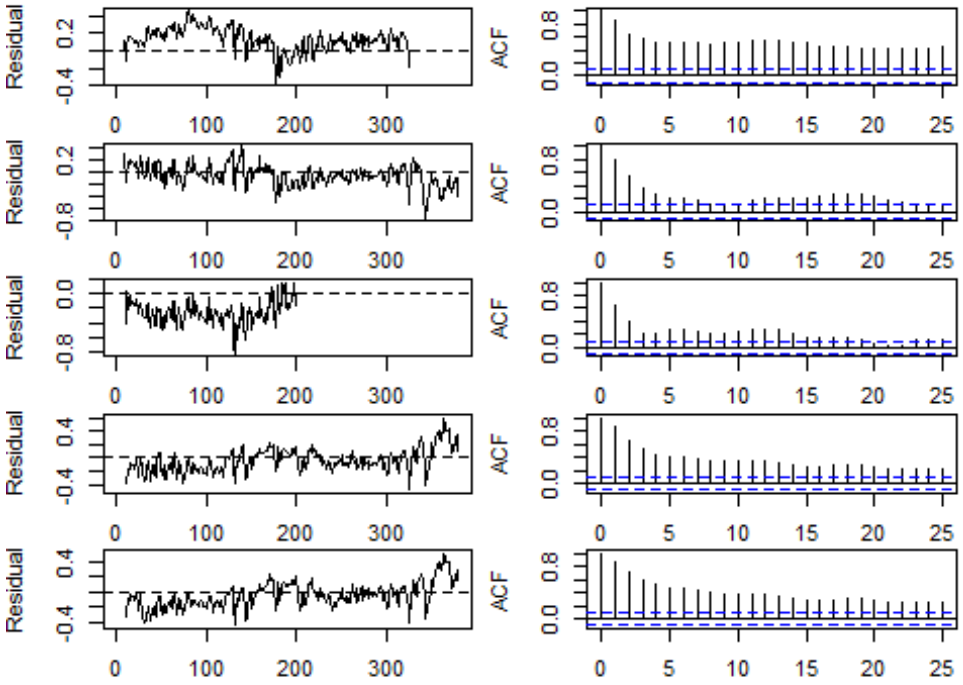




###model 3

```
#Hypothesis 3, Model 3: Tributary versus tributary
mod13_klamath <- mod11_klamath
```

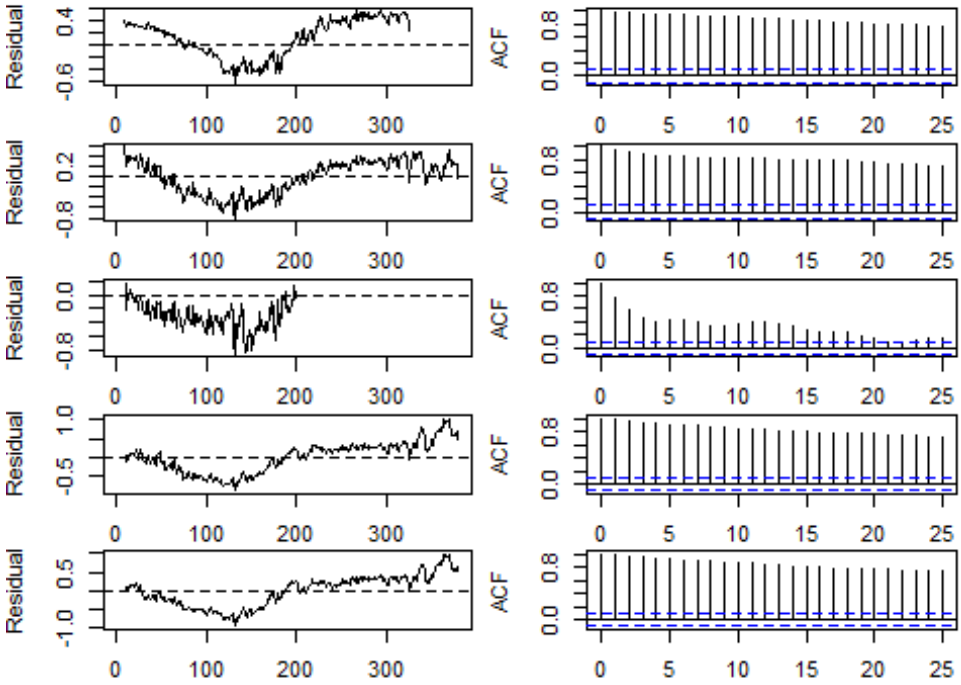
```r
mod13_klamath$Z = matrix4_klamath
mod13_klamath.fit = MARSS(transformed_dat_klamath, model=mod13_klamath,
control=list(maxit=10000))

## Success! abstol and log-log tests passed at 53 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 53 iterations.
## Log-likelihood: -1045.504
## AIC: 2123.008   AICc: 2123.069
##
##           Estimate
## R.diag    0.066270
## Q.(X1,X1) 0.006797
## Q.(X2,X2) 0.005902
## Q.(X3,X3) 0.001860
## Q.(X4,X4) 0.008371
## Q.(X5,X5) 0.004792
## x0.X1     1.259193
## x0.X2     1.138327
## x0.X3     0.939603
## x0.X4     1.067854
## x0.X5     1.007397
## C.X1      0.000275
## C.X2      0.000357
## C.X3      0.000390
## C.X4      0.000519
## C.X5      0.000202
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.

mod13_klamath.params = MARSSparamCIs(mod13_klamath.fit)
saveRDS(mod13_klamath.fit,"mod13_klamath.fit.rds")
saveRDS(mod13_klamath.params,"mod13_klamath.params.rds")

par(mfrow=c(5,2), mai=c(0.1,0.5,0.2,0.1), omi=c(0.5,0,0,0))
  for (j in 1:5) {
    plot.ts(residuals<-MARSSresiduals(mod13_klamath.fit, type =
"tt1")$model.residuals[j, ],
            ylab = "Residual")
    abline(h = 0, lty = "dashed")
    acf(residuals,na.action = na.pass)
  }
```



###model 4

```
#Hypothesis 4, Model 4: All same
mod14_klamath <- mod11_klamath
mod14_klamath$Z <- matrix5_klamath
mod14_klamath.fit = MARSS(transformed_dat_klamath, model=mod14_klamath,
control=list(maxit=10000))

## Success! abstol and log-log tests passed at 21 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 21 iterations.
## Log-likelihood: -4232.919
## AIC: 8473.839   AICc: 8473.843
##
##        Estimate
## R.diag 0.148267
## Q.Q    0.003658
## x0.x0  0.975406
## C.C    0.000435
## Initial states (x0) defined at t=0
##
```

```
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.

mod14_klamath.params =MARSSparamCIs(mod14_klamath.fit)
saveRDS(mod14_klamath.fit,"mod14_klamath.fit.rds")
saveRDS(mod14_klamath.params,"mod14_klamath.params.rds")

par(mfrow=c(5,2), mai=c(0.1,0.5,0.2,0.1), omi=c(0.5,0,0,0))
  for (j in 1:5) {
    plot.ts(residuals<-MARSSresiduals(mod14_klamath.fit, type =
"tt1")$model.residuals[j, ],
            ylab = "Residual")
    abline(h = 0, lty = "dashed")
    acf(residuals,na.action = na.pass)
  }
```



##AICc

```
data.frame(Model=c("Model11_klamath", "Model12_klamath", "Model13_klamath",
"Model14_klamath"),
           AICc=round(c(mod11_klamath.fit$AICc,
                        mod12_klamath.fit$AICc,
                        mod13_klamath.fit$AICc,
                        mod14_klamath.fit$AICc),1))

##              Model    AICc
## 1 Model11_klamath -3057.7
```

```
## 2 Model12_klamath  8272.7
## 3 Model13_klamath  2123.1
## 4 Model14_klamath  8473.8
```