Homework #3

Cameron Bracken

CVEN6833 Fall, 2009

Problem 1

```
source('lib.R')
sst <- as.matrix(read.table('data/kaplan-sst-wy-1925-2003-revised.txt'))</pre>
sst <- t(matrix(sst[,3],nrow=length(unique(sst[,1])),byrow=T))</pre>
sst.lat <- as.matrix(read.table('data/kaplan-sst-wy-1925-2003-II.txt'))</pre>
sst.lon <- sst.lat[,2]; sst.lat <- sst.lat[,1]</pre>
sst.lon[sst.lon < 0] <- sst.lon[sst.lon < 0] + 360
pdsi <- as.matrix(read.table('data/pdsi-wy-1925-2003.txt'))</pre>
pdsi <- t(matrix(pdsi[,3],nrow=length(unique(pdsi[,1])),byrow=T))</pre>
pdsi.lat <- as.matrix(read.table('data/pdsi-wy-1925-2003-II.txt'))</pre>
pdsi.lon <- pdsi.lat[,2]; pdsi.lat <- pdsi.lat[,1]</pre>
pdsi.lon[pdsi.lon < 0] <- pdsi.lon[pdsi.lon < 0] + 360</pre>
pacific <- sst.lat > -20 & sst.lon >= 120 & sst.lon <= 280
atlantic <- sst.lat > -20 & sst.lat < 70 & sst.lon >= 250 & sst.lon <= 360
states <- pdsi.lat > 15 & pdsi.lat < 60 & pdsi.lon >= 230 & pdsi.lon <= 295
lon.pac <- sst.lon[pacific]</pre>
lat.pac <- sst.lat[pacific]</pre>
sst.pac <- sst[,pacific]</pre>
lon.atl <- sst.lon[atlantic]</pre>
lat.atl <- sst.lat[atlantic]</pre>
sst.atl <- sst[,atlantic]</pre>
lon.usa <- pdsi.lon[states]</pre>
lat.usa <- pdsi.lat[states]</pre>
pdsi.usa <- pdsi[,states]</pre>
glo <- my.pca(sst)</pre>
pac <- my.pca(sst.pac)</pre>
atl <- my.pca(sst.atl)</pre>
usa <- my.pca(pdsi.usa)</pre>
save(lat, lon, lat.pac, lon.pac, lat.atl, lon.atl, lat.usa, lon.usa, pac, atl,
        glo, usa, sst, sst.lat, sst.lon, sst.pac, sst.atl, pdsi.usa,
        file='output/1.Rdata')
```

Figure 1: Reading the data and calculating the statistics.

```
my.pca <- function(x){
    s <- svd(var(x))

#do an Eigen decomposition..
    eigv <- s$u
    eig <- s$d

#Principal Components...
    pcs <- t(t(eigv) %*% t(x))

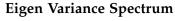
#Eigen Values.. - fraction variance
    eigf <- (eig/sum(eig))

return(list(eigv=eigv,eigf=eigf,eig=eig,pc=pcs))
}</pre>
```

Figure 2: PCA function.

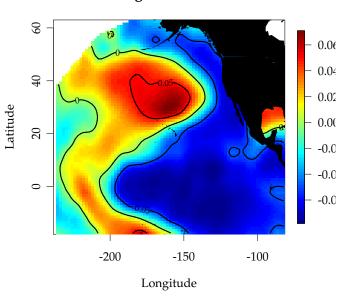
Problem 1 (i)

```
> layout(rbind(c(1,2),c(3,4)))
> plot(pac$eigf[1:12], type="b", xlab="Modes",
          ylab="Frac. Var. explained", main="Eigen Variance Spectrum")
 for(i in 1:3){
          surf <- Tps(cbind(lon.pac-360,lat.pac),pac$eigv[,i])</pre>
          surface(surf,xlab="Longitude", ylab="Latitude",main=sprintf("Eigen Vector %d",i))
          map('world',add=TRUE,fill=TRUE)
+ }
```



0.30 0.25 Frac. Var. explained 0.20 0.15 0.10 0.05 2 10 12 Modes

Eigen Vector 1



Longitude

Eigen Vector 2

Longitude

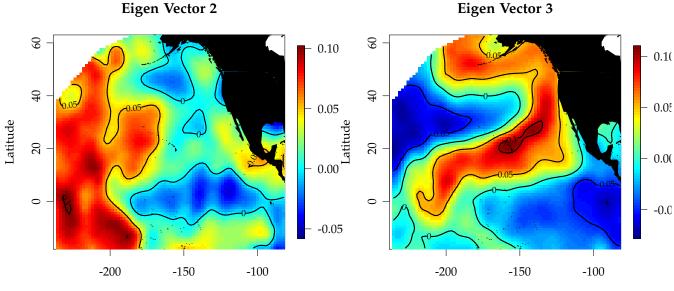


Figure 3: Pacific SST

```
> layout(cbind(c(1,2,3)))
> for(i in 1:3){
           plot(ts(pac$pc[,i],start=1925,frequency=1),
                      main=sprintf("PC %d",i),ylab='')
+ }
                                                      PC 1
    20
    10
    -10
    -50
                           1940
                                                                         1980
                                                                                                2000
                                                  1960
                                                      Time
                                                      PC 2
    20
    10
    -10
                          1940
                                                  1960
                                                                         1980
                                                                                                2000
                                                      Time
                                                      PC 3
    10
    rO
    0
    ιĊ
    -15
```

Figure 4: PC's of Pacific SST

Time

1980

2000

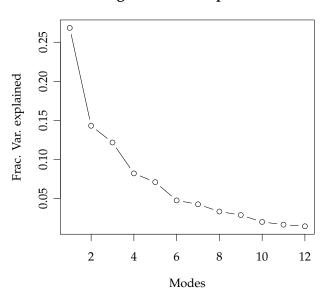
1960

1940

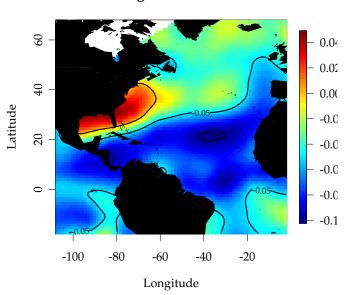
Problem 1 (ii)

```
> layout(rbind(c(1,2),c(3,4)))
> plot(atl$eigf[1:12], type="b", xlab="Modes",
          ylab="Frac. Var. explained",main="Eigen Variance Spectrum")
 for(i in 1:3){
          surf <- Tps(cbind(lon.atl-360,lat.atl),atl$eigv[,i])</pre>
          surface(surf,xlab="Longitude", ylab="Latitude",main=sprintf("Eigen Vector %d",i))
          map('world',add=TRUE,fill=T)
+ }
```

Eigen Variance Spectrum



Eigen Vector 1





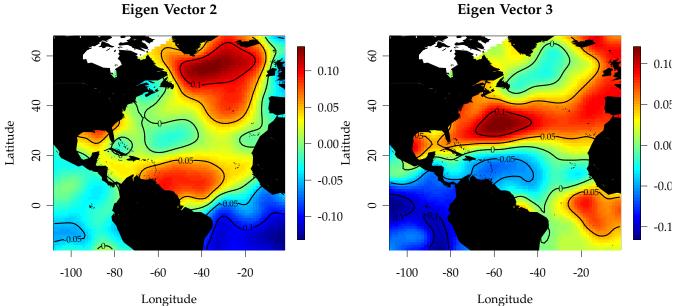


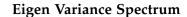
Figure 5: Atlantic SST

```
> layout(cbind(c(1,2,3)))
> for(i in 1:3){
            plot(ts(atl$pc[,i],start=1925,frequency=1),
                      main=sprintf("PC %d",i),ylab='')
+ }
                                                       PC 1
    20
    10
    0
    -10
    -20
    -30
                           1940
                                                   1960
                                                                          1980
                                                                                                  2000
                                                       Time
                                                       PC 2
    10
    5
    ċ
                           1940
                                                   1960
                                                                          1980
                                                                                                  2000
                                                       Time
                                                       PC 3
    10
    ιĊ
    -10
    -15
                           1940
                                                   1960
                                                                          1980
                                                                                                  2000
```

Figure 6: PC's of Atlantic SST

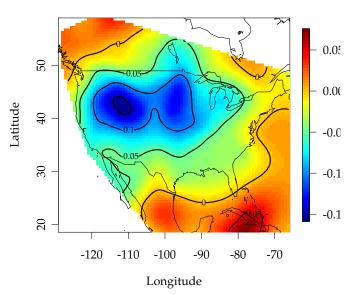
Time

Problem 1 (iii)

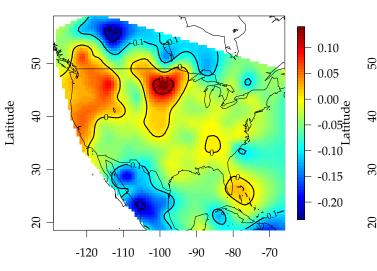


Frac. Var. explained 0.05 0.10 0.05 0.10 2 4 6 8 10 12 Modes

Eigen Vector 1







Longitude

Eigen Vector 3

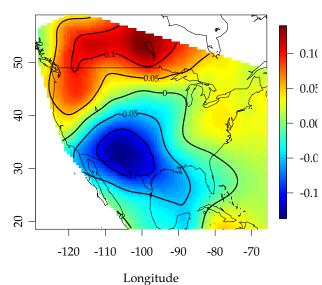
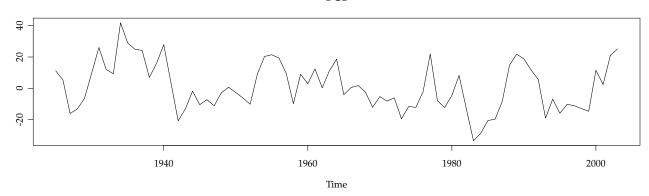
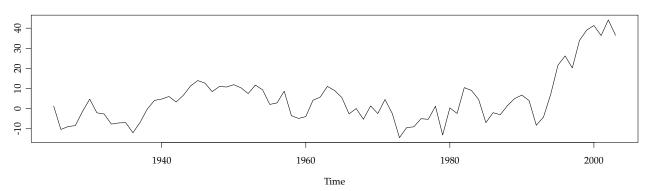


Figure 7: PDSI over the United States

PC1



PC2



PC3

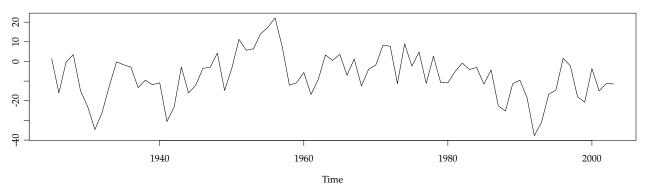


Figure 8: PC's of US PDSI

Below is the code to calculate the correlation maps and local poynomial fits for SST and PDSI.

```
source('lib.R')
if(file.exists('output/1.Rdata')) load('output/1.Rdata') else source('1.R')
library(locfit)
#usa - x
#pac - y
lfpc <- list()</pre>
for(i in 1:2)
        for(j in 1:2){
                 b <- best.par(pac$pc[,i],usa$pc[,j])</pre>
                 lfpc[[paste(i,j,sep='')]] <- locfit(usa$pc[,j]~pac$pc[,i],alpha=b$a,deg=b$p)</pre>
        }
#correlation maps
cor.pdsi.sst.pac1 <- as.vector(cor(pac$pc[,1],pdsi.usa))</pre>
cor.pdsi.sst.pac2 <- as.vector(cor(pac$pc[,2],pdsi.usa))</pre>
cor.pdsi.sst.atl1 <- as.vector(cor(atl$pc[,1],pdsi.usa))</pre>
cor.pdsi.sst.atl2 <- as.vector(cor(atl$pc[,2],pdsi.usa))</pre>
cor.map <- list()</pre>
cor.map[[1]] <- Tps(cbind(lon.usa-360,lat.usa),cor.pdsi.sst.pac1)</pre>
cor.map[[2]] <- Tps(cbind(lon.usa-360,lat.usa),cor.pdsi.sst.pac2)</pre>
cor.map[[3]] <- Tps(cbind(lon.usa-360,lat.usa),cor.pdsi.sst.atl1)</pre>
cor.map[[4]] <- Tps(cbind(lon.usa-360,lat.usa),cor.pdsi.sst.atl2)</pre>
save(lfpc,cor.map,file='output/2.Rdata')
```

Figure 9: Code for problem 2.

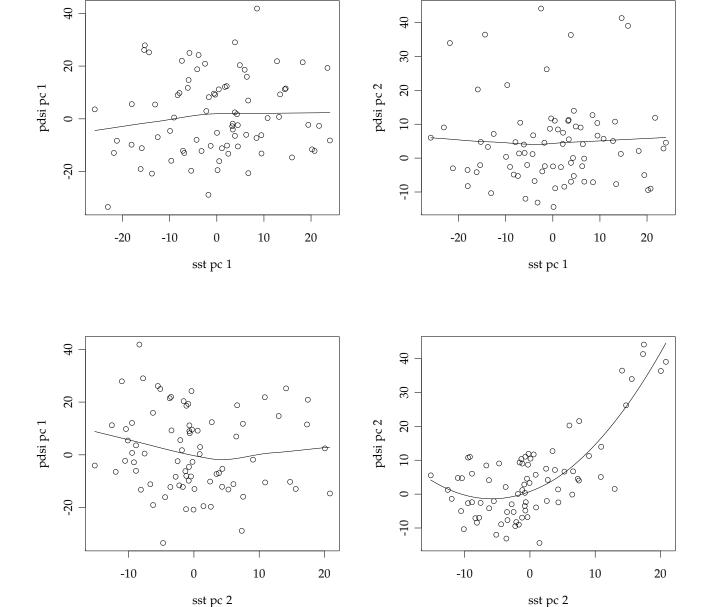
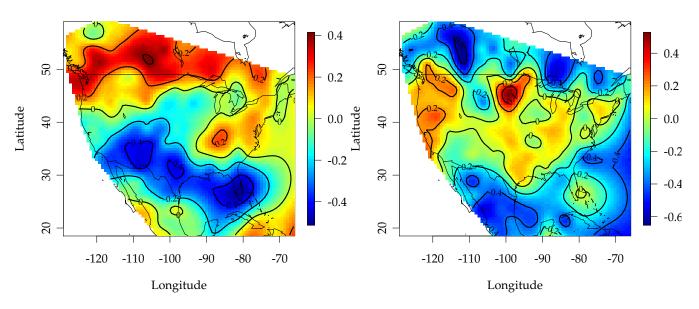


Figure 10: States PC

PDSI correlated with Pacific SST PC 1

PDSI correlated with Pacific SST PC 2



PDSI correlated with Atlantic SST PC 1

PDSI correlated with Atlantic SST PC 2

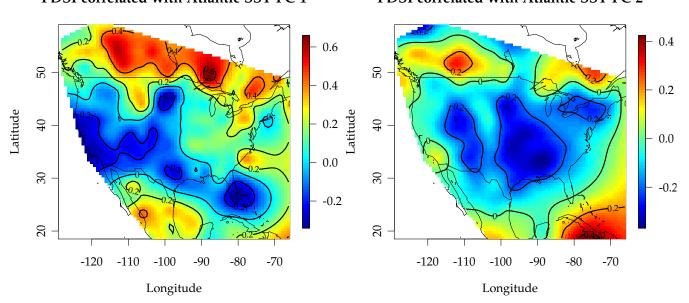


Figure 11: SST principal components correlated with PDSI

Below is the code which performs SVD and calcualtes the heterogeneous correlation maps.

Figure 12: Code for problem 3.

```
> layout(rbind(c(1,2),c(3,4)))
> plot(ts(sst.tc[,1],start=1925,frequency=1),ylab="SST TC 1")
> plot(ts(pdsi.tc[,1],start=1925,frequency=1),ylab="PDSI TC 1")
> surface(cor.map.sst[[1]], xlab="Longitude", ylab="Latitude",
                  main='Het. Correlation map of SST (mode 1)')
> map('world',add=TRUE,fill=TRUE)
 surface(cor.map.pdsi[[1]], xlab="Longitude", ylab="Latitude",
                  main='Het. Correlation map of PDSI (mode 1)')
> map('world',add=TRUE)
```

0

-20

-40

-150 -100

-50

0

Longitude

50

100

150

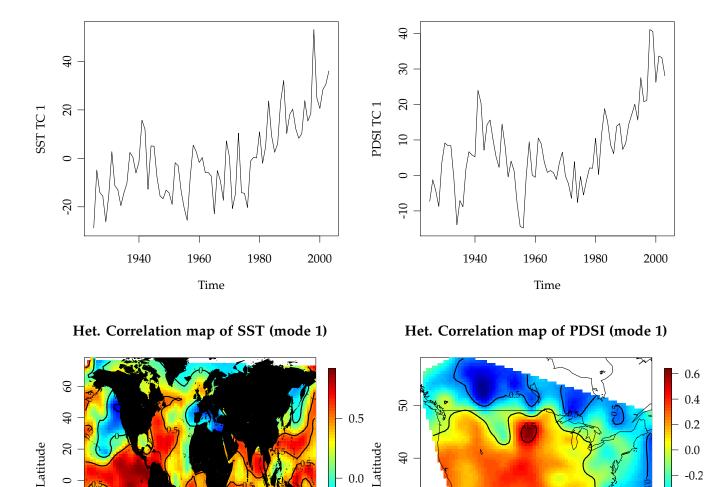


Figure 13: Heterogeneous correlation maps and time coefficients for mode 1

40

30

20

-120

-110

-100

Longitude

-90

-80

-70

-0.2

-0.4

-0.6

-0.8

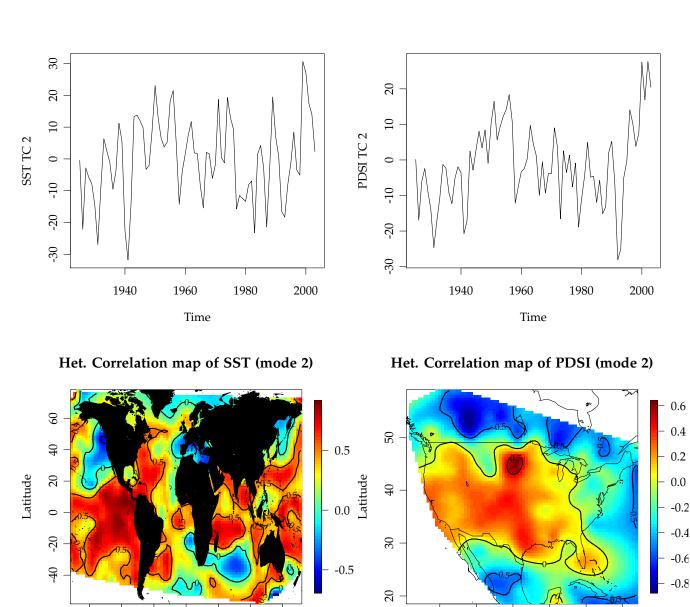


Figure 14: Heterogeneous correlation maps and time coefficients for mode 2

-120

-110

-100

Longitude

-90

-80

-70

-150 -100

-50

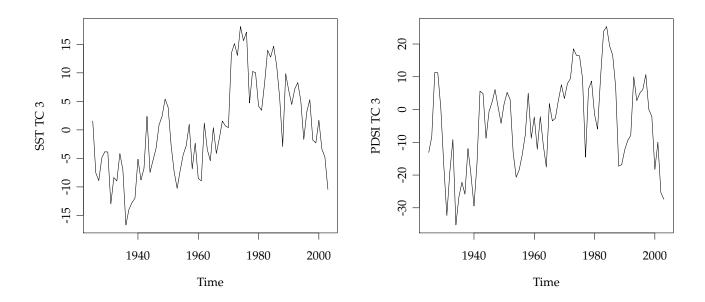
0

Longitude

50

100

150



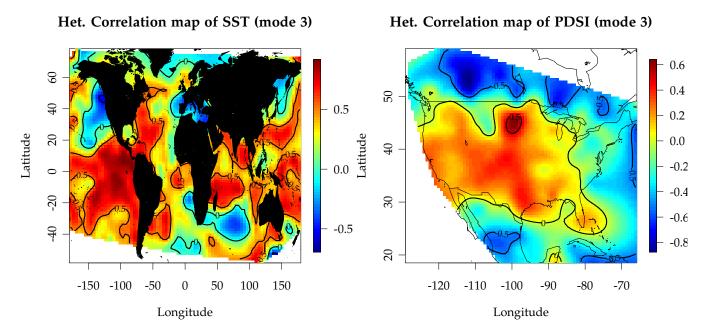


Figure 15: Heterogeneous correlation maps and time coefficients for mode 3

```
source('lib.R')
flow <- as.matrix(read.table("data/AMJJFLOW-49-99.txt"))/(10^3)</pre>
swe <- as.matrix(read.table("data/March1SWE-1949-99.txt"))</pre>
nsim <- 250
#Singular value decomposition
C \leftarrow var(flow,swe) #note that the variable with fewer columns should be first
S \leftarrow svd(C)
#Time coefficients
flow.tc <- flow %*% S$u
swe.tc <- swe %*% S$v
#heterogeneous Correlation maps
cor.map.swe <- cor.map.flow <- list()</pre>
for(i in 1:3){
        cor.map.swe[[i]] <- as.vector(cor(swe.tc[,1],swe))</pre>
        cor.map.flow[[i]] <- as.vector(cor(flow.tc[,1],flow))</pre>
}
#Local polynomial fit of TC
lftc <- list()</pre>
for(i in 1:2)
        for(j in 1:2){
                 b <- best.par(swe.tc[,i],flow.tc[,j])</pre>
                 lftc[[paste(i,j,sep='')]] <-</pre>
                          locfit(flow.tc[,j]~swe.tc[,i],alpha=b$a,deg=b$p)
        }
#Forecasting
ypred.svd <- fc.svd(flow,swe,nsim)</pre>
#get the rpss and median correlation stats
stats.svd <- fc.stats(flow,ypred.svd,nsim)</pre>
stats.svd$rpss <-
save(swe.tc, flow.tc, cor.map.swe, cor.map.flow, lftc, stats.svd, ypred.svd,
        flow, file='output/4.Rdata')
```

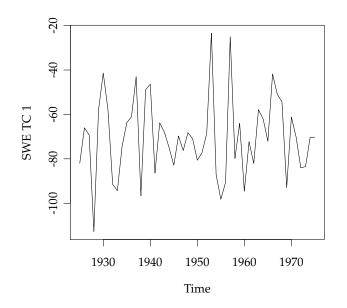
Figure 16: SVD code.

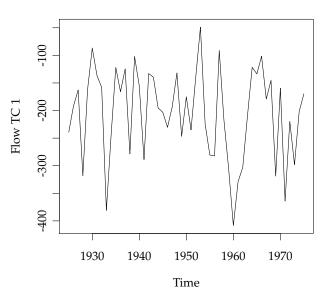
```
fc.svd <- function(flow,swe,nsim){</pre>
        n <- nrow(flow)</pre>
        n.sites <- ncol(flow)</pre>
        nsim <- 100
        ypred <- array(NA,c(n.sites,nsim,n))</pre>
        yy <- numeric(n.sites)</pre>
        for(i in 1:n){
                 #drop a point..
                 swe.cv <- swe[-i,]</pre>
                 flow.cv <- flow[-i,]</pre>
                 #perform SVD
                 C <- var(flow.cv,swe.cv)</pre>
                 S \leftarrow svd(C)
                 #Get the tc's
                 flow.cv.tc <- flow.cv %*% S$u
                 swe.cv.tc <- swe.cv %*% S$v
                 cv.model <- lsfit(swe.cv.tc[,1],flow.cv.tc[,1])</pre>
                 stderr <- sum((cv.model$resid)^2) / (nrow(flow.cv) - 2)</pre>
                 #prediction error..
                 Sxx \leftarrow sum((swe.cv.tc[,1] - mean(swe.cv.tc[,1]))^2)
                 #the TCs of the dropped point..
                 xp <- swe[i,] %*% S$v
                 #generate an ensemble..
                 for(isim in 1:nsim){
                          this.stderr <- sqrt(stderr *</pre>
                                   (1 + (1/(n-1)) +
                                            ((xp[1] - mean(swe.cv.tc[,1]))^2)/Sxx))
                          yy[1] \leftarrow cv.model\\coef[1] +
                                   cv.model$coef[2]*xp[1] + rnorm(1,0,this.stderr)
                          #grab random TCs for the remaining TCs
                          for(site in 2:n.sites){
                                   r.tc <- round(runif(1,1,(n-1)))
                                   yy[site] <- flow.cv.tc[r.tc,site]</pre>
                          ypred[1:n.sites,isim,i]=yy %*% t(S$u)
                 }
        ypred[ypred < 0] <- 0
        return(ypred)
}
```

Figure 17: SVD forecast code.

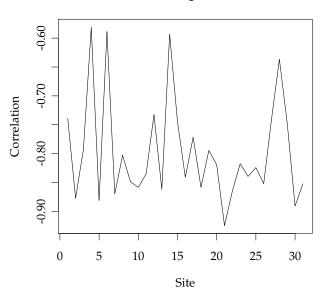
```
fc.stats <- function(flow,ypred,nsim){</pre>
        n.sites <- ncol(flow)
        site.rpss <- site.mc <- numeric(n.sites)</pre>
        n <- nrow(flow)</pre>
        ##Calculate rpss
        for(i in 1:n.sites){
                 thresh <- quantile(flow[,i], c(0.33, 0.66))</pre>
                 # climatological forecast..
                 climo = cumsum(c(1/3, 1/3, 1/3))
                 rpss = numeric(n)
                 for(jj in 1:n){
                         # forecast categorical probabilities
                         fcastprob=1:3
                         yypred=ypred[i,,jj]
                         fcastprob[1] <- length(yypred[yypred <= thresh[1]]) / nsim</pre>
                         fcastprob[2] <-
                                  length(yypred[yypred > thresh[1] &
                                          yypred < thresh[2]]) / nsim</pre>
                         fcastprob[3] <- length(yypred[yypred >= thresh[2]]) / nsim
                         fcastprob=cumsum(fcastprob)
                         # actual..
                         actual=rep(0,3)
                         if(flow[jj,i] <= thresh[1])actual[1]=1</pre>
                         if(flow[jj,i] > thresh[1] & flow[jj,i] < thresh[2])actual[2]=1</pre>
                         if(flow[jj,i] >= thresh[2])actual[3]=1
                         rpsclimo = sum((climo-actual)^2)
                         rpsfcast = sum((fcastprob - actual)^2)
                         rpss[jj] = 1 - (rpsfcast/rpsclimo)
                 }
                 #print out the median RPSS
                 site.rpss[i] <- median(rpss)</pre>
                 site.mc[i] <- cor(flow[,i],apply(ypred[i,,],2,median))</pre>
        }
        return(list(rpss=site.rpss,mc=site.mc))
}
```

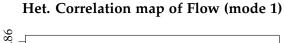
Figure 18: SVD forecast stats code.





Het. Correlation map of SWE (mode 1)





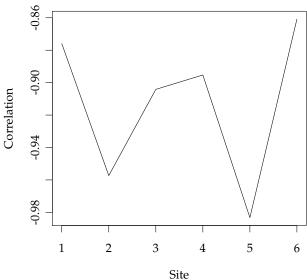
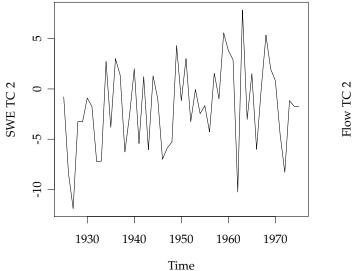
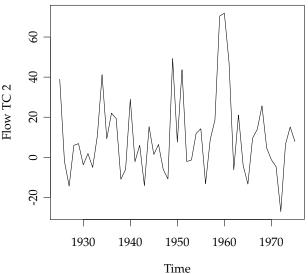
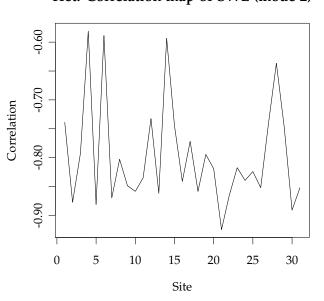


Figure 19: Heterogeneous correlation maps and time coefficients for mode 1





Het. Correlation map of SWE (mode 2)



Het. Correlation map of Flow (mode 2)

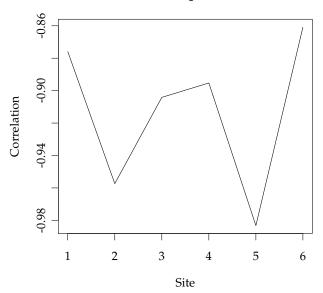


Figure 20: Heterogeneous correlation maps and time coefficients for mode 2

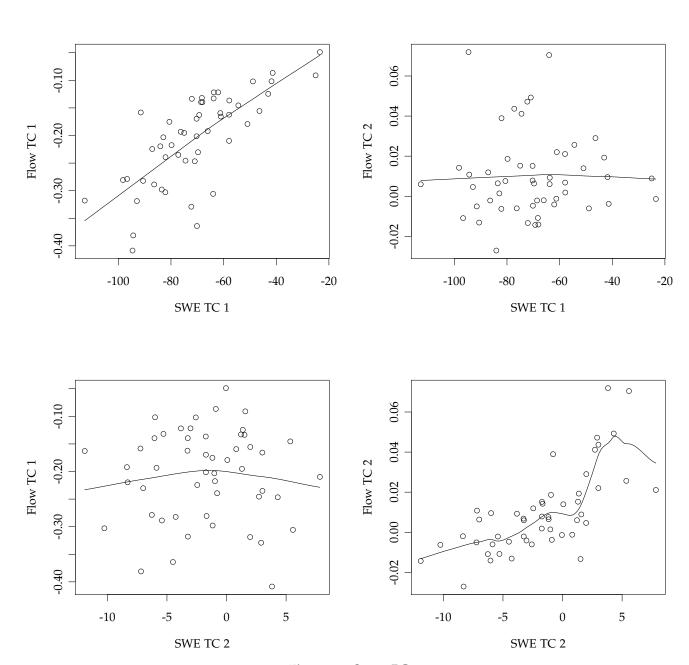
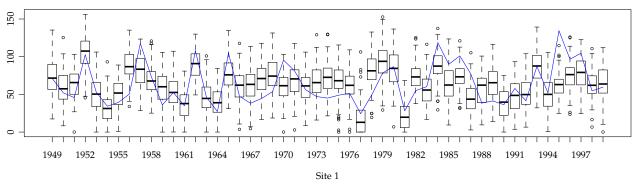
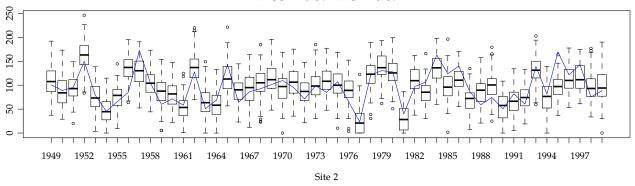


Figure 21: States PC

RPSS = 0.405 MC = 0.405



RPSS = 0.39 MC = 0.39



RPSS = 0.401 MC = 0.401

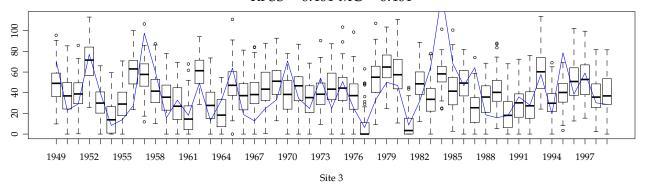
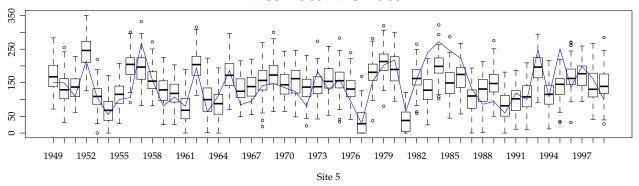


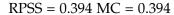
Figure 22: Svd predictions for first three sites

RPSS = 0.398 MC = 0.398

RPSS = 0.354 MC = 0.354

Site 4





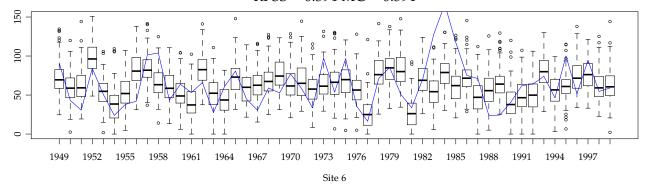


Figure 23: Svd predictions for second three sites

I did not significantly modeify the CCA code from the class page so it is not shown here, but it was used to generate forecasts.

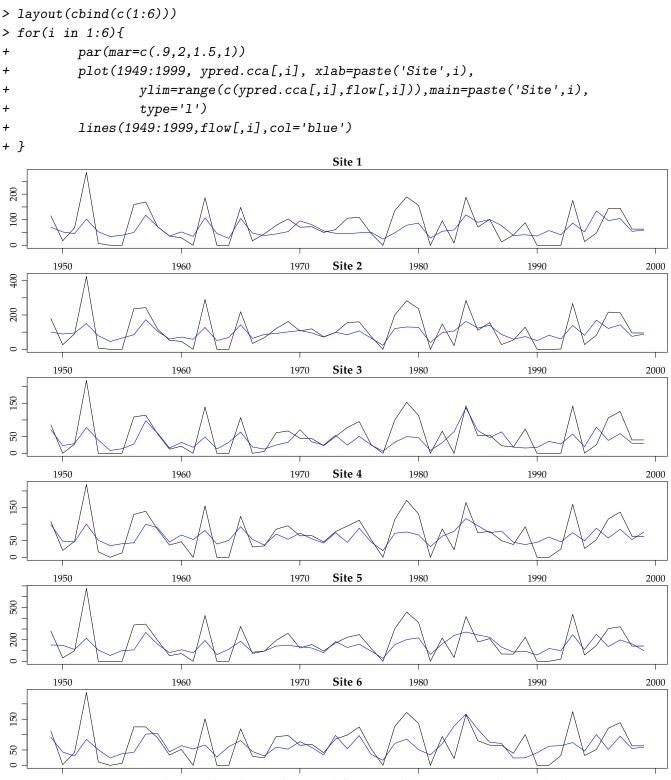


Figure 24: CCA predictions for all sites, historical flow is in blue. Units are thousand cubic meters

Below is the code that does the Markov KNN simulation.

```
source('lib.R')
nyears <- 95
nsim <- nyears * 100
        #read data (ac-ft) and convert to cms
x <- as.matrix(read.table('data/Leesferry-mon-data.txt')[,-1])*0.000469050
x.raw \leftarrow array(t(x))
x.ann <- x.bin <- ts.annual.mean(ts(x.raw,start=c(1906,1),frequency=12))
n <- length(x.ann)</pre>
        #historical stats
x.mean \leftarrow mean(x.ann); x.sd \leftarrow sd(x.ann)
x.skew <- skew(x.ann); x.lag1 <- mylag(x.ann,1,docor=T)</pre>
        #binary series
x.bin[(x.ann > median(x.ann))] <- 1
x.bin[!(x.ann > median(x.ann))] <- 0
x.wd <- x.ww <- x.dw <- x.dd <- numeric()
p.wd <- p.ww <- p.dw <- p.dd <- n.wd <- n.ww <- n.dw <- n.dd <- 0
for(i in 2:length(x.bin)){
        if(x.bin[i-1] == 0 \&\& x.bin[i] == 0){n.dd <- n.dd + 1; x.dd[n.dd] <- x.ann[i]}
        if(x.bin[i-1] == 0 \&\& x.bin[i] == 1) \{n.dw <- n.dw + 1; x.dw[n.dw] <- x.ann[i]\}
        if(x.bin[i-1] == 1 \&\& x.bin[i] == 0) \{n.wd <- n.wd + 1; x.wd[n.wd] <- x.ann[i]\}
        if(x.bin[i-1] == 1 \&\& x.bin[i] == 1) \{n.ww <- n.ww + 1; x.ww[n.ww] <- x.ann[i]\}
p.wd <- n.wd / (n.wd+n.ww); p.ww <- n.ww / (n.wd+n.ww)
p.dw \leftarrow n.dw / (n.dw+n.dd); p.dd \leftarrow n.dd / (n.dw+n.dd)
#Simulate
x.sim.state <- x.sim <- numeric(nsim)</pre>
x.sim.state[1] <- 1
x.sim[1] <- quantile(x.ann, .75)</pre>
for(i in 2:nsim){
        r <- runif(1)
        if(x.sim.state[i-1] == 1){
                 x.sim.state[i] \leftarrow if(r < p.ww) 1 else 0
                 pool <- if(r < p.ww) x.ww else x.wd
        }else{
                  x.sim.state[i] \leftarrow if(r < p.dd) 0 else 1
                 pool <- if(r < p.dd) x.dd else x.dw
        x.sim[i] <- sample(pool,1)</pre>
#calculate stats
x.sim <- matrix(x.sim,ncol=nyears)</pre>
x.sim.stats <- annual.stats(x.sim)</pre>
save(x.sim.stats, x.sim, x.ann, x.mean, x.sd, x.skew, x.lag1, nsim, nyears,
        file='output/6.Rdata')
```

Figure 25: Markov KNN resampling code.

```
> layout(rbind(1:4))
> boxplot(x.sim.stats[,1],ylim=range(c(x.sim.stats[,1],x.mean)),xlab='Mean')
> points(x.mean,col='red')
> boxplot(x.sim.stats[,2],ylim=range(c(x.sim.stats[,2],x.sd)),xlab='SD')
> points(x.sd,col='red')
> boxplot(x.sim.stats[,3],ylim=range(c(x.sim.stats[,3],x.skew)),xlab='Skew')
> points(x.skew,col='red')
> boxplot(x.sim.stats[,4],ylim=range(c(x.sim.stats[,4],x.lag1)),xlab='Lag1 Cor')
> points(x.lag1,col='red')
```

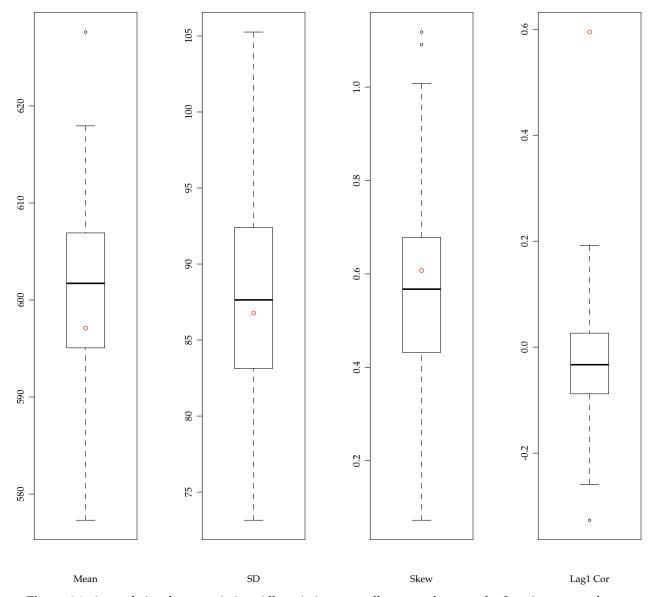


Figure 26: Annual simulates statistics. All statistics are well captured except for Lag 1 autocorrelation. I believe this is to to the way values re sampled from each 'bin.' The only way yo get enough sampling variation is to select from all of the vaues in a bin.

One interesting result I noticed was that the historical pdf was only reroduced when I used a uniform weight function and selected from all the neighbors in a bin. If I used a 1/k weight function and set k to \sqrt{n} , the simulated values did not have very much variability at all.

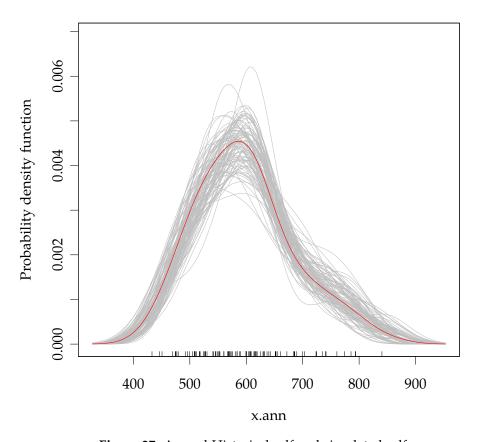


Figure 27: Annual Historical pdf and simulated pdf