

2021_Wavelets

#Import historical data #ALEXANDER ##Read in Data

```
# Water temperature - response variable
# Hourly temperature time series dataset from Alexander Pond called "APH"
(Alexander Pond Historical)
# Includes data from 16 December 2010 to 24 November 2021
# Data collected by Mid Klamath Watershed Council, see metadata for more
details

APH <- read.csv("Alexander_Historical_2.csv")
APH$date <- lubridate::mdy_hm(APH$Date_Time) #convert dates to POSIXct format
and bin by hour

#Check for missing data
missing_data <- APH[!complete.cases(APH),]
missing_data

#Bin data by hour
APH$hour <- lubridate::round_date(APH$date, unit="hour")
head(APH) #check the dataset start date, use for "hour" sequence
tail(APH) #check the dataset end date, use for "hour" sequence

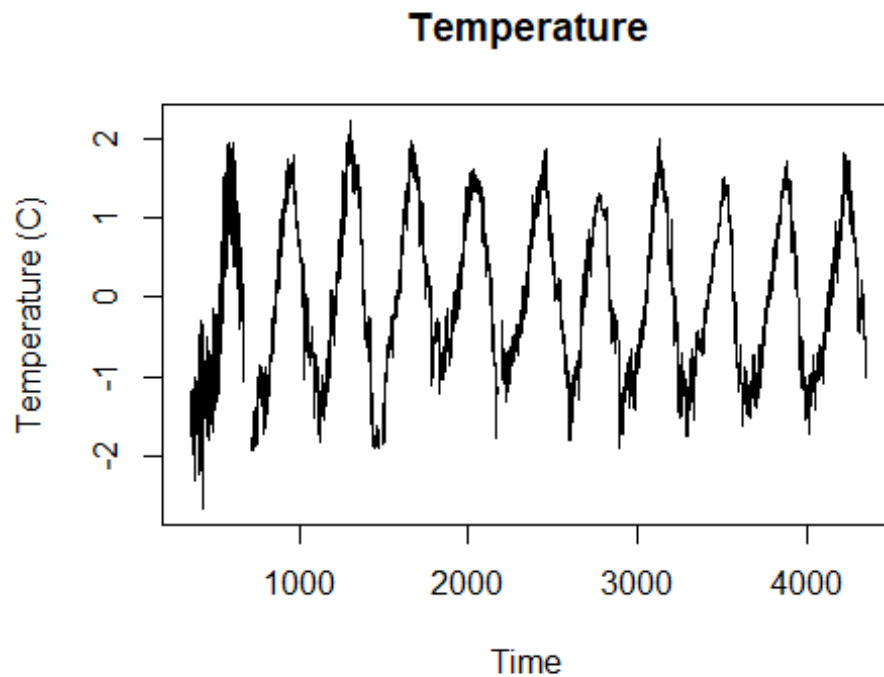
#Create hourly sequence to ensure all missing data is accounted for
hour <- seq(mdy_h('12/16/2010 13'),mdy_h('11/24/2021 14'),by = "hour")
#Create an object that goes hour by hour for the entire time series
hour <- as.data.frame(hour)
APH <- left_join(hour, APH)

## Joining, by = "hour"

missing_data <- APH[!complete.cases(APH),]
missing_data

#z score s
APH$zTemp <- zscore(APH$Temp)

#Convert to time series
APH_ts <- ts(APH$zTemp, start = c(351, 13), frequency = 24) # This time
series starts on 16 Dec 2010 at~13:00, so it starts on day 351 at hour 13 and
the frequency is 24 (24 hours per day)
ts.plot(APH_ts,main="Temperature",ylab = "Temperature (C)", xlab = "Time")
```



##Interpolate missing data

#Run ARIMA to interpolate missing data

y <- APH_ts

date_s <- APH\$hour

y_na <- ifelse(is.na(y),0,NA)

fit <- auto.arima(y,trace=TRUE) *#fit limited number of models (faster)*

##

Fitting models using approximations to speed things up...

##

## ARIMA(2,0,2)(1,1,1)[24] with drift	: Inf
## ARIMA(0,0,0)(0,1,0)[24] with drift	: -180159.6
## ARIMA(1,0,0)(1,1,0)[24] with drift	: -455692.7
## ARIMA(0,0,1)(0,1,1)[24] with drift	: -151172.4
## ARIMA(0,0,0)(0,1,0)[24]	: -180160.3
## ARIMA(1,0,0)(0,1,0)[24] with drift	: -450186.9
## ARIMA(1,0,0)(2,1,0)[24] with drift	: -463544.8
## ARIMA(1,0,0)(2,1,1)[24] with drift	: Inf
## ARIMA(1,0,0)(1,1,1)[24] with drift	: Inf
## ARIMA(0,0,0)(2,1,0)[24] with drift	: -184292.9
## ARIMA(2,0,0)(2,1,0)[24] with drift	: Inf
## ARIMA(1,0,1)(2,1,0)[24] with drift	: -346161
## ARIMA(0,0,1)(2,1,0)[24] with drift	: -152991.4
## ARIMA(2,0,1)(2,1,0)[24] with drift	: -350220.9
## ARIMA(1,0,0)(2,1,0)[24]	: -463546.7

```

## ARIMA(1,0,0)(1,1,0)[24] : -455694.7
## ARIMA(1,0,0)(2,1,1)[24] : Inf
## ARIMA(1,0,0)(1,1,1)[24] : Inf
## ARIMA(0,0,0)(2,1,0)[24] : -184292.5
## ARIMA(2,0,0)(2,1,0)[24] : Inf
## ARIMA(1,0,1)(2,1,0)[24] : -346162.9
## ARIMA(0,0,1)(2,1,0)[24] : -152986.9
## ARIMA(2,0,1)(2,1,0)[24] : -350222.8
##
## Now re-fitting the best model(s) without approximations...
##
## ARIMA(1,0,0)(2,1,0)[24] : Inf
## ARIMA(1,0,0)(2,1,0)[24] with drift : Inf
## ARIMA(1,0,0)(1,1,0)[24] : Inf
## ARIMA(1,0,0)(1,1,0)[24] with drift : Inf
## ARIMA(1,0,0)(0,1,0)[24] with drift : Inf
## ARIMA(2,0,1)(2,1,0)[24] : Inf
## ARIMA(2,0,1)(2,1,0)[24] with drift : Inf
## ARIMA(1,0,1)(2,1,0)[24] : -461214
##
## Best model: ARIMA(1,0,1)(2,1,0)[24]

summary(fit) #Take a closer look at the best fitted model

## Series: y
## ARIMA(1,0,1)(2,1,0)[24]
##
## Coefficients:
##          ar1      ma1      sar1      sar2
##      0.9796  0.0360 -0.2904 -0.2942
## s.e.  0.0007  0.0024  0.0032  0.0032
##
## sigma^2 estimated as 0.0004044: log likelihood=230612
## AIC=-461214 AICc=-461214 BIC=-461166.6
##
## Training set error measures:
##              ME          RMSE          MAE          MPE          MAPE
MASE
## Training set 9.161849e-06 0.02010788 0.008321832 1.233202 6.684451
0.1293441
##              ACF1
## Training set -0.3061128

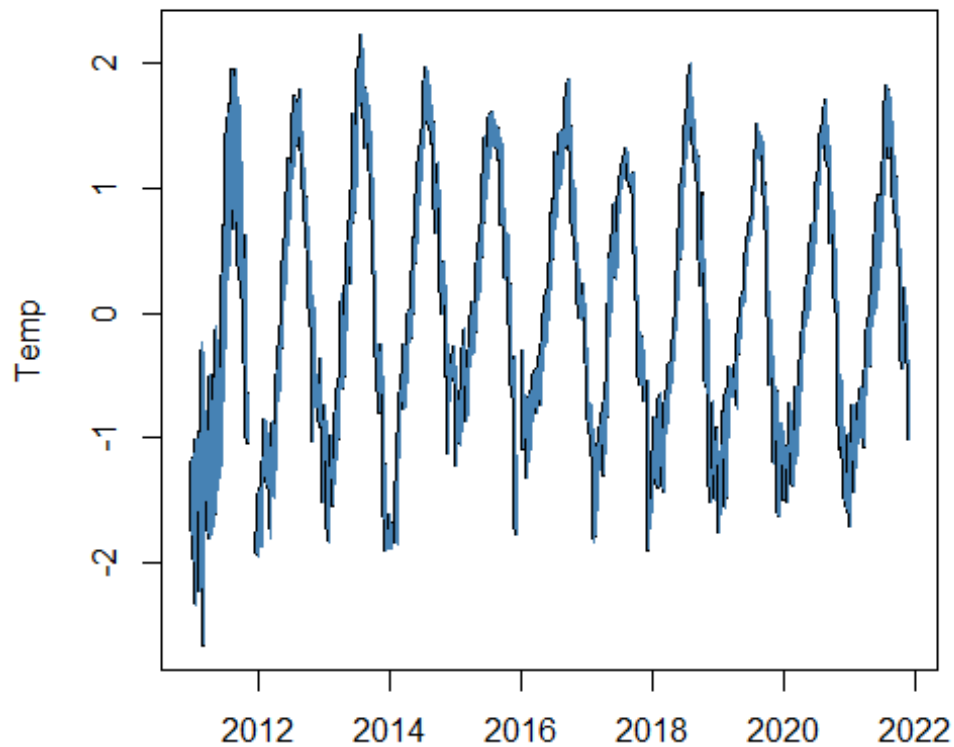
forecast_fit <- forecast(y,model=fit) #Predict values using the calibration
dataset

##Plot interpolated data

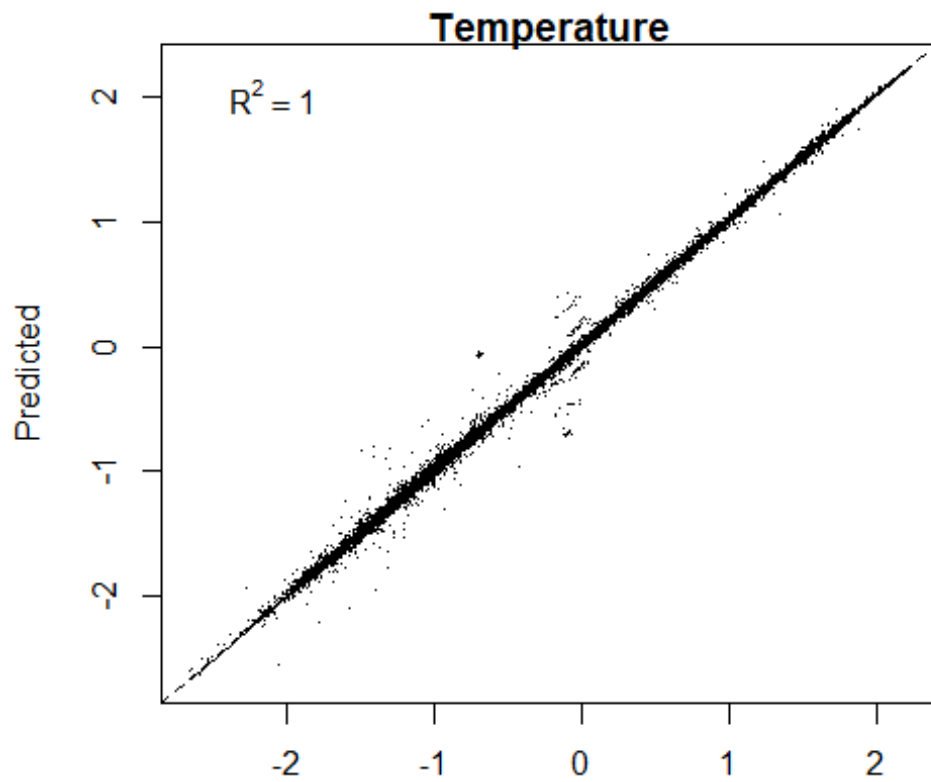
#Plot the observed and interpolated temperature regimes
par(mar=c(2,4,1,1))

```

```
plot(date_s,y,xlab="Time",ylab="Temp",lwd=2,type="l")
lines(date_s,forecast_fit$fitted,col="steelblue")
```



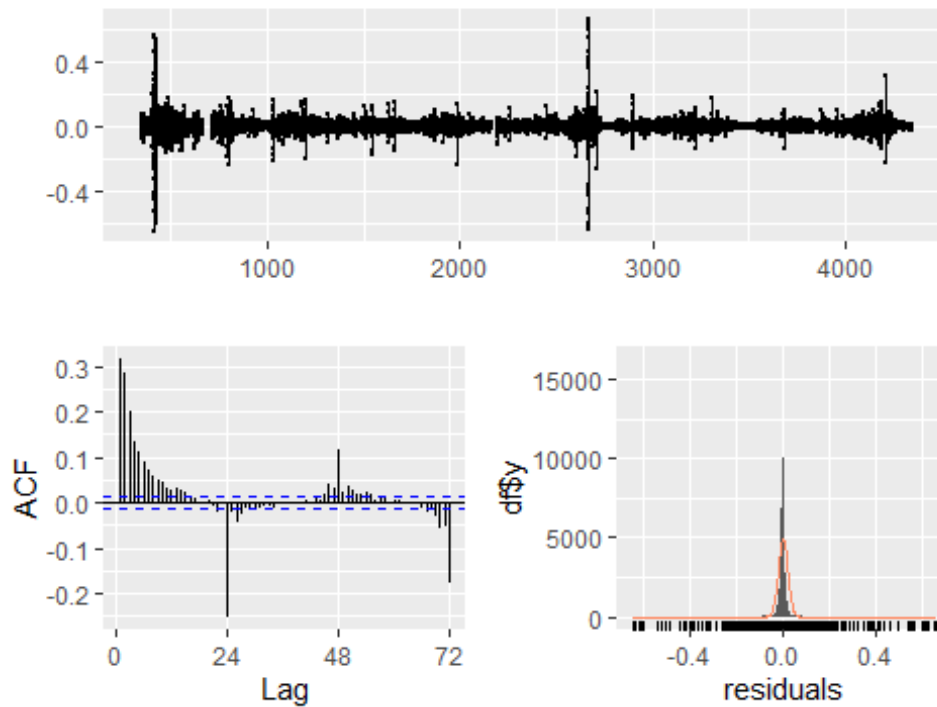
```
#Plot predicted versus observed values
scatter.smooth(y,forecast_fit$fitted,xlab="Observed",ylab="Predicted",pch="."
,main = "Temperature")
abline(0,1,lty=2)
R2 = round(cor.test(y,forecast_fit$fitted,na.rm=T)$estimate^2,2)
mtext(side=3,line=-2,adj=0.1,bquote(R^2 == .(R2)))
```



##Check residuals of interpolated data

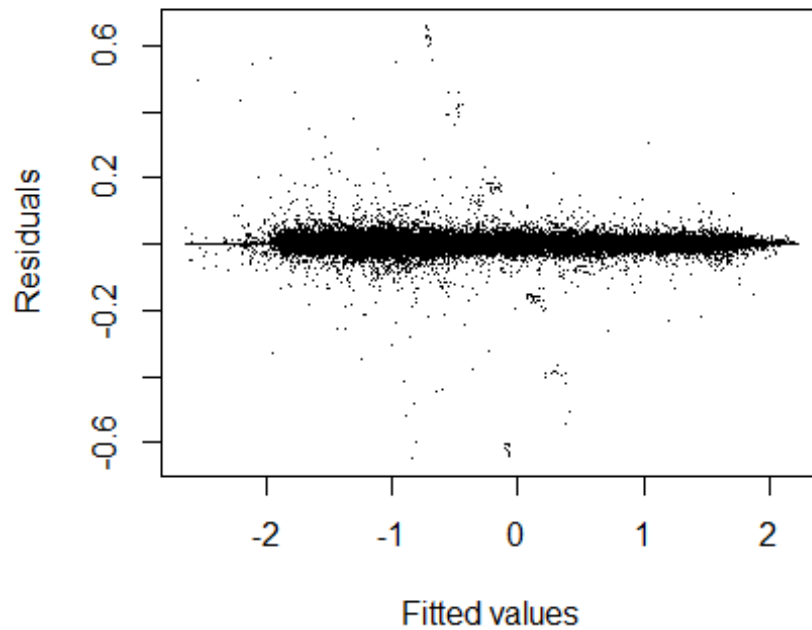
```
checkresiduals(fit) #also gives the results for the Ljung_Box test with H0 = randomly distributed errors (white noise)
```

Residuals from ARIMA(1,0,1)(2,1,0)[24]



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,1)(2,1,0)[24]
## Q* = 180154, df = 44, p-value < 2.2e-16
##
## Model df: 4.    Total lags used: 48

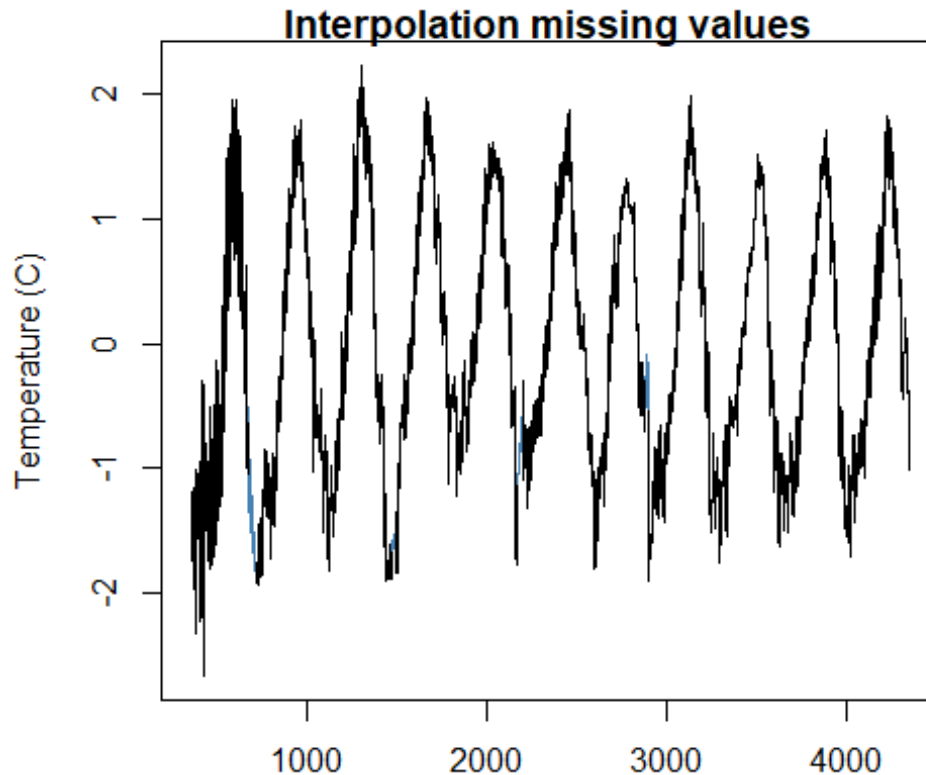
#plot residuals versus fitted values (=check for heterosedasticity)
par(mar=c(4,4,4,4))
scatter.smooth(forecast_fit$fitted,forecast_fit$residuals,pch =
".",ylab="Residuals",xlab="Fitted values")
```



##Smooth interpolated data

```
#Interpolate missing values using a Kalman filter (=smoother)  
y_inter <- na_kalman(y,model=fit$model)
```

```
#Plot the results  
par(mar=c(2,4,1,1))  
plot(y_inter,xlab="",ylab="Temperature  
(C)",col="steelblue",main="Interpolation missing values")  
lines(y,col="black")
```



```
##Format interpolated time series into a dataframe
```

```
#Put the interpolated temperature dataset (y_inter) into a dataset with the correct dates
x <- as.data.frame(y_inter) #change y_inter from a ts object to a dataframe
x$ID <- seq.int(nrow(x)) #add a unique ID
date <- as.data.frame(APH$hour) #make the unique "hour" index from APH into a separate dataframe
date$ID <- seq.int(nrow(date)) #create unique ID that aligns with x
y_inter_df <- merge(x,date,"ID") #merge the two dataframes
colnames(y_inter_df)<-c("ID","temp","date") #rename columns
saveRDS(y_inter_df,"y_inter_df.rds")
```

```
##Check for NAs
```

```
missing_data <- y_inter_df[!complete.cases(y_inter_df),]
missing_data
```

```
## [1] ID    temp date
## <0 rows> (or 0-length row.names)
```

```
##Wavelet
```

```
APH.w <- analyze.wavelet(y_inter_df, "temp",
                        loess.span = 0,
                        dt = 1/24,
                        make.pval = TRUE, n.sim = 1000,
                        date.format = "%Y-%m-%d-%h")
```



```
## Starting wavelet transformation...
```

```
## ... and simulations...
```

```
## |
```

		0%
		1%
		1%
		2%
		2%
		3%
		4%
		4%
		5%
		5%
		6%
		6%
		7%
		8%
		8%
		9%
		9%
		10%
		11%
		11%
		12%
		12%
		13%
		14%

=====		14%
=====		15%
=====		15%
=====		16%
=====		16%
=====		17%
=====		18%
=====		18%
=====		19%
=====		19%
=====		20%
=====		21%
=====		21%
=====		22%
=====		22%
=====		23%
=====		24%
=====		24%
=====		25%
=====		25%
=====		26%
=====		26%
=====		27%
=====		28%
=====		28%

=====	29%
=====	29%
=====	30%
=====	31%
=====	31%
=====	32%
=====	32%
=====	33%
=====	34%
=====	34%
=====	35%
=====	35%
=====	36%
=====	36%
=====	37%
=====	38%
=====	38%
=====	39%
=====	39%
=====	40%
=====	41%
=====	41%
=====	42%
=====	42%
=====	43%

=====	44%
=====	44%
=====	45%
=====	45%
=====	46%
=====	46%
=====	47%
=====	48%
=====	48%
=====	49%
=====	49%
=====	50%
=====	51%
=====	51%
=====	52%
=====	52%
=====	53%
=====	54%
=====	54%
=====	55%
=====	55%
=====	56%
=====	56%
=====	57%
=====	58%

=====	58%
=====	59%
=====	59%
=====	60%
=====	61%
=====	61%
=====	62%
=====	62%
=====	63%
=====	64%
=====	64%
=====	65%
=====	65%
=====	66%
=====	66%
=====	67%
=====	68%
=====	68%
=====	69%
=====	69%
=====	70%
=====	71%
=====	71%
=====	72%
=====	72%

=====	73%
=====	74%
=====	74%
=====	75%
=====	75%
=====	76%
=====	76%
=====	77%
=====	78%
=====	78%
=====	79%
=====	79%
=====	80%
=====	81%
=====	81%
=====	82%
=====	82%
=====	83%
=====	84%
=====	84%
=====	85%
=====	85%
=====	86%
=====	86%
=====	87%

=====	88%
=====	88%
=====	89%
=====	89%
=====	90%
=====	91%
=====	91%
=====	92%
=====	92%
=====	93%
=====	94%
=====	94%
=====	95%
=====	95%
=====	96%
=====	96%
=====	97%
=====	98%
=====	98%
=====	99%
=====	99%
=====	100%

```
## Class attributes are accessible through following names:
## series loess.span dt dj Wave Phase Ampl Power Power.avg Power.pval
Power.avg.pval Ridge Period Scale nc nr coi.1 coi.2 axis.1 axis.2 date.format
date.tz
```

```
str(APH.w)
```

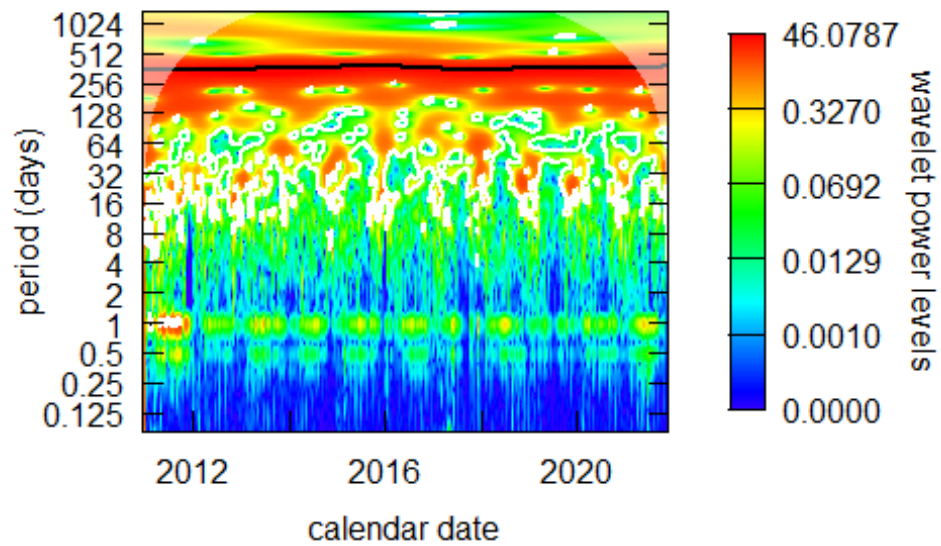
```
## List of 22
## $ series      : 'data.frame':  95933 obs. of  2 variables:
## ..$ date: POSIXct[1:95933], format: "2010-12-16 13:00:00" "2010-12-16
14:00:00" ...
## ..$ temp: num [1:95933] -1.48 -1.45 -1.44 -1.45 -1.47 ...
## $ loess.span   : num 0
## $ dt          : num 0.0417
## $ dj          : num 0.05
## $ Wave        : cplx [1:280, 1:95933] -0.197+0.042i -0.226+0.052i -
0.254+0.063i ...
## $ Phase       : num [1:280, 1:95933] 2.93 2.91 2.9 2.88 2.85 ...
## $ Ampl        : num [1:280, 1:95933] 0.714 0.808 0.896 0.972 1.034 ...
## $ Power       : num [1:280, 1:95933] 0.51 0.653 0.803 0.945 1.069 ...
## $ Power.avg   : num [1:280] 0.00223 0.00229 0.00217 0.00192 0.00158 ...
## $ Power.pval  : num [1:280, 1:95933] 0.848 0.845 0.839 0.832 0.816
0.809 0.799 0.802 0.789 0.783 ...
## $ Power.avg.pval: num [1:280] 1 1 1 1 1 1 1 1 1 1 ...
## $ Ridge       : num [1:280, 1:95933] 0 0 0 0 0 0 0 0 0 0 ...
## $ Period      : num [1:280] 0.0833 0.0863 0.0893 0.0925 0.0957 ...
## $ Scale       : num [1:280] 0.0796 0.0824 0.0853 0.0883 0.0914 ...
## $ nc         : int 95933
## $ nr         : int 280
## $ coi.1       : num [1:95937] 0.979 0.979 1 1.042 1.083 ...
## $ coi.2       : num [1:95937] 10.39 -3.61 -20.63 -4.02 -3.02 ...
## $ axis.1      : num [1:95933] 1 1.04 1.08 1.12 1.17 ...
## $ axis.2      : num [1:280] -3.58 -3.53 -3.48 -3.43 -3.38 ...
## $ date.format  : chr "%Y-%m-%d-%h"
## $ date.tz     : NULL
## - attr(*, "class")= chr "analyze.wavelet"
```

```
saveRDS(APH.w, "APH.w.rds")
```

```
##Wavelet Image
```

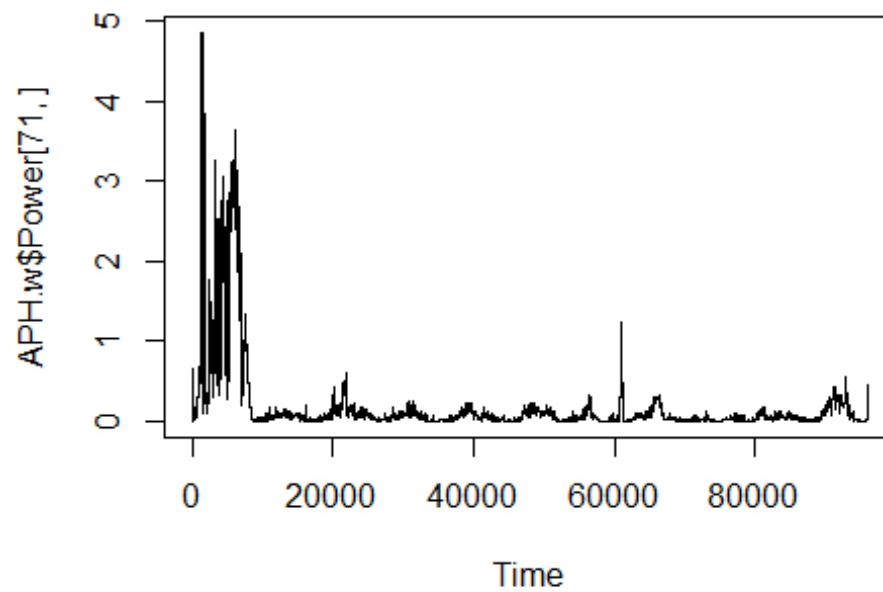
```
wt.image(APH.w, color.key = "quantile", n.levels = 250, main = "Alexander
Pond Wavelet",
         legend.params = list(lab = "wavelet power levels", mar = 6.5,
lab.line=4, label.digits = 4), label.time.axis=TRUE, show.date=TRUE,
         periodlab = "period (days)")
```


Alexander Pond Wavelet



##Pull 24 hr period

```
plot.ts(APH.w$Power[71,])
```



#STENDER ##Read in Data

```
# Water temperature - response variable
# Hourly temperature time series dataset from Stender Pond called "SPH"
# (Stender Pond Historical)
# Includes data from 16 December 2010 to 24 November 2021
# Data collected by Mid Klamath Watershed Council, see metadata for more
# details

SPH <- read.csv("Stender_Historical_2.csv")
SPH$date <- lubridate::mdy_hm(SPH$Date_Time) #convert dates to POSIXct format
#and bin by hour

#Check for missing data
missing_data <- SPH[!complete.cases(SPH),]
missing_data

#Bin data by hour
SPH$hour <- lubridate::round_date(SPH$date, unit="hour")
head(SPH) #check the dataset start date, use for "hour" sequence
tail(SPH) #check the dataset end date, use for "hour" sequence

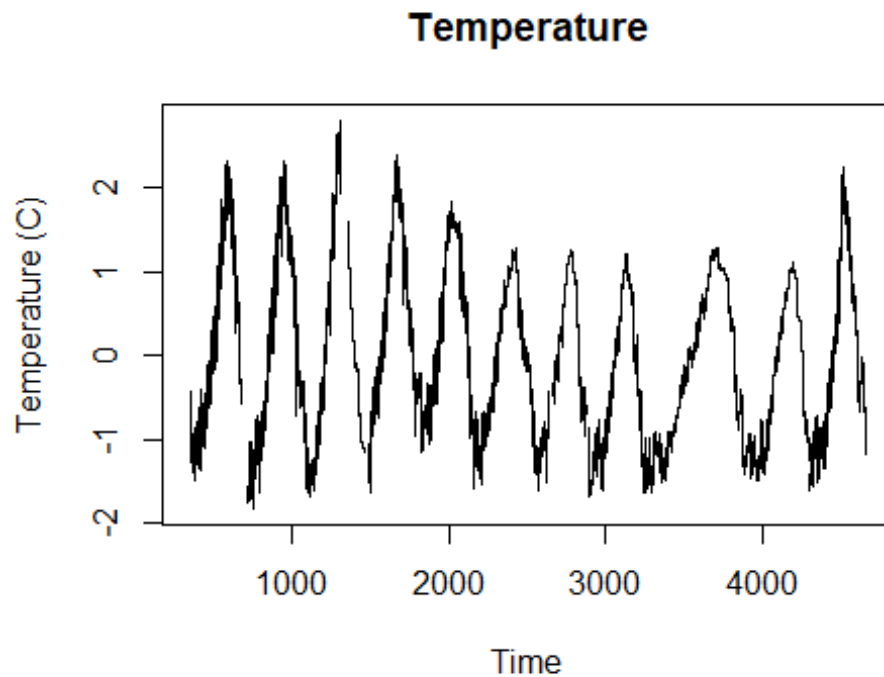
#Create hourly sequence to ensure all missing data is accounted for
hour <- seq(mdy_h('12/16/2010 13'),mdy_h('11/24/2021 14'),by = "hour")
#Create an object that goes hour by hour for the entire time series
hour <- as.data.frame(hour)
SPH <- left_join(hour, SPH)

## Joining, by = "hour"

missing_data <- SPH[!complete.cases(SPH),]
missing_data

#z score
SPH$zTemp <- zscore(SPH$Temp)

#Convert to time series
SPH_ts <- ts(SPH$zTemp, start = c(351, 13), frequency = 24) # This time
#series starts on 16 Dec 2010 at~13:00, so it starts on day 351 at hour 13 and
#the frequency is 24 (24 hours per day)
ts.plot(SPH_ts,main="Temperature",ylab = "Temperature (C)", xlab = "Time")
```



##Interpolate missing data

#Run ARIMA to interpolate missing data

```
y2 <- SPH_ts
```

```
date_s2 <- SPH$hour
```

```
y_na2 <- ifelse(is.na(y2),0,NA)
```

```
fit2 <- auto.arima(y2,trace=TRUE) #fit limited number of models (faster)
```

```
##
```

```
## Fitting models using approximations to speed things up...
```

```
##
```

```
## ARIMA(2,0,2)(1,1,1)[24] with drift : Inf
## ARIMA(0,0,0)(0,1,0)[24] with drift : -214977.1
## ARIMA(1,0,0)(1,1,0)[24] with drift : Inf
## ARIMA(0,0,1)(0,1,1)[24] with drift : -293411.7
## ARIMA(0,0,0)(0,1,0)[24] : -214976.4
## ARIMA(0,0,1)(0,1,0)[24] with drift : -293136.8
## ARIMA(0,0,1)(1,1,1)[24] with drift : -294401.7
## ARIMA(0,0,1)(1,1,0)[24] with drift : -294313.2
## ARIMA(0,0,1)(2,1,1)[24] with drift : -294559.4
## ARIMA(0,0,1)(2,1,0)[24] with drift : -294201.1
## ARIMA(0,0,1)(2,1,2)[24] with drift : -294587.1
## ARIMA(0,0,1)(1,1,2)[24] with drift : -294402.4
## ARIMA(0,0,0)(2,1,2)[24] with drift : -183150.8
## ARIMA(1,0,1)(2,1,2)[24] with drift : Inf
## ARIMA(0,0,2)(2,1,2)[24] with drift : -368593.8
```

```

## ARIMA(0,0,2)(1,1,2)[24] with drift : -368442.3
## ARIMA(0,0,2)(2,1,1)[24] with drift : -368159.5
## ARIMA(0,0,2)(1,1,1)[24] with drift : -368452.1
## ARIMA(1,0,2)(2,1,2)[24] with drift : Inf
## ARIMA(0,0,3)(2,1,2)[24] with drift : -417015.9
## ARIMA(0,0,3)(1,1,2)[24] with drift : -416732
## ARIMA(0,0,3)(2,1,1)[24] with drift : -416091.3
## ARIMA(0,0,3)(1,1,1)[24] with drift : -416666
## ARIMA(1,0,3)(2,1,2)[24] with drift : Inf
## ARIMA(0,0,4)(2,1,2)[24] with drift : -449608.3
## ARIMA(0,0,4)(1,1,2)[24] with drift : -448985.7
## ARIMA(0,0,4)(2,1,1)[24] with drift : -448763.6
## ARIMA(0,0,4)(1,1,1)[24] with drift : -448800.3
## ARIMA(1,0,4)(2,1,2)[24] with drift : Inf
## ARIMA(0,0,5)(2,1,2)[24] with drift : -471490.3
## ARIMA(0,0,5)(1,1,2)[24] with drift : -471272.3
## ARIMA(0,0,5)(2,1,1)[24] with drift : -470562.8
## ARIMA(0,0,5)(1,1,1)[24] with drift : -471100
## ARIMA(1,0,5)(2,1,2)[24] with drift : Inf
## ARIMA(0,0,5)(2,1,2)[24] : -471474.5
##
## Now re-fitting the best model(s) without approximations...
##
## ARIMA(0,0,5)(2,1,2)[24] with drift : Inf
## ARIMA(0,0,5)(2,1,2)[24] : Inf
## ARIMA(0,0,5)(1,1,2)[24] with drift : Inf
## ARIMA(0,0,5)(1,1,1)[24] with drift : -544057.7
##
## Best model: ARIMA(0,0,5)(1,1,1)[24] with drift

summary(fit2) #Take a closer look at the best fitted model

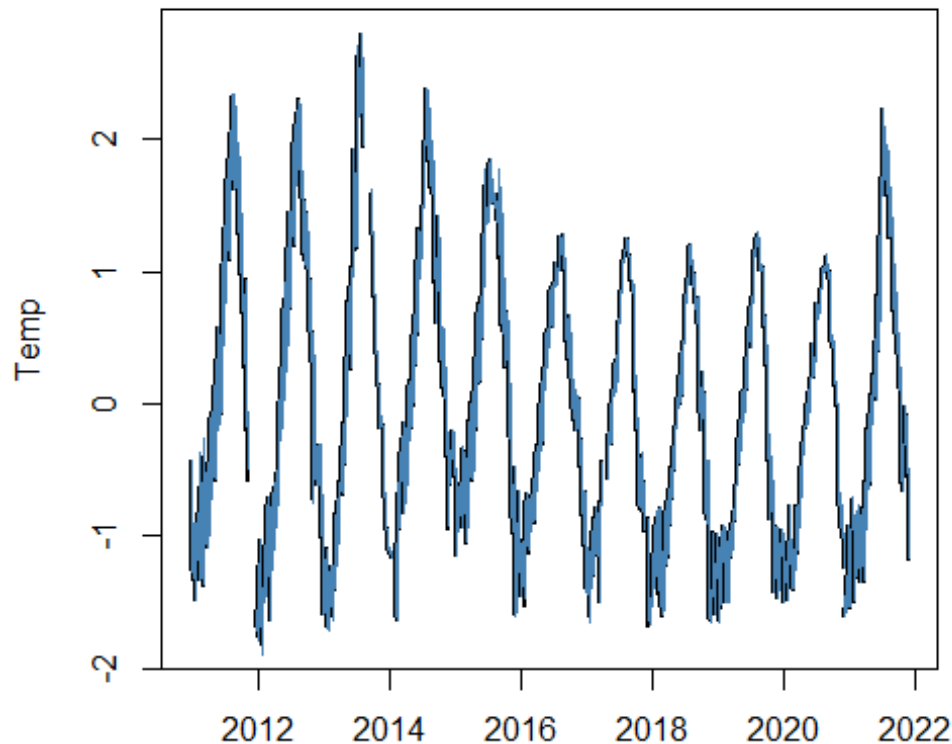
## Series: y2
## ARIMA(0,0,5)(1,1,1)[24] with drift
##
## Coefficients:
##          ma1      ma2      ma3      ma4      ma5      sar1      sma1      drift
##          1.7500  2.1459  1.8663  1.1753  0.4220 -0.5075  0.2327      0
## s.e.  0.0037  0.0064  0.0065  0.0044  0.0024  0.0147  0.0173      0
##
## sigma^2 estimated as 0.0002425:  log likelihood=272037.9
## AIC=-544057.7  AICc=-544057.7  BIC=-543971.8
##
## Training set error measures:
##              ME          RMSE          MAE          MPE          MAPE
MASE
## Training set -2.014778e-06 0.01556897 0.0106746 0.195905 5.954043
0.1806112
##              ACF1
## Training set 0.1827068

```

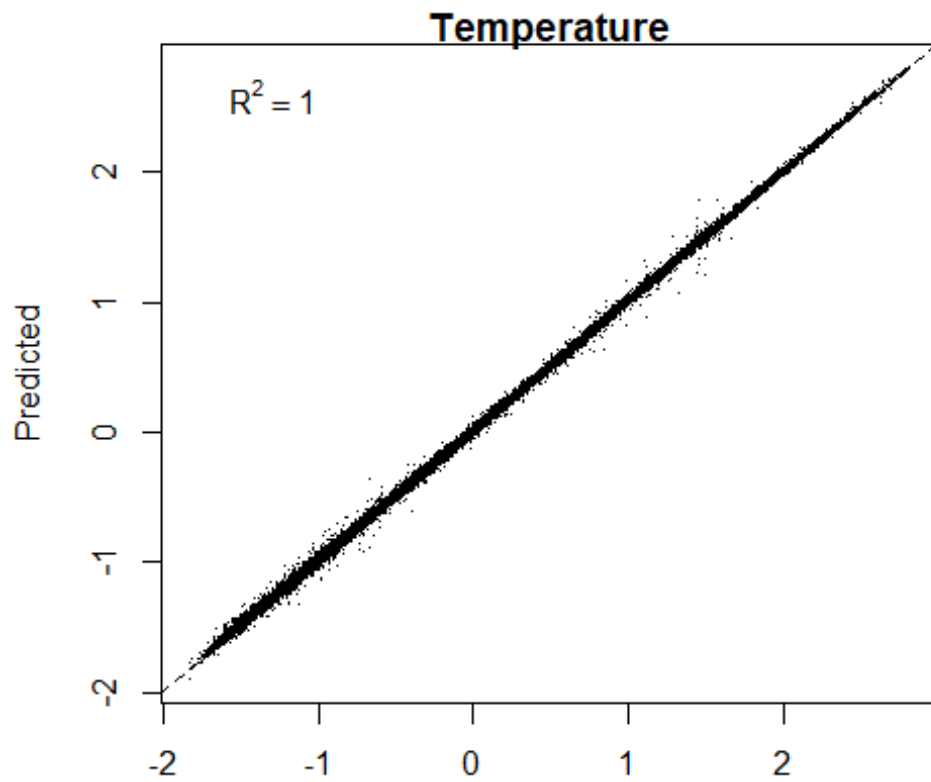
```
forecast_fit2 <- forecast(y2,model=fit2) #Predict values using the  
calibration dataset
```

```
##Plot interpolated data
```

```
#Plot the observed and interpolated temperature regimes  
par(mar=c(2,4,1,1))  
plot(date_s2,y2,xlab="Time",ylab="Temp",lwd=2,type="l")  
lines(date_s2,forecast_fit2$fitted,col="steelblue")
```



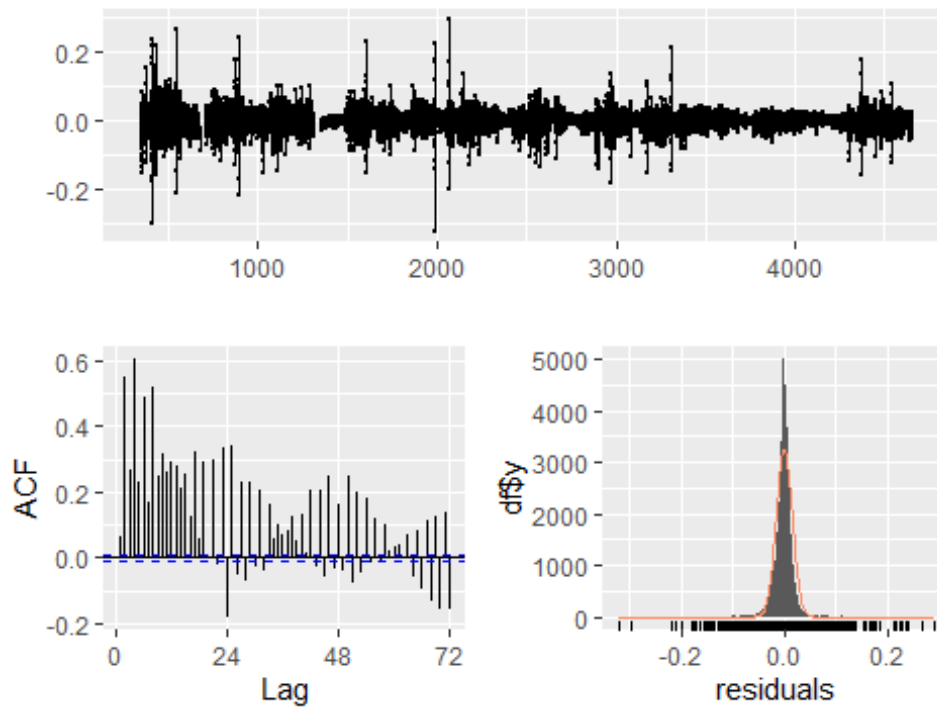
```
#Plot predicted versus observed values  
scatter.smooth(y2,forecast_fit2$fitted,xlab="Observed",ylab="Predicted",pch="."  
.,main = "Temperature")  
abline(0,1,lty=2)  
R2 = round(cor.test(y2,forecast_fit2$fitted,na.rm=T)$estimate^2,2)  
mtext(side=3,line=-2,adj=0.1,bquote(R^2 == .(R2)))
```



##Check residuals of interpolated data

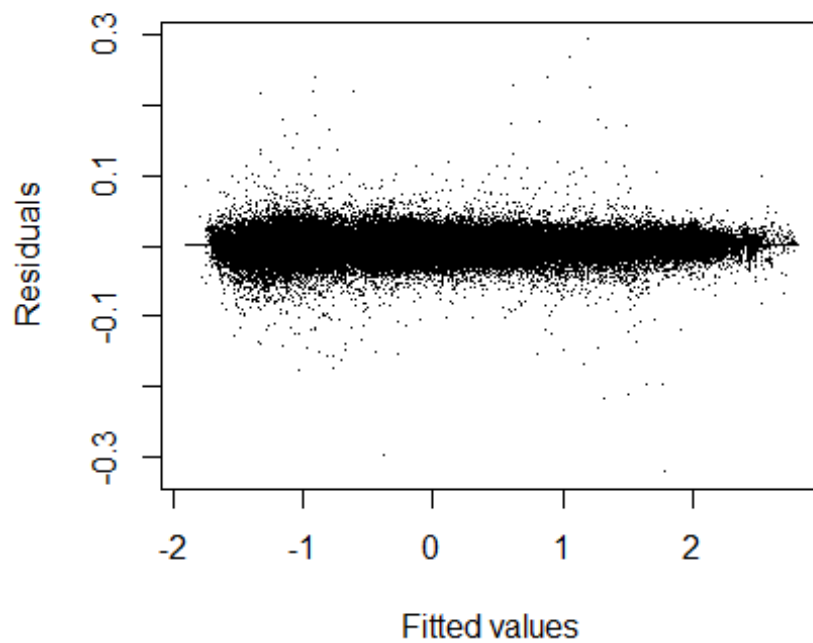
#Check residuals of the interpolation process
`checkresiduals(fit2)` *#also gives the results for the Ljung_Box test with H_0 = randomly distributed errors (white noise)*

Residuals from ARIMA(0,0,5)(1,1,1)[24] with drift



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,5)(1,1,1)[24] with drift
## Q* = 741908, df = 40, p-value < 2.2e-16
##
## Model df: 8.    Total lags used: 48

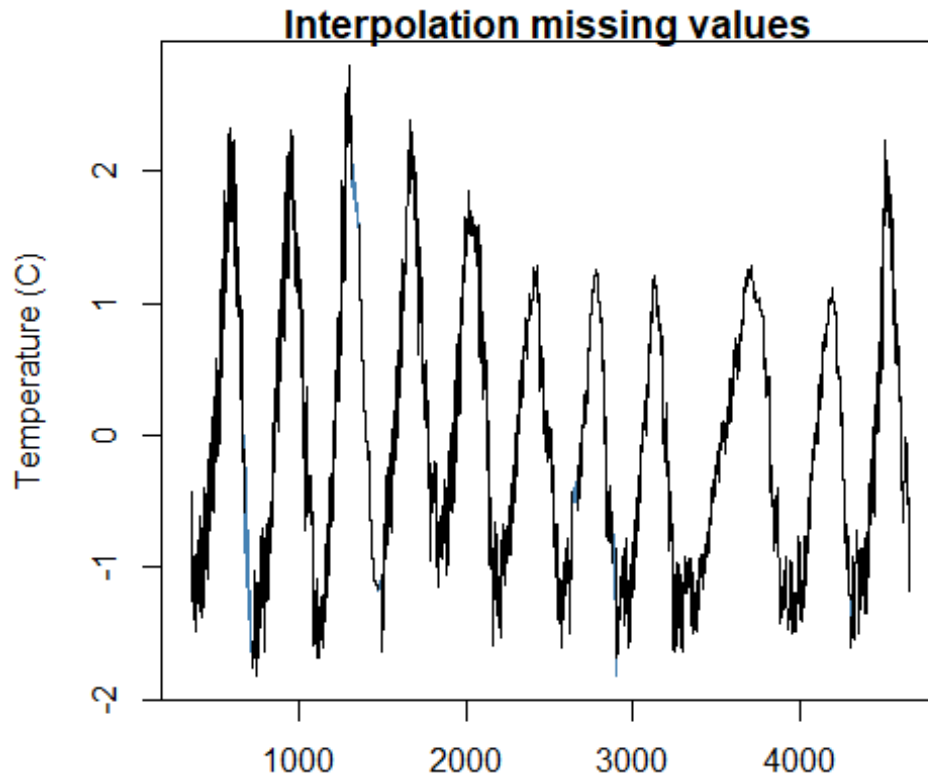
#plot residuals versus fitted values (=check for heterosedasticity)
par(mar=c(4,4,4,4))
scatter.smooth(forecast_fit2$fitted,forecast_fit2$residuals,pch =
".",ylab="Residuals",xlab="Fitted values")
```



##Smooth interpolated data

```
#Interpolate missing values using a Kalman filter (=smoother)  
y_inter2 <- na_kalman(y2,model=fit2$model)
```

```
#Plot the results  
par(mar=c(2,4,1,1))  
plot(y_inter2,xlab="",ylab="Temperature  
(C)",col="steelblue",main="Interpolation missing values")  
lines(y2,col="black")
```

```
##Format interpolated time series into a dataframe
```

```
#Put the interpolated temperature dataset (y_inter) into a dataset with the correct dates (
x2 <- as.data.frame(y_inter2) #change y_inter from a ts to a dataframe
x2$ID <- seq.int(nrow(x2)) #add a unique ID, check it is correct length
date2 <- as.data.frame(SPH$hour) #make the unique "hour" index from SPH into a separate dataframe
date2$ID <- seq.int(nrow(date2)) #give that a unique ID that aligns with x
y_inter2_df <- merge(x2,date2,"ID") #merge the two dataframes
colnames(y_inter2_df)<-c("ID","temp","date") #rename columns
saveRDS(y_inter2_df,"y_inter2_df.rds")
```

```
##Check for NAs
```

```
missing_data <- y_inter2_df[!complete.cases(y_inter2_df),]
missing_data
```

```
## [1] ID    temp date
## <0 rows> (or 0-length row.names)
```

```
##Wavelet
```

```
#run the wavelet
SPH.w <- analyze.wavelet(y_inter2_df, "temp",
                        loess.span = 0,
                        dt = 1/24,
```

```
make.pval = TRUE, n.sim = 1000,  
date.format = "%Y-%m-%d-%h")
```

```
## Starting wavelet transformation...
```

```
## ... and simulations...
```

```
## |
```

		0%
		1%
		1%
		2%
		2%
		3%
		4%
		4%
		5%
		5%
		6%
		6%
		7%
		8%
		8%
		9%
		9%
		10%
		11%
		11%
		12%
		12%

=====	13%
=====	14%
=====	14%
=====	15%
=====	15%
=====	16%
=====	16%
=====	17%
=====	18%
=====	18%
=====	19%
=====	19%
=====	20%
=====	21%
=====	21%
=====	22%
=====	22%
=====	23%
=====	24%
=====	24%
=====	25%
=====	25%
=====	26%
=====	26%
=====	27%

=====	28%
=====	28%
=====	29%
=====	29%
=====	30%
=====	31%
=====	31%
=====	32%
=====	32%
=====	33%
=====	34%
=====	34%
=====	35%
=====	35%
=====	36%
=====	36%
=====	37%
=====	38%
=====	38%
=====	39%
=====	39%
=====	40%
=====	41%
=====	41%
=====	42%

=====	42%
=====	43%
=====	44%
=====	44%
=====	45%
=====	45%
=====	46%
=====	46%
=====	47%
=====	48%
=====	48%
=====	49%
=====	49%
=====	50%
=====	51%
=====	51%
=====	52%
=====	52%
=====	53%
=====	54%
=====	54%
=====	55%
=====	55%
=====	56%
=====	56%

=====	57%
=====	58%
=====	58%
=====	59%
=====	59%
=====	60%
=====	61%
=====	61%
=====	62%
=====	62%
=====	63%
=====	64%
=====	64%
=====	65%
=====	65%
=====	66%
=====	66%
=====	67%
=====	68%
=====	68%
=====	69%
=====	69%
=====	70%
=====	71%
=====	71%

=====	72%
=====	72%
=====	73%
=====	74%
=====	74%
=====	75%
=====	75%
=====	76%
=====	76%
=====	77%
=====	78%
=====	78%
=====	79%
=====	79%
=====	80%
=====	81%
=====	81%
=====	82%
=====	82%
=====	83%
=====	84%
=====	84%
=====	85%
=====	85%
=====	86%

=====	86%
=====	87%
=====	88%
=====	88%
=====	89%
=====	89%
=====	90%
=====	91%
=====	91%
=====	92%
=====	92%
=====	93%
=====	94%
=====	94%
=====	95%
=====	95%
=====	96%
=====	96%
=====	97%
=====	98%
=====	98%
=====	99%
=====	99%
=====	100%

```
## Class attributes are accessible through following names:
## series loess.span dt dj Wave Phase Ampl Power Power.avg Power.pval
```



```
Power.avg.pval Ridge Period Scale nc nr coi.1 coi.2 axis.1 axis.2 date.format
date.tz
```

```
str(SPH.w) # Output
```

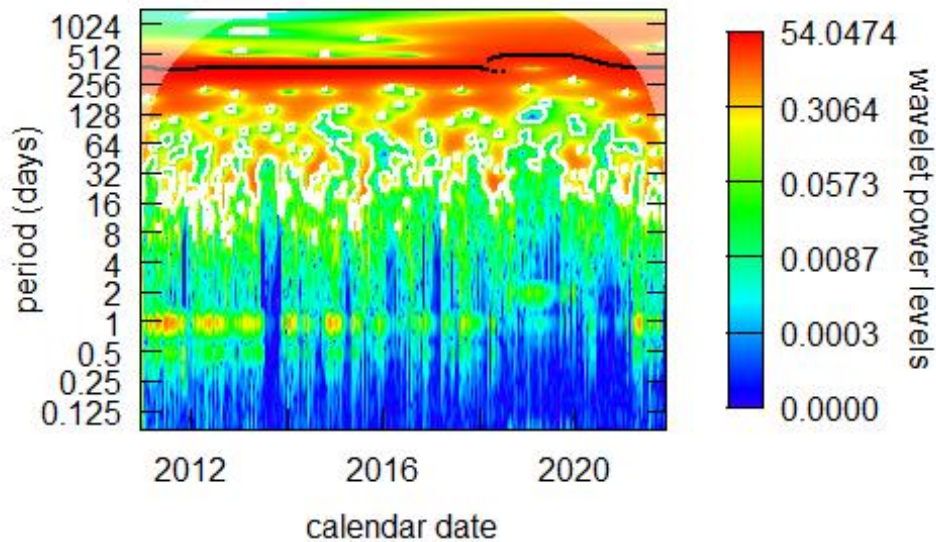
```
## List of 22
## $ series      : 'data.frame': 103302 obs. of 2 variables:
## ..$ date: POSIXct[1:103302], format: "2010-12-16 13:00:00" "2010-12-16
14:00:00" ...
## ..$ temp: num [1:103302] -0.434 -0.587 -0.575 -0.587 -0.609 ...
## $ loess.span   : num 0
## $ dt          : num 0.0417
## $ dj          : num 0.05
## $ Wave        : cplx [1:282, 1:103302] -0.0357+0.0195i -0.0411+0.0237i
-0.0463+0.0283i ...
## $ Phase       : num [1:282, 1:103302] 2.64 2.62 2.59 2.56 2.53 ...
## $ Ampl        : num [1:282, 1:103302] 0.144 0.165 0.186 0.205 0.223 ...
## $ Power       : num [1:282, 1:103302] 0.0208 0.0273 0.0345 0.0421
0.0495 ...
## $ Power.avg    : num [1:282] 0.000116 0.000136 0.000152 0.000162
0.000167 ...
## $ Power.pval   : num [1:282, 1:103302] 0.989 0.991 0.99 0.988 0.987
0.988 0.982 0.982 0.99 0.984 ...
## $ Power.avg.pval: num [1:282] 1 1 1 1 1 1 1 1 1 1 ...
## $ Ridge       : num [1:282, 1:103302] 0 0 0 0 0 0 0 0 0 0 ...
## $ Period      : num [1:282] 0.0833 0.0863 0.0893 0.0925 0.0957 ...
## $ Scale       : num [1:282] 0.0796 0.0824 0.0853 0.0883 0.0914 ...
## $ nc         : int 103302
## $ nr         : int 282
## $ coi.1      : num [1:103306] 0.979 0.979 1 1.042 1.083 ...
## $ coi.2      : num [1:103306] 10.49 -3.61 -20.63 -4.02 -3.02 ...
## $ axis.1     : num [1:103302] 1 1.04 1.08 1.12 1.17 ...
## $ axis.2     : num [1:282] -3.58 -3.53 -3.48 -3.43 -3.38 ...
## $ date.format : chr "%Y-%m-%d-%h"
## $ date.tz    : NULL
## - attr(*, "class")= chr "analyze.wavelet"
```

```
saveRDS(SPH.w, "SPH.w.rds")
```

```
##Wavelet Image
```

```
wt.image(SPH.w, color.key = "quantile", n.levels = 250, main = "Stender Pond
Wavelet",
         legend.params = list(lab = "wavelet power levels", mar = 6.5,
lab.line=4, label.digits = 4), label.time.axis=TRUE, show.date=TRUE,
         periodlab = "period (days)")
```

Stender Pond Wavelet



##Pull 24 hr period

SPH.w\$Period

```
## [1] 8.333333e-02 8.627208e-02 8.931446e-02 9.246412e-02 9.572486e-02
## [6] 9.910059e-02 1.025954e-01 1.062134e-01 1.099590e-01 1.138367e-01
## [11] 1.178511e-01 1.220071e-01 1.263097e-01 1.307640e-01 1.353754e-01
## [16] 1.401494e-01 1.450918e-01 1.502084e-01 1.555055e-01 1.609894e-01
## [21] 1.666667e-01 1.725442e-01 1.786289e-01 1.849282e-01 1.914497e-01
## [26] 1.982012e-01 2.051907e-01 2.124268e-01 2.199180e-01 2.276734e-01
## [31] 2.357023e-01 2.440143e-01 2.526194e-01 2.615280e-01 2.707508e-01
## [36] 2.802988e-01 2.901835e-01 3.004168e-01 3.110110e-01 3.219788e-01
## [41] 3.333333e-01 3.450883e-01 3.572578e-01 3.698565e-01 3.828995e-01
## [46] 3.964024e-01 4.103815e-01 4.248535e-01 4.398360e-01 4.553468e-01
## [51] 4.714045e-01 4.880286e-01 5.052389e-01 5.230561e-01 5.415016e-01
## [56] 5.605976e-01 5.803670e-01 6.008336e-01 6.220220e-01 6.439576e-01
## [61] 6.666667e-01 6.901766e-01 7.145156e-01 7.397130e-01 7.657989e-01
## [66] 7.928047e-01 8.207629e-01 8.497071e-01 8.796719e-01 9.106935e-01
## [71] 9.428090e-01 9.760571e-01 1.010478e+00 1.046112e+00 1.083003e+00
## [76] 1.121195e+00 1.160734e+00 1.201667e+00 1.244044e+00 1.287915e+00
## [81] 1.333333e+00 1.380353e+00 1.429031e+00 1.479426e+00 1.531598e+00
## [86] 1.585609e+00 1.641526e+00 1.699414e+00 1.759344e+00 1.821387e+00
## [91] 1.885618e+00 1.952114e+00 2.020955e+00 2.092224e+00 2.166006e+00
## [96] 2.242390e+00 2.321468e+00 2.403335e+00 2.488088e+00 2.575830e+00
## [101] 2.666667e+00 2.760706e+00 2.858063e+00 2.958852e+00 3.063196e+00
## [106] 3.171219e+00 3.283052e+00 3.398828e+00 3.518688e+00 3.642774e+00
## [111] 3.771236e+00 3.904229e+00 4.041911e+00 4.184449e+00 4.332013e+00
```

```

## [116] 4.484781e+00 4.642936e+00 4.806669e+00 4.976176e+00 5.151660e+00
## [121] 5.333333e+00 5.521413e+00 5.716125e+00 5.917704e+00 6.126391e+00
## [126] 6.342438e+00 6.566104e+00 6.797657e+00 7.037376e+00 7.285548e+00
## [131] 7.542472e+00 7.808457e+00 8.083822e+00 8.368897e+00 8.664026e+00
## [136] 8.969562e+00 9.285873e+00 9.613338e+00 9.952352e+00 1.030332e+01
## [141] 1.066667e+01 1.104283e+01 1.143225e+01 1.183541e+01 1.225278e+01
## [146] 1.268488e+01 1.313221e+01 1.359531e+01 1.407475e+01 1.457110e+01
## [151] 1.508494e+01 1.561691e+01 1.616764e+01 1.673779e+01 1.732805e+01
## [156] 1.793912e+01 1.857175e+01 1.922668e+01 1.990470e+01 2.060664e+01
## [161] 2.133333e+01 2.208565e+01 2.286450e+01 2.367082e+01 2.450556e+01
## [166] 2.536975e+01 2.626441e+01 2.719063e+01 2.814950e+01 2.914219e+01
## [171] 3.016989e+01 3.123383e+01 3.233529e+01 3.347559e+01 3.465610e+01
## [176] 3.587825e+01 3.714349e+01 3.845335e+01 3.980941e+01 4.121328e+01
## [181] 4.266667e+01 4.417130e+01 4.572900e+01 4.734163e+01 4.901113e+01
## [186] 5.073950e+01 5.252883e+01 5.438125e+01 5.629900e+01 5.828438e+01
## [191] 6.033978e+01 6.246766e+01 6.467057e+01 6.695118e+01 6.931220e+01
## [196] 7.175649e+01 7.428698e+01 7.690671e+01 7.961882e+01 8.242657e+01
## [201] 8.533333e+01 8.834261e+01 9.145800e+01 9.468326e+01 9.802226e+01
## [206] 1.014790e+02 1.050577e+02 1.087625e+02 1.125980e+02 1.165688e+02
## [211] 1.206796e+02 1.249353e+02 1.293411e+02 1.339024e+02 1.386244e+02
## [216] 1.435130e+02 1.485740e+02 1.538134e+02 1.592376e+02 1.648531e+02
## [221] 1.706667e+02 1.766852e+02 1.829160e+02 1.893665e+02 1.960445e+02
## [226] 2.029580e+02 2.101153e+02 2.175250e+02 2.251960e+02 2.331375e+02
## [231] 2.413591e+02 2.498706e+02 2.586823e+02 2.678047e+02 2.772488e+02
## [236] 2.870260e+02 2.971479e+02 3.076268e+02 3.184753e+02 3.297063e+02
## [241] 3.413333e+02 3.533704e+02 3.658320e+02 3.787330e+02 3.920890e+02
## [246] 4.059160e+02 4.202306e+02 4.350500e+02 4.503920e+02 4.662751e+02
## [251] 4.827182e+02 4.997413e+02 5.173646e+02 5.356094e+02 5.544976e+02
## [256] 5.740520e+02 5.942959e+02 6.152536e+02 6.369505e+02 6.594125e+02
## [261] 6.826667e+02 7.067409e+02 7.316640e+02 7.574661e+02 7.841781e+02
## [266] 8.118321e+02 8.404613e+02 8.701001e+02 9.007841e+02 9.325501e+02
## [271] 9.654365e+02 9.994825e+02 1.034729e+03 1.071219e+03 1.108995e+03
## [276] 1.148104e+03 1.188592e+03 1.230507e+03 1.273901e+03 1.318825e+03
## [281] 1.365333e+03 1.413482e+03

```

```
plot.ts(SPH.w$Power[71,])
```

