Time series topic 2: Decomposition

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Objectives for the session (3:30-4:15)

- What is and why do we use time series decomposition
- Functions in SWMPr
- Application to NERRS data
  - Data prep
  - Execution
  - Interpretation

Interactive portion

Follow along as we go:

- flash drive
- online: swmprats.net 2016 workshop tab

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You will run examples whenever you see this guy:

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We will use functions in the SWMPr package

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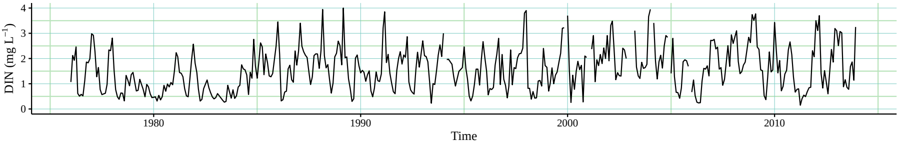
Option 2, install the source file from the flash drive:

```r
# change as needed
path_to_file <- 'C:/Users/mbeck/Desktop/SWMPr-v2.1.7.9000.tar.gz'

# install, load
install.packages(path_to_file, repos = NULL, type="source")
library(SWMPr)
```

Theory and background

Observed data represents effects of many processes



Climate	***Local***	***Regional/historical***
precipitation	light/turbidity	watershed inputs
temperature	residence time	point sources
wind events	invasive species	management actions
ENSO effects	trophic effects	flow changes

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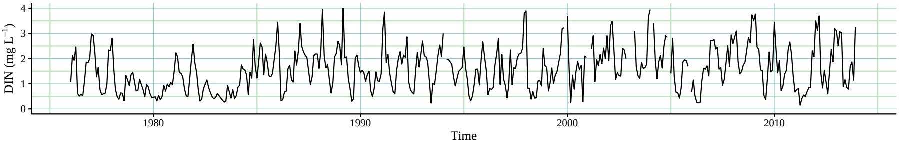

Models should describe components to evaluate effects

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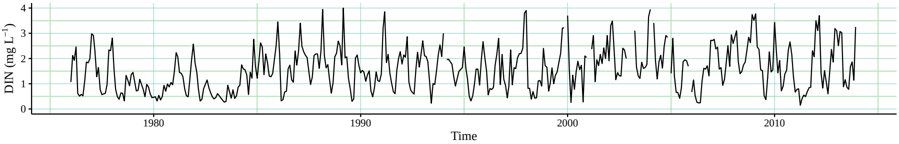

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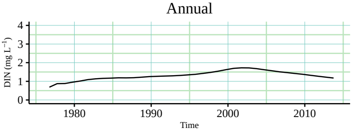

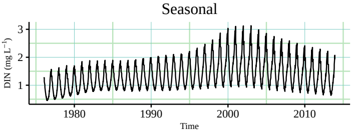

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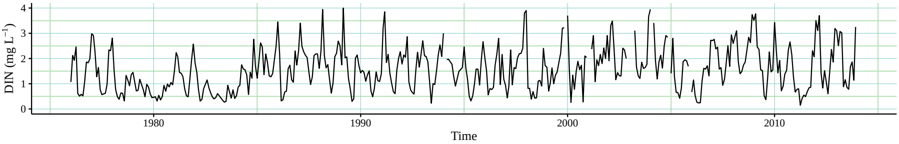

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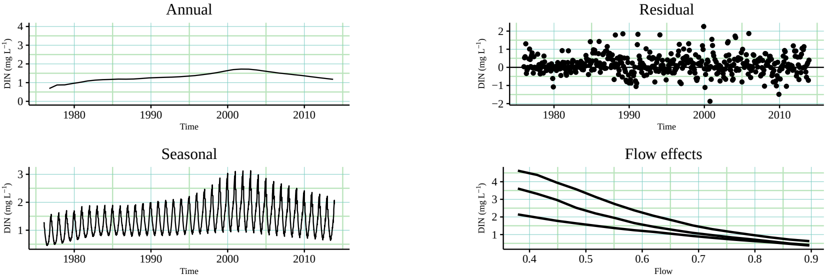

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- There are more generic and simpler approaches
- Objective is to decompose a time series into individual components, isolate or otherwise remove components of interests
- The individual components are sometimes additive or multiplicative components of the complete time series
- But be warned... just because you can doesn't mean you should

Theory and background

Two very general decomposition methods are provided in SWMPr: `decomp()` and `decomp_cj`

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2. Gets seasonal variation by averaging across time periods
3. Gets error as the remainder from the trend and seasonal components

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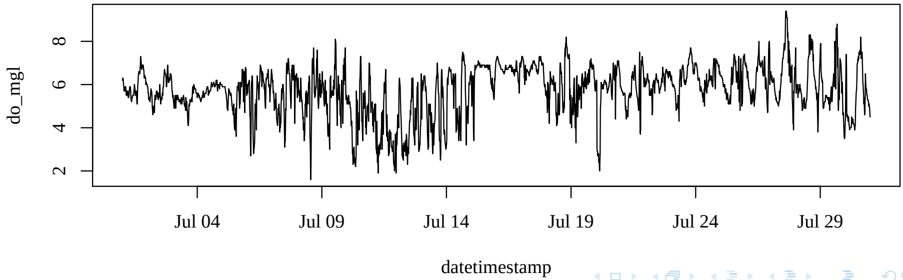
3. Seasonal trend as averages between periods, removes from time series
4. Events as remainder

Using decomp with NERRS data

Load some water quality data from Apalachicola Bay, Dry Bar station

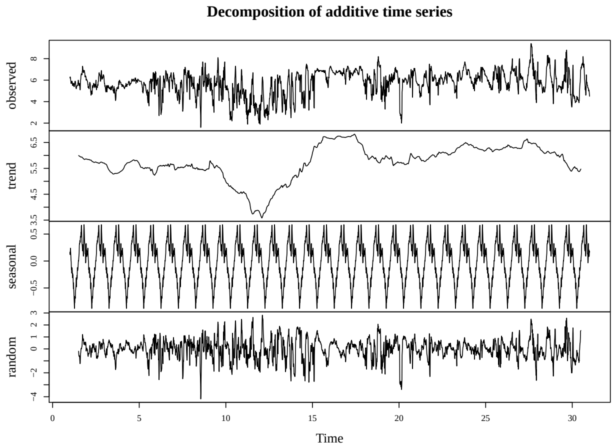
Let's look at DO variation over one month

```r
# load SWMPr
library(SWMPr)

# subset for daily decomposition
dat <- subset(apadbwq, subset = c('2013-07-01 00:00', '2013-07-31 00:00'),
  select = 'do_mgl')
plot(dat)
```



Using decomp with NERRS data

```
dat_add <- decomp(dat, param = 'do_mgl', frequency = 'daily', type = 'additive')
plot(dat_add)
```



Using decomp with NERRS data

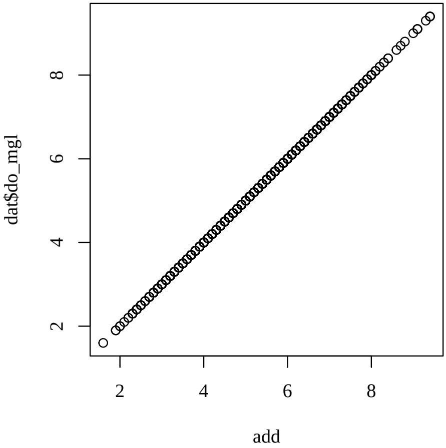
What's in the decomposed object?

```
str(dat_add)

## List of 6
##  $ x       : Time-Series [1:2881] from 1 to 31: 6.2 6.3 6.3 6.2 6 5.9 5.7 5.8 5.
##  $ seasonal: Time-Series [1:2881] from 1 to 31: 0.165 0.12 0.178 0.239 0.163 ...
##  $ trend   : Time-Series [1:2881] from 1 to 31: NA NA NA NA NA NA NA NA NA NA ..
##  $ random  : Time-Series [1:2881] from 1 to 31: NA NA NA NA NA NA NA NA NA NA ..
##  $ figure  : num [1:96] 0.165 0.12 0.178 0.239 0.163 ...
##  $ type    : chr "additive"
##  - attr(*, "class")= chr "decomposed.ts"

str(dat_add$trend)

##  Time-Series [1:2881] from 1 to 31: NA NA NA NA NA NA NA NA NA NA ...
```

Using decomp with NERRS data

What does additive mean?

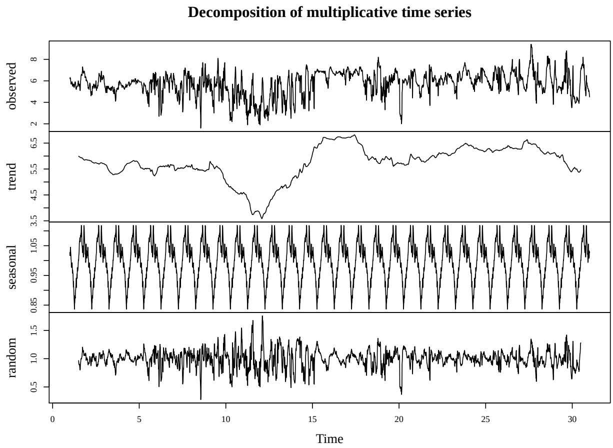
```
add <- with(dat_add, seasonal + trend + random)
plot(add, dat$do_mgl)
```



Using decomp with NERRS data

Let's try a multiplicative decomposition

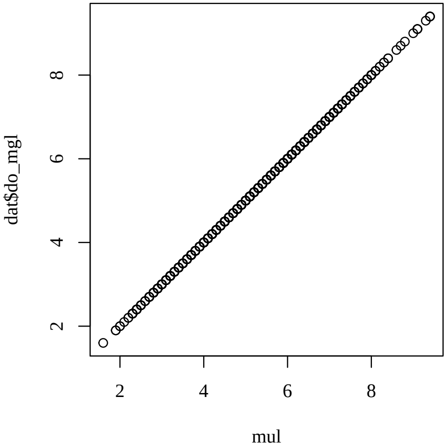
```
dat_mul <- decomp(dat, param = 'do_mgl', frequency = 'daily',
  type = 'multiplicative')
plot(dat_mul)
```



Using decomp with NERRS data

What does multiplicative mean?

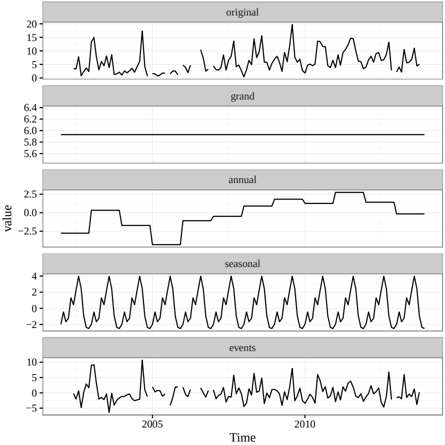
```
mul <- with(dat_mul, seasonal * trend * random)
plot(mul, dat$do_mgl)
```



Using decomp_cj with NERRS data

Use discrete, monthly data with `decomp_cj`: Apalachicola Bay, Cat Point nutrient station

```
apacpnut <- qaqc(apacpnut, qaqc_keep = c(0, 4))
decomp_cj(apacpnut, param = 'chla_n', type = 'add')
```



Using decomp_cj with NERRS data

Note that the default behavior for `decomp_cj` is a plot, use `vals_out = TRUE` for values

```
add <- decomp_cj(apacpnut, param = 'chla_n', type = 'add', vals_out = TRUE)
head(add)
```

```
##         Time original    grand    annual   seasonal     events
## 1 2002-01-01       NA 5.929384 -2.760634 -1.9742526         NA
## 2 2002-02-01       NA 5.929384 -2.760634 -0.4467677         NA
## 3 2002-03-01       NA 5.929384 -2.760634 -1.6590556         NA
## 4 2002-04-01      1.6 5.929384 -2.760634 -1.2348774 -0.3338726
## 5 2002-05-01       NA 5.929384 -2.760634  1.3020742         NA
## 6 2002-06-01      3.4 5.929384 -2.760634  0.4469690 -0.2157190
```

Using decomp_cj with NERRS data

A word of caution, `decomp_cj` uses `setstep` before decomposing

```
head(apacpnut)

##          datetimestamp  po4f  nh4f  no2f  no3f no23f chla_n
## 1 2002-04-02 11:55:00 0.004 0.027 0.002 0.048 0.050    1.8
## 2 2002-04-02 11:56:00 0.004 0.029 0.002 0.046 0.048    1.8
## 3 2002-04-30 11:15:00 0.014 0.138 0.005 0.115 0.120    1.2
## 4 2002-06-04 11:03:00 0.006 0.049 0.002 0.024 0.026    3.4
## 5 2002-07-02 09:53:00 0.014 0.083 0.002    NA 0.039    3.7
## 6 2002-07-02 09:55:00 0.017 0.093 0.002    NA 0.040    3.0

head(add)

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```
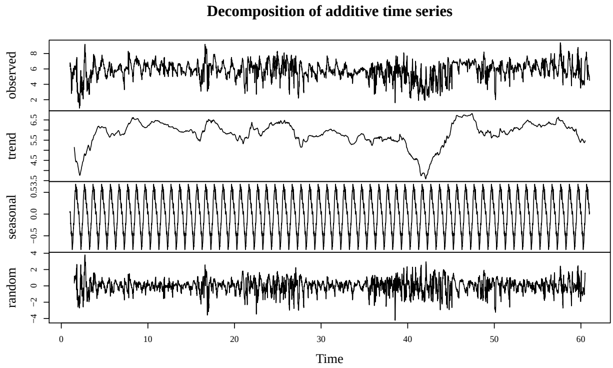

Summary

A word of caution, `decomp` does not work with missing data

```
dat <- subset(apadbwq, subset = c('2013-06-01 00:00', '2013-07-31 00:00'))

# this returns an error
test <- decomp(dat, param = 'do_mgl', frequency = 'daily')

## Error in na.omit.ts(x):  time series contains internal NAs
```

Summary

```r
# use na.approx to interpolate missing data
dat <- subset(apadbwq, subset = c('2013-06-01 00:00', '2013-07-31 00:00'))
dat <- na.approx(dat, params = 'do_mgl', maxgap = 10)

# decomposition and plot
dat_fl <- decomp(dat, param = 'do_mgl', frequency = 'daily')
plot(dat_fl)
```



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Things to ask before decomposition:

- What is the time step? Is it regular? Does it need be standardized?
- How do I deal with missing data?
- Is there any expected cyclical variation? If so, what is the period (e.g., seasonal, daily)?
- Is stationarity a reasonable expectation of the cyclical variation (yes = additive, no = multiplicative)?

Up next... Time Series Topic 3: Seasonal Kendall

Questions??

References

Cloern JE, Jassby AD. 2010.
Patterns and scales of phytoplankton variability in estuarine-coastal ecosystems.
Estuaries and Coasts, 33(2):230–241.