Exploratory Data Analysis with SWMP

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Objectives and agenda

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  - What are some basic time series analysis techniques and when would you use them?
  - How are the data set up, what functions are used, and how are the results interpreted?

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  - What are some basic time series analysis techniques and when would you use them?
  - How are the data set up, what functions are used, and how are the results interpreted?
- Agenda
  - Analysis 1 - missing data and interpolation
  - Analysis 2 - smoothing and aggregation
  - Analysis 3 - basic trend analysis

Interactive portion

You can follow along in this module:

- dataset3
- script3

Interactive!

What is exploratory data analysis (EDA)?

A general term that describes preliminary evaluation of a variable or multiple variables in a dataset to assess quantitative properties for further analysis or hypothesis generation

EDA can inform you of the types of variables (categorical, continuous), distribution of variables (central tendency, spread), correlations between variables, and presence of outliers

You may decide to omit variables or specific observations, transform, standardize, etc.

Many of the same principles that apply to standard data analysis apply to time series analysis

What is exploratory data analysis (EDA)?

R has many functions available for EDA - see the R reference card and the cookbook for some ideas

We will cover a few basic techniques but keep in mind EDA is a general term and much of what we have already covered, and will cover, can be considered exploratory

A quick google search of 'exploratory data analysis in r' will point you in the right direction for generic approaches you might consider

For now, we will focus on some tasks that have specific relevance to SWMP

Analysis 1 - Missing data and interpolation

Time series will usually include missing data - you will have to decide how to handle missing values

Let's import some wq data

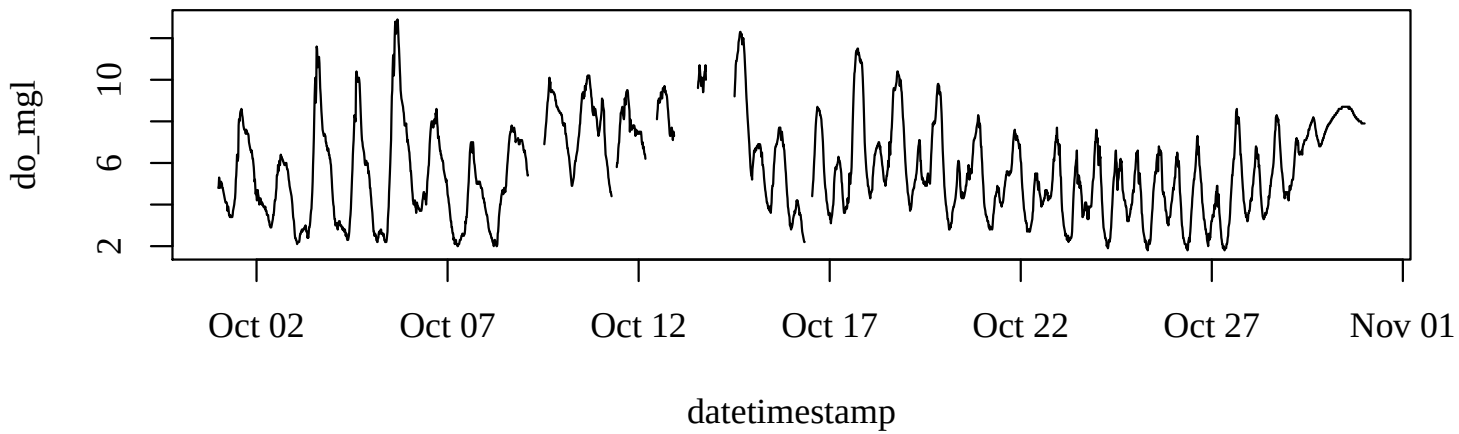
```
# import data, qaqc, and subset
# change this path for the flash drive
path <- 'C:/data/dataset3'
wq_dat <- import_local(path, 'cbmmcwq2012')
```

```
# qaqc and subset do_mgl
wq_dat <- qaqc(wq_dat)
wq_dat <- subset(wq_dat, select = 'do_mgl')

# how many missing values?
sum(is.na(wq_dat$do_mgl))

## [1] 419
```

Analysis 1 - Missing data and interpolation

Introducing the 'na.approx' function - this method can interpolate missing data

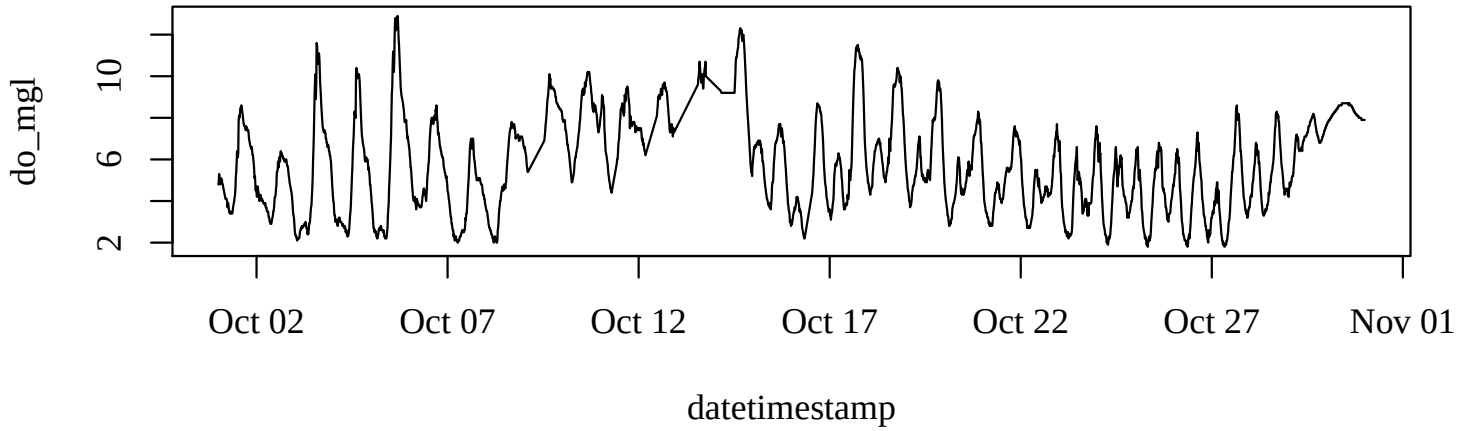
```
# subset the do time series for plotting
wq_dat <- subset(wq_dat, subset = c('2012-10-01 0:0', '2012-10-31 0:0'))
plot(do_mgl ~ datetimestamp, wq_dat, type = 'l')
```



Notice the missing values around October 12th

Analysis 1 - Missing data and interpolation

Here's what the time series looks like after using 'na.approx'



The missing values have been linearly interpolated - a simple function that predicts missing values based on the starting and ending values in gaps

May not be a true representation but better than some other approaches

Analysis 1 - Missing data and interpolation

The 'na.approx' function has only a few arguments

- swmpr_in: input swmpr data
- params: which parameters to interplate, default is all
- maxgap: what is the maximum gap size to interpolate?

Analysis 1 - Missing data and interpolation

Now you try an analysis! Open a new script and try the following:

- Import the file 'cbmmcwq2012.csv' in the dataset3 folder
- Handle QAQC flags and subset by October 1 to 31
- Plot the data - where are the missing values?
- Use 'na.approx.swmpr' to interpolate the missing values - what value to use for maxgap?
- Plot the data again - how does it look?

Analysis 1 - Missing data and interpolation

```
# the analysis should start like this

# change path as needed
path <- 'C:/data/dataset3'
dat <- import_local(path, 'cbmmcwq2012')

# qaqc and subset imported data
dat <- qaqc(dat)
dat <- subset(dat, subset = c('2012-10-01 00:00', '2012-10-31 00:00'))

# plot
plot(do_mgl ~ datetimestamp, data = dat, type = 'l')
```

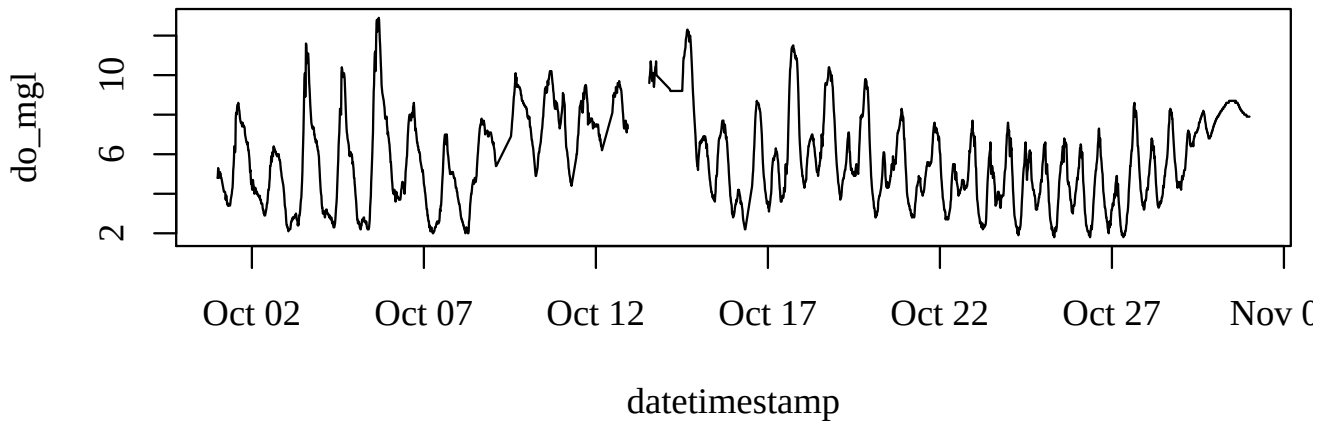
Now use na.approx using the data and an appropriate gap size (try 50)

Save the results to a new object and plot again

Try different gap values, how does this affect the plot or mean DO?

Analysis 1 - Missing data and interpolation

```
new_dat <- na.approx(dat, maxgap = 50) # try different maxgaps

# plot
par(mar = c(4.1, 4.1, 0.5, 0.5))
plot(do_mgl ~ datetimestamp, data = new_dat, type = 'l')
```




```
mean(dat$do_mgl, na.rm = T)

## [1] 5.8

mean(new_dat$do_mgl, na.rm = T)

## [1] 5.9
```

Analysis 2 - Smoothing and aggregation

Problem: trend evaluation is difficult if the data are noisy

Noise can be caused by many factors (e.g., measurement error, process uncertainty), we are usually more concerned with the true signal in a time series

Noise can be addressed by aggregating or smoothing data, both are similar

The 'aggregate.swmpr' function aggregates a time series by set periods of observation and calculates summary data for a variable

The 'smoother.swmpr' function calculates a moving window average of a time series

Analysis 2 - Smoothing and aggregation

The (relevant) arguments for 'aggregate.swmpr':

- swmpr_in: Input data object
- by: How are the data aggregated - 'year', 'quarters', 'months', 'weeks', 'days', 'hours'
- FUN: What function is used to aggregate the data? Defaults to mean.

```
# see help for all arguments
?aggregate.swmpr
```

Analysis 2 - Smoothing and aggregation

The (relevant) arguments for 'smoother.swmpr':

- swmpr_in: Input data object
- window: the size of the smoothing window, defaults to five observations at the current time step
- sides: what defines the window, centered on an observation (2) or use only the preceding observations (1)

```
# see help for all arguments
?smoother.swmpr
```

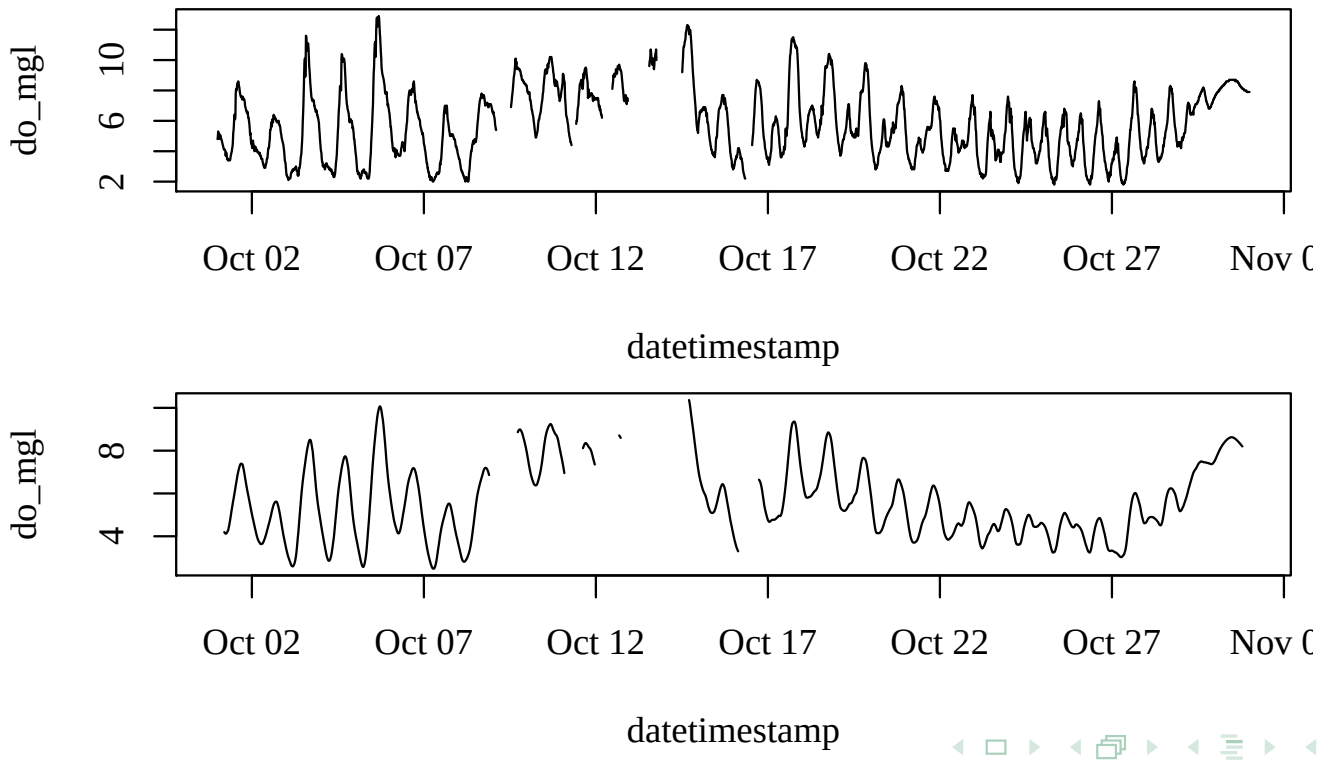
Analysis 2 - Smoothing and aggregation

Now you try an analysis! Open a new script and try the following:

- Import the the same data as before - 'cbmmcwq2012.csv' in the dataset3 folder
- Handle QAQC flags and subset by October 1 to 31
- Plot the raw data
- Use 'smoother.swmpr', save to new object, plot again. How does it look? Try different window sizes.
- Aggregate the data by weeks and view the raw data (do not plot). Now try aggregation by months, what's the difference?

Analysis 2 - Smoothing and aggregation

```r
# use the same data as in analysis 1

# smooth
new_dat <- smoother.swmpr(dat, window = 40)

# plot original, then new
plot(do_mgl ~ datetimestamp, data = dat, type = 'l')
plot(do_mgl ~ datetimestamp, data = new_dat, type = 'l')
```



Analysis 2 - Smoothing and aggregation

```
# try an aggregation by 'weeks'
aggregate(dat, by = 'weeks')
```

```
##   datetimestamp temp spcond  sal do_pct do_mgl depth cdepth level clevel  ph
## 1    2012-09-30   21   0.75 0.36     61    5.4  0.47    NaN   NaN    NaN 6.5
## 2    2012-10-07   16   0.67 0.33     65    6.4  0.51    NaN   NaN    NaN 6.6
## 3    2012-10-14   15   0.70 0.34     67    6.6  0.51    NaN   NaN    NaN 6.8
## 4    2012-10-21   16   0.71 0.35     46    4.5  0.52    NaN   NaN    NaN 6.8
## 5    2012-10-28   14   0.57 0.29     59    6.2  0.64    NaN   NaN    NaN 6.7
##   turb chlfluor
## 1   22       23
## 2   34       23
## 3   35       20
## 4   31       14
## 5   88       14
```

```
# try an aggregation by 'months'
aggregate(dat, by = 'months')
```

```
##   datetimestamp temp spcond  sal do_pct do_mgl depth cdepth level clevel  ph
## 1    2012-10-01   16   0.69 0.33     59    5.8  0.52    NaN   NaN    NaN 6.7
##   turb chlfluor
## 1   39       19
```

Analysis 3 - Basic trend analysis

Numerical summaries, filling missing data, and smoothing improve our ability to describe the data

More often, we are concerned with long-term trends over time – a missing data point here or there or noisy data on short time periods are not very important

We need plots to characterize long-term trends over time – both raw and summarized data

This analysis will show you two ways to evaluate trends by plotting – we will go through it together

Analysis 3 - Basic trend analysis

Start by importing all the water quality data for the 'Iron Pot Landing' station at the Chesapeake Bay Maryland reserve

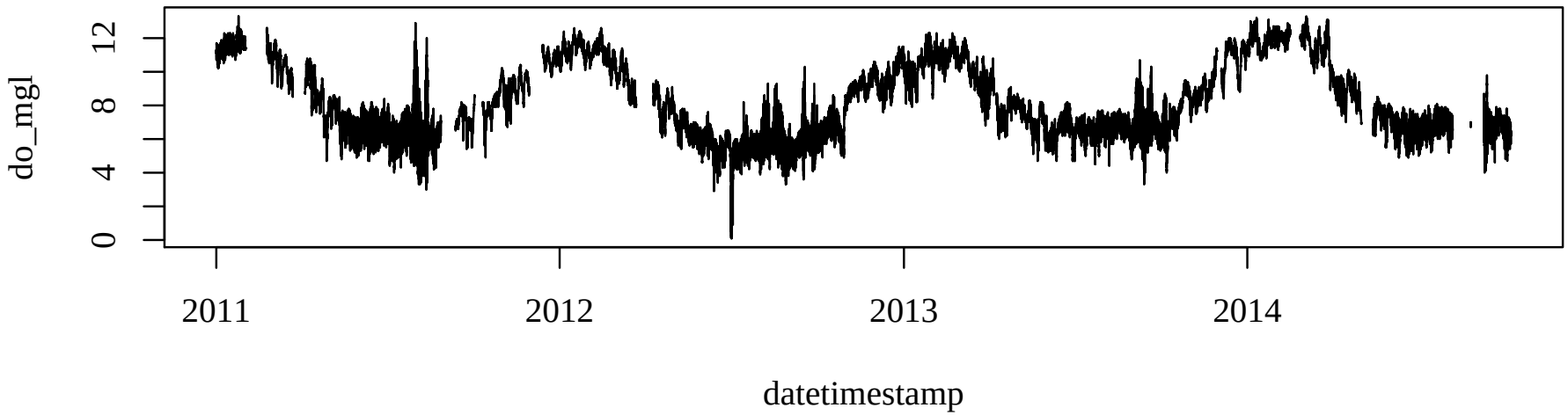
```
# import all wq data for cbmrr
# change path as needed
path <- 'C:/data/dataset3/'
dat <- import_local(path, 'cbmipwq')

# qaqc checks
dat <- qaqc(dat)
```

What are the dissolved oxygen dynamics over the last four years? Can we characterize trends, both seasonal and annual?

Analysis 3 - Basic trend analysis

First a simple plot...

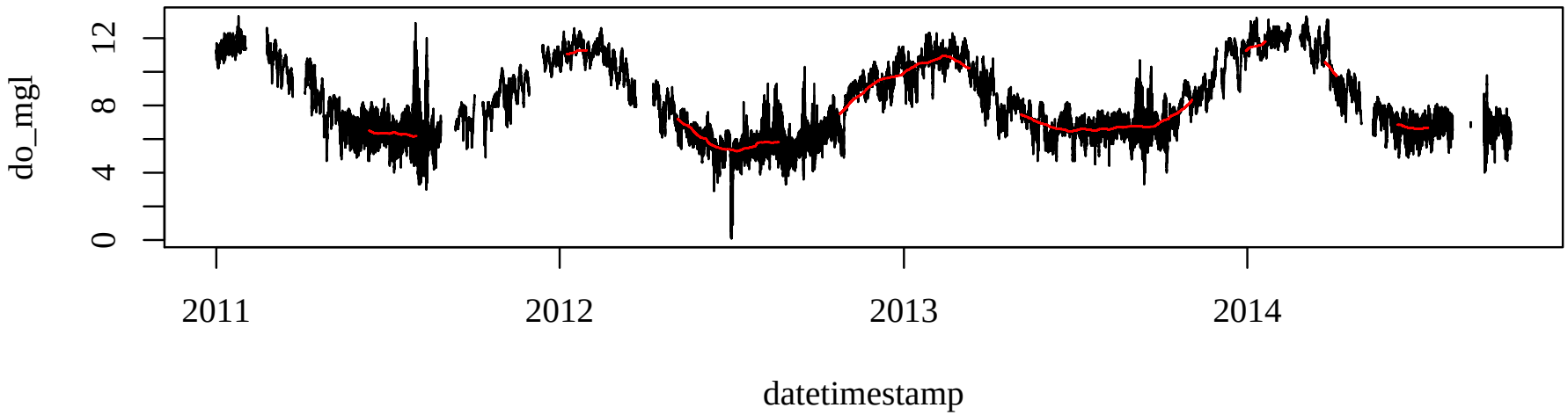
```
# plot DO for the time series
plot(do_mgl ~ datetimestamp, data = dat, type = 'l')
```



Analysis 3 - Basic trend analysis

If we are concerned with long-term trends, we want to reduce the noise related to intra-annual variability... we can use the smoother function

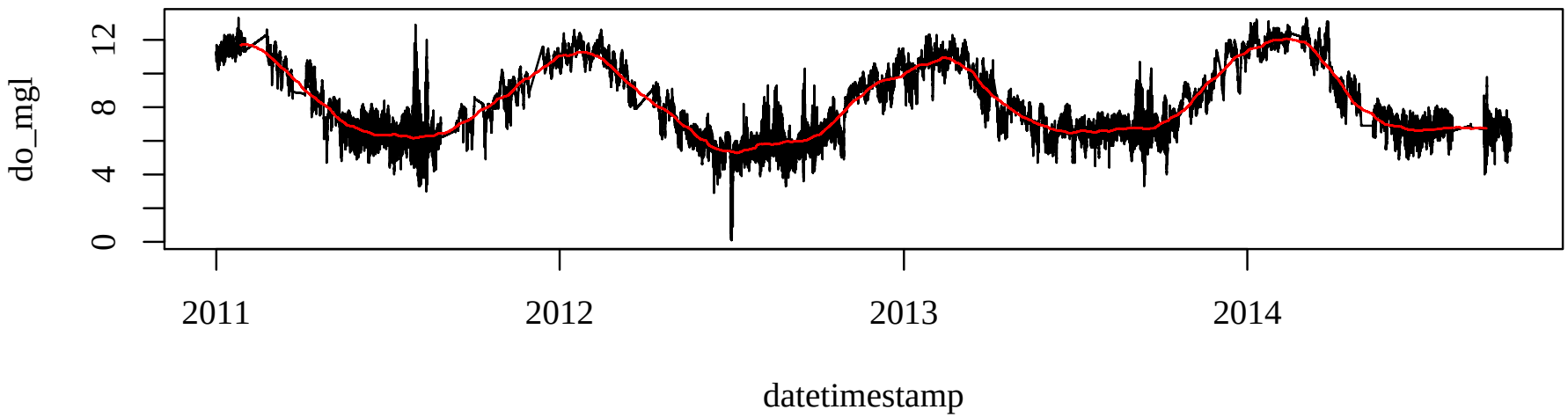
```
# smoother using a large window
do_smooth <- smoother(dat, params = 'do_mgl', window = 5000)
plot(do_mgl ~ datetimestamp, data = dat, type = 'l')
lines(do_smooth$datetimestamp, do_smooth$do_mgl, col = 'red')
```



Analysis 3 - Basic trend analysis

Try it again but use 'na.approx' first to fill gaps

```
# use na.approx, then smooth
new_dat <- na.approx(dat, param = 'do_mgl', maxgap = 3000)
do_smooth <- smoother(new_dat, params = 'do_mgl', window = 5000)
plot(do_mgl ~ datetimestamp, data = new_dat, type = 'l')
lines(do_smooth$datetimestamp, do_smooth$do_mgl, col = 'red')
```



This is kind of cheating but now we have a time series that primarily shows inter-annual variation

Analysis 3 - Basic trend analysis

Finally, we can use the 'aggregate.swmpr' function with boxplots for an alternative interpretation

The 'aggs˙out' argument in the function can be used to return the data with the datetimestamp formatted according to the 'by' argument

```
# get reformatted data from aggregate for plotting
agg_dat <- aggregate(dat, by = 'months', params = 'do_mgl', aggs_out = T)
head(agg_dat)
```

```
##   datetimestamp do_mgl
## 1    2011-01-01     11
## 2    2011-01-01     11
## 3    2011-01-01     11
## 4    2011-01-01     11
## 5    2011-01-01     11
## 6    2011-01-01     11
```

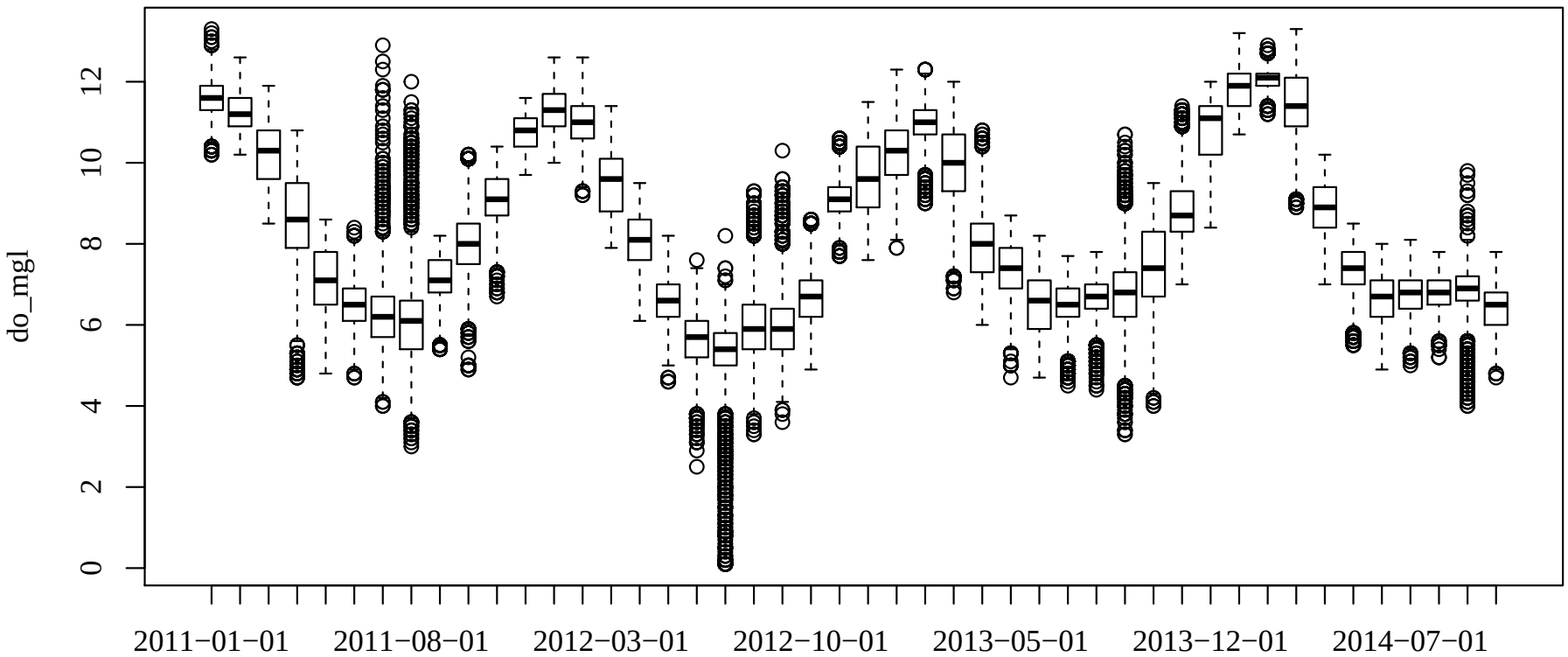
```
# note same row number in aggregated data
dim(agg_dat)
```

```
## [1] 132132      2
```

Analysis 3 - Basic trend analysis

Plot the aggregated data

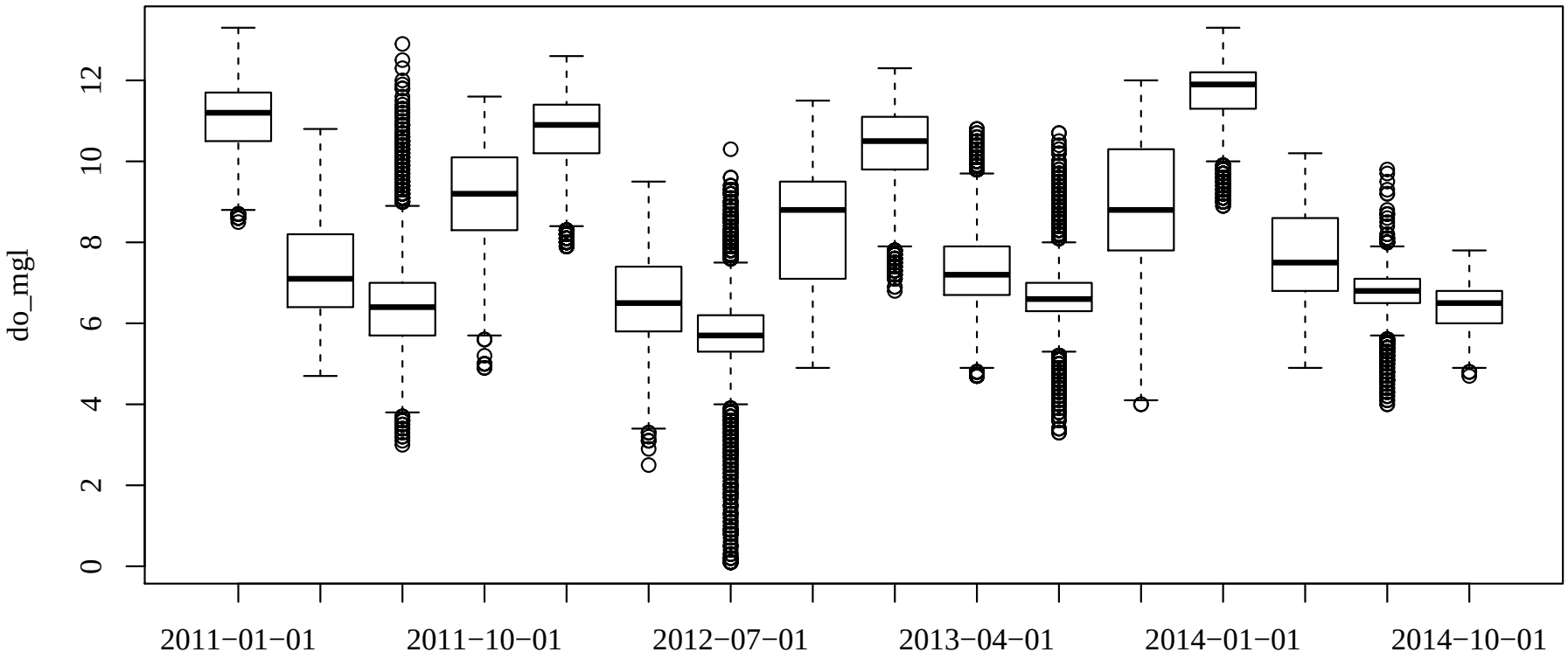
```
# use boxplots
boxplot(do_mgl ~ datetimestamp, data = agg_dat, ylab = 'do_mgl')
```



Analysis 3 - Basic trend analysis

This can be repeated for different time steps...

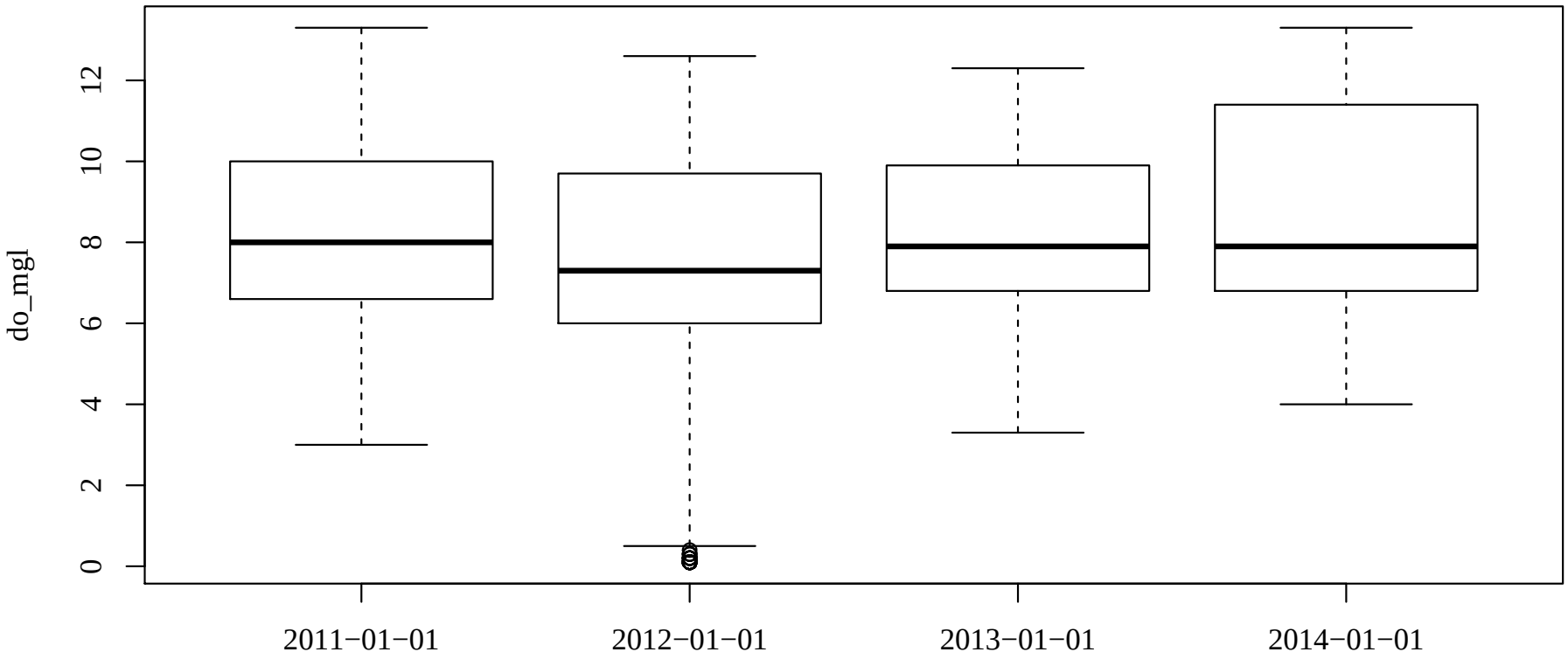
```
# by season
agg_dat <- aggregate(dat, by = 'quarters', params = 'do_mgl', aggs_out = T)
boxplot(do_mgl ~ datetimestamp, data = agg_dat, ylab = 'do_mgl')
```



Analysis 3 - Basic trend analysis

This can be repeated for different time steps...

```
# by year
agg_dat <- aggregate(dat, by = 'years', params = 'do_mgl', aggs_out = T)
boxplot(do_mgl ~ datetimestamp, data = agg_dat, ylab = 'do_mgl')
```



Analysis 3 - Basic trend analysis

A final note about trend analysis – this can be as simple or as complex as you like

The key question - has my variable of interest significantly changed and when did it occur?

You must define what change means and how you will assess

E.g., Has it increased/decreased? How has the central tendency changed? Has the variance changed? What factors could have influenced this change?

As a first step, always plot the raw or summarized data!

More detailed approaches are beyond the scope of this workshop - but check out the CRAN task view on time series for more you can do in R!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Questions??