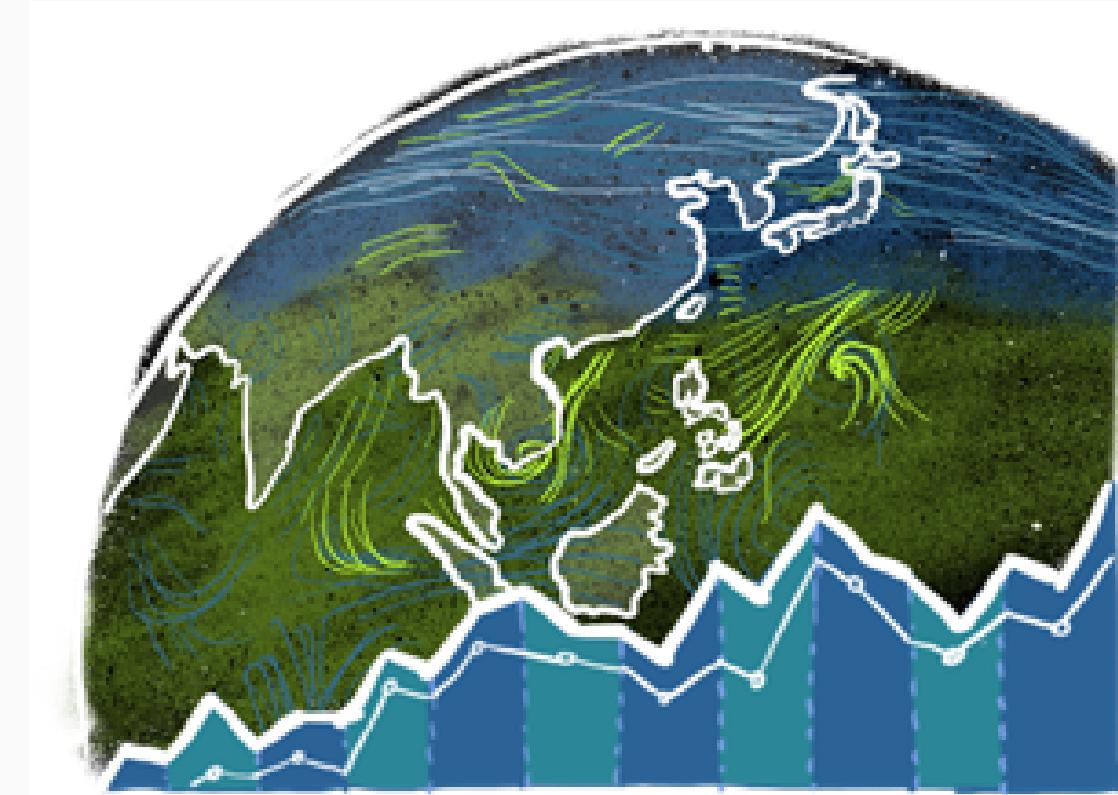


Fundamental of Data Science for EESS

R session 07 - Time series

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2020-04-13



CNRS • SORBONNE UNIVERSITÉ
Station Biologique
de Roscoff



Outline

- Time series in earth sciences
- Phytoplankton time series
- Manipulating dates: lubridate package
- Time series objects: tsibble and feasts packages
- Other time series analysis strategies

Installation and Resources

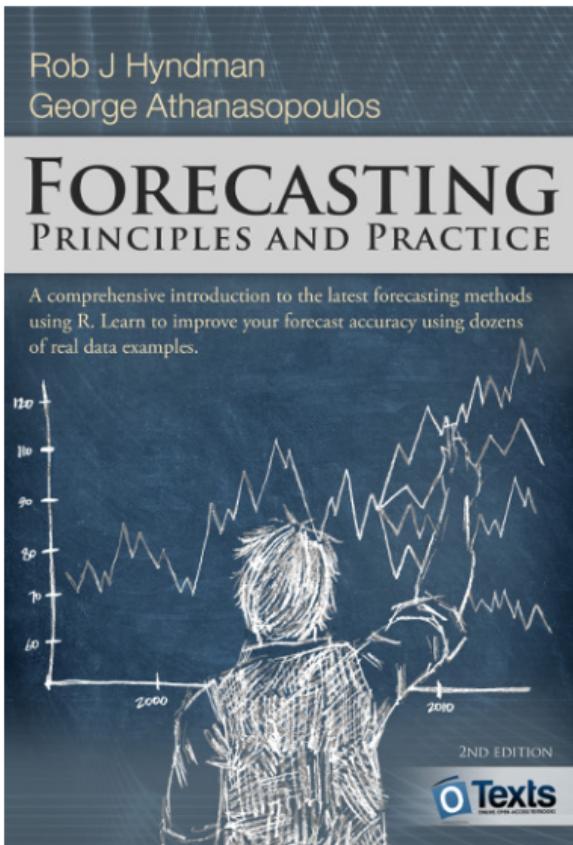
Packages

New

- lubridate
- tsibble
- feasts
- tsibbledata
- slider
- fable
- zoo
- WaveletComp

Previously used

- ggplot2
- stringr
- dplyr



Reading list

Book

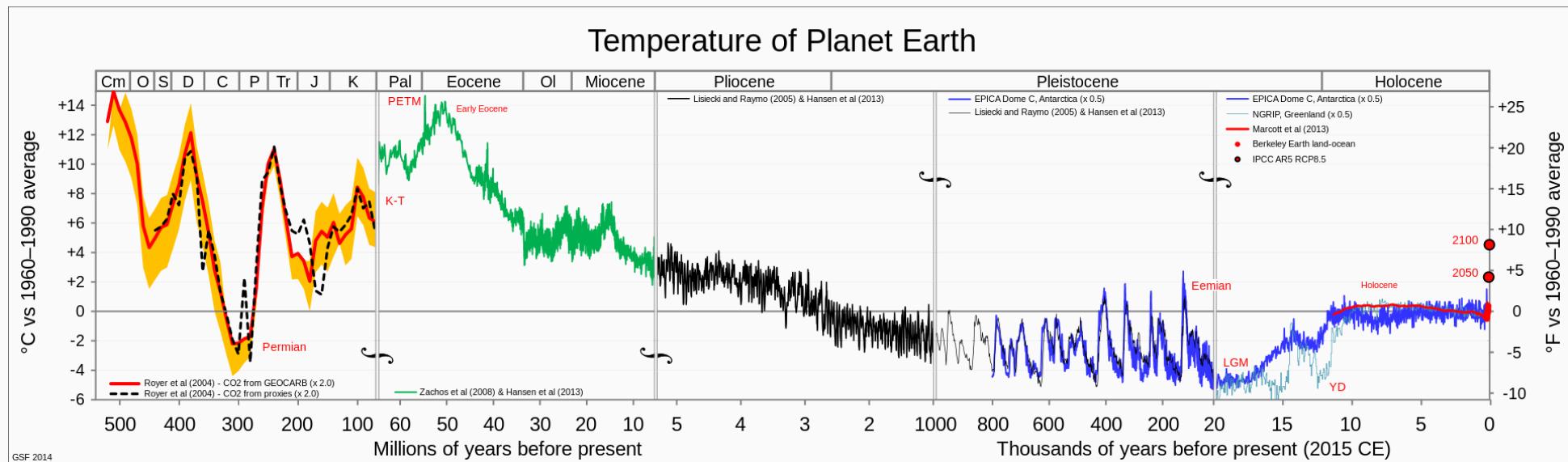
- Forecasting in practice Chapters 1-4:
<https://otexts.com/fpp3/>

Paper

- Hunter-Cevera et al. 2016. Physiological and ecological drivers of early spring blooms of a coastal phytoplankton. *Science* 354:326–329.

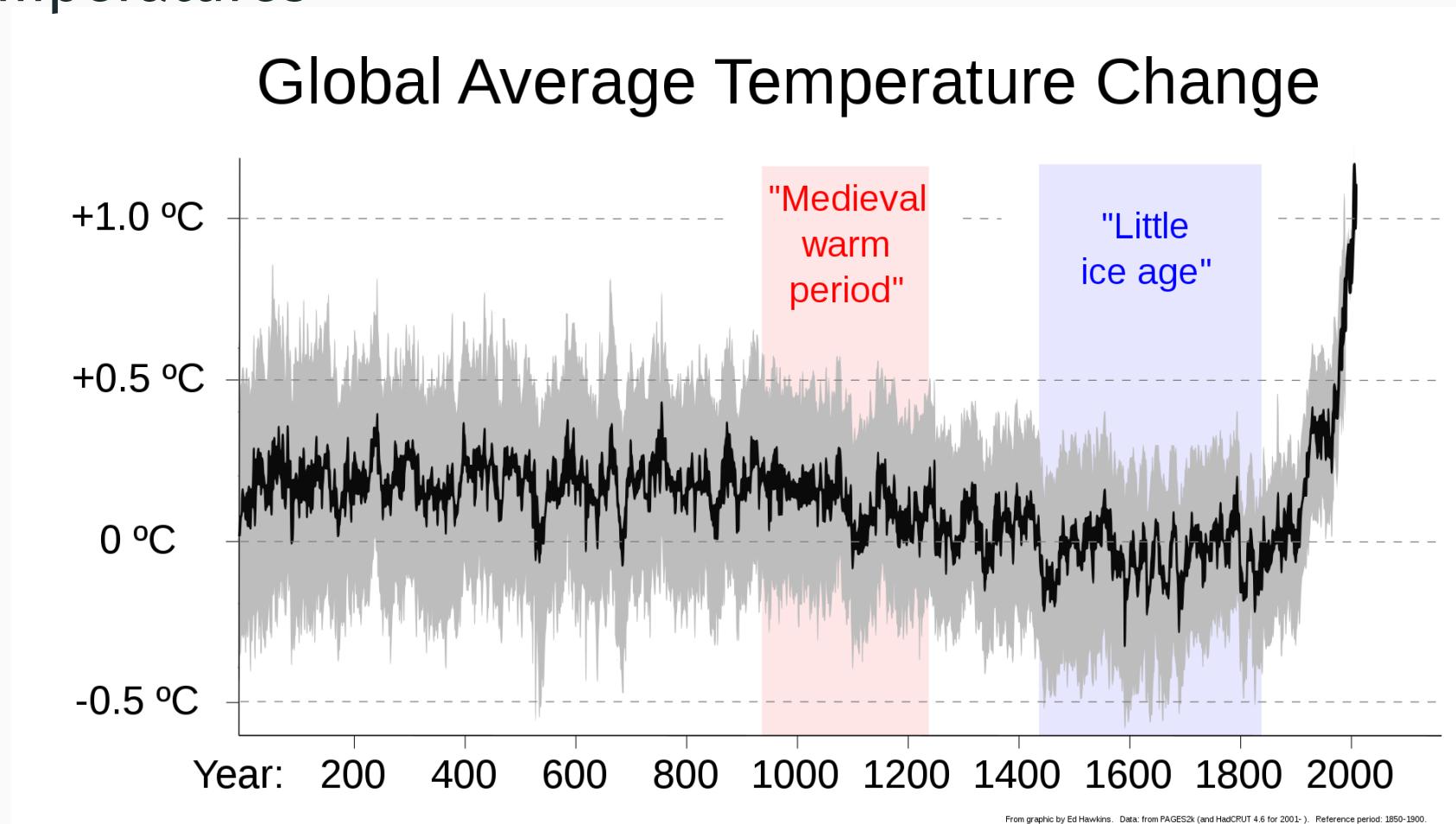
Time series in Earth Sciences

Paleo-temperatures



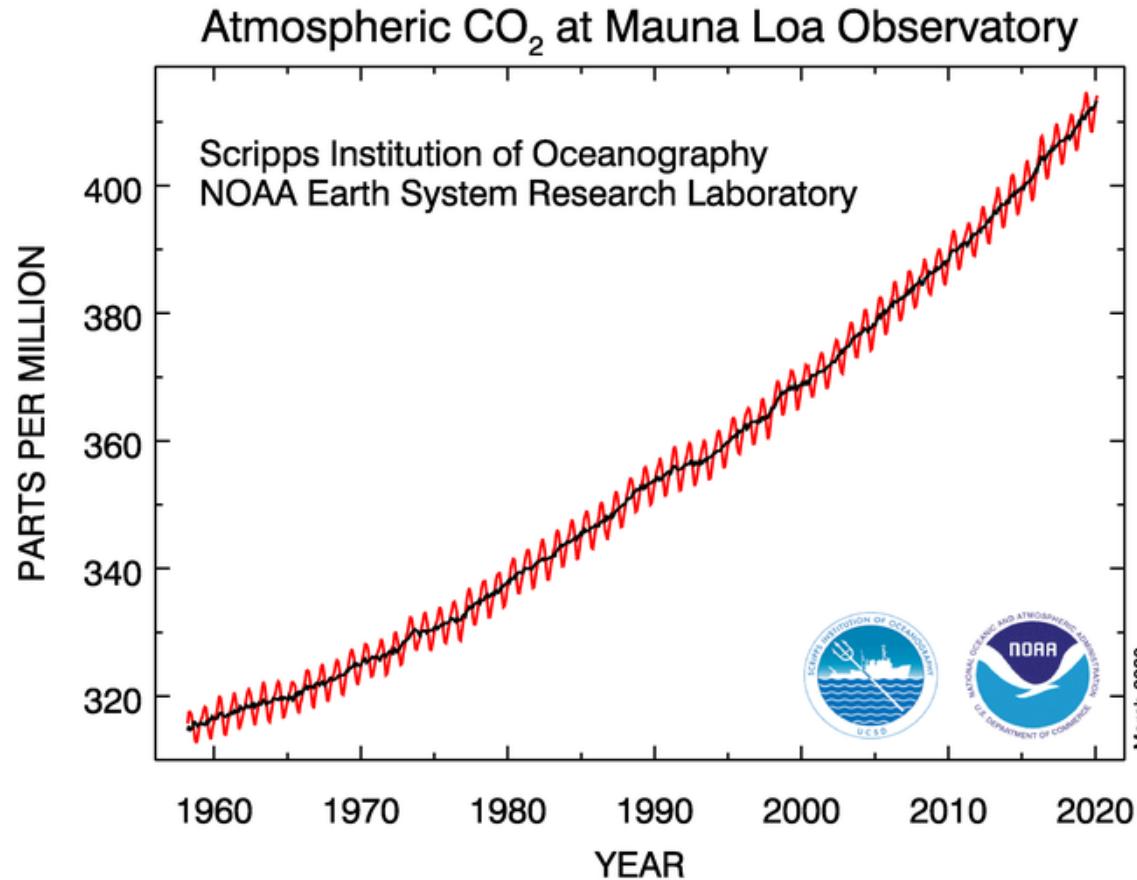
Time series in Earth Sciences

Paleo-temperatures



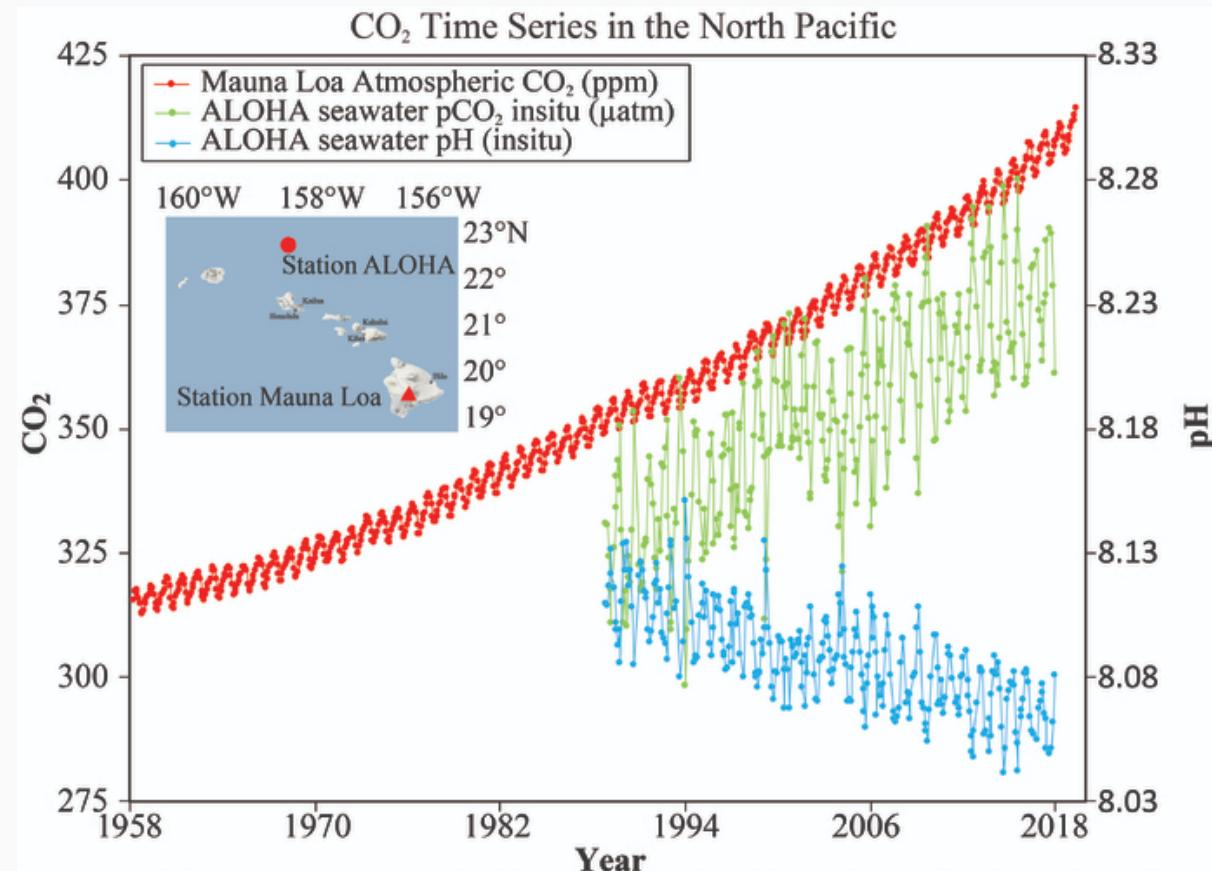
Time series in Earth Sciences

CO₂ in the atmosphere



Time series in Earth Sciences

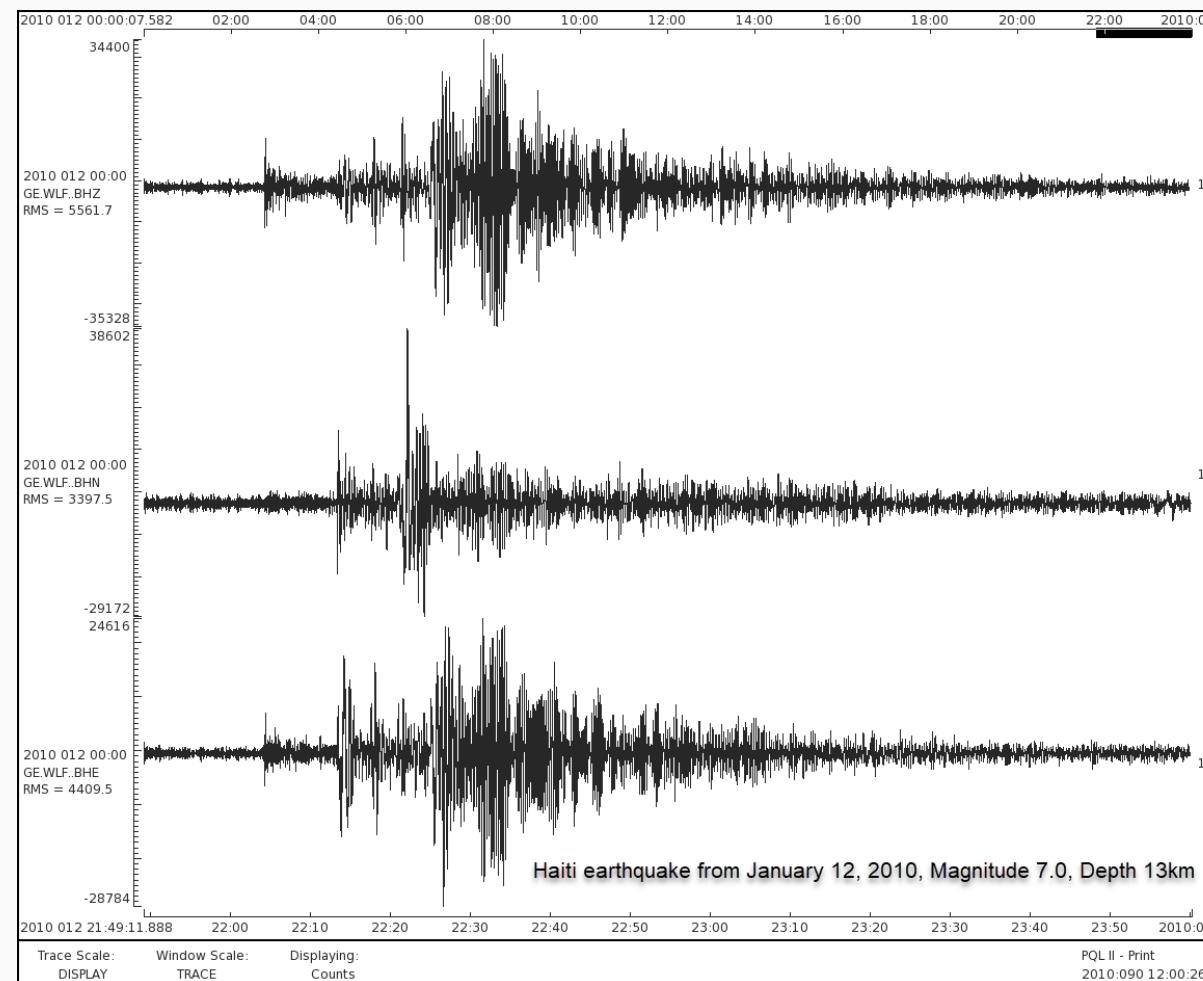
CO₂ in the atmosphere in the ocean



Data: Mauna Loa (http://aftp.cmdl.noaa.gov/products/trends/co2/co2_mm_mlo.txt) ALOHA (http://hahana.soest.hawaii.edu/hot/products/HOT_surface_CO2.txt)
Ref: J.E. Dore et al, 2009. Physical and biogeochemical modulation of ocean acidification in the central North Pacific. *Proc Natl Acad Sci USA* 106:12235-12240.

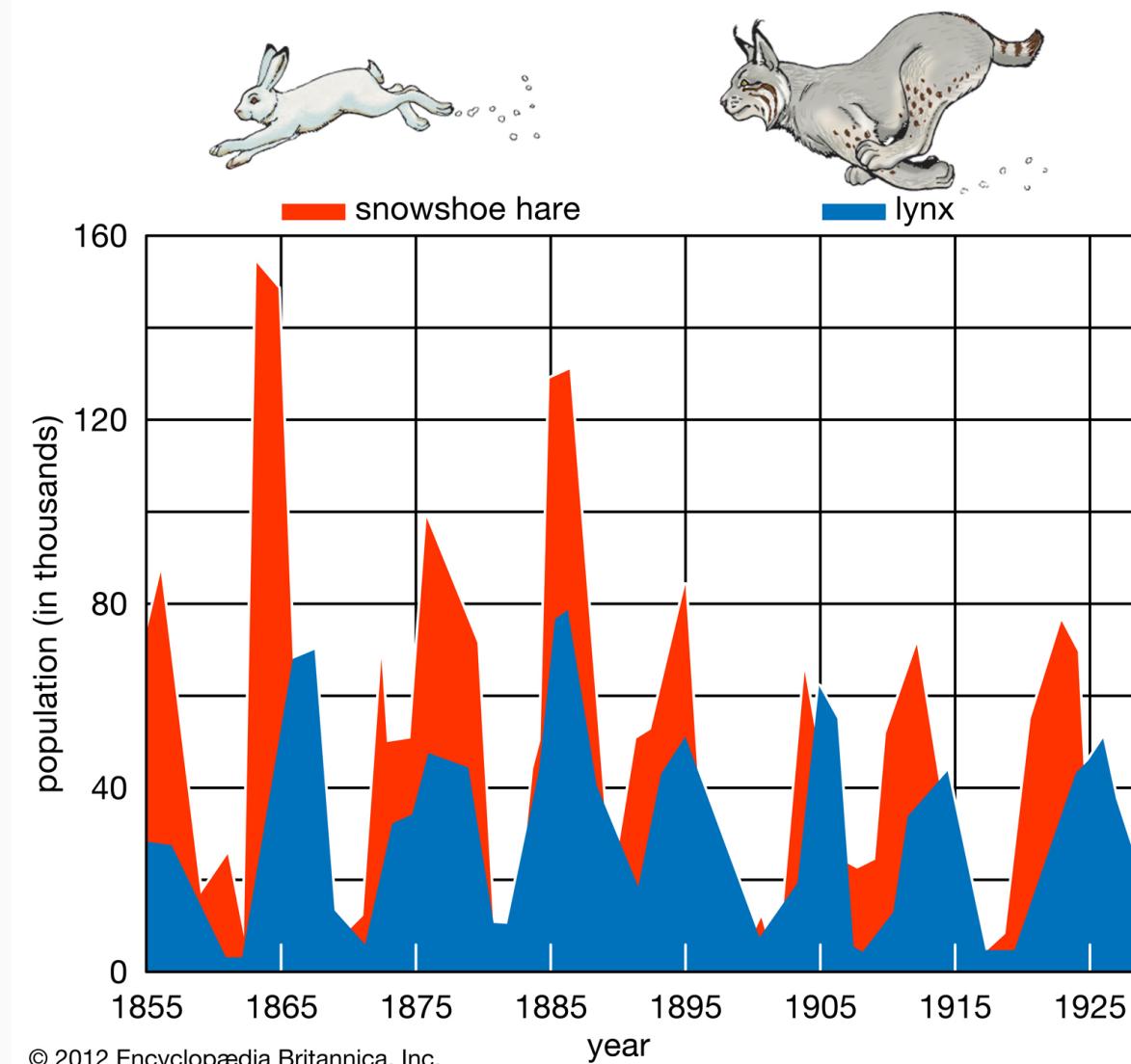
Time series in Earth Sciences

Seismic records



Time series in Earth Sciences

Ecology



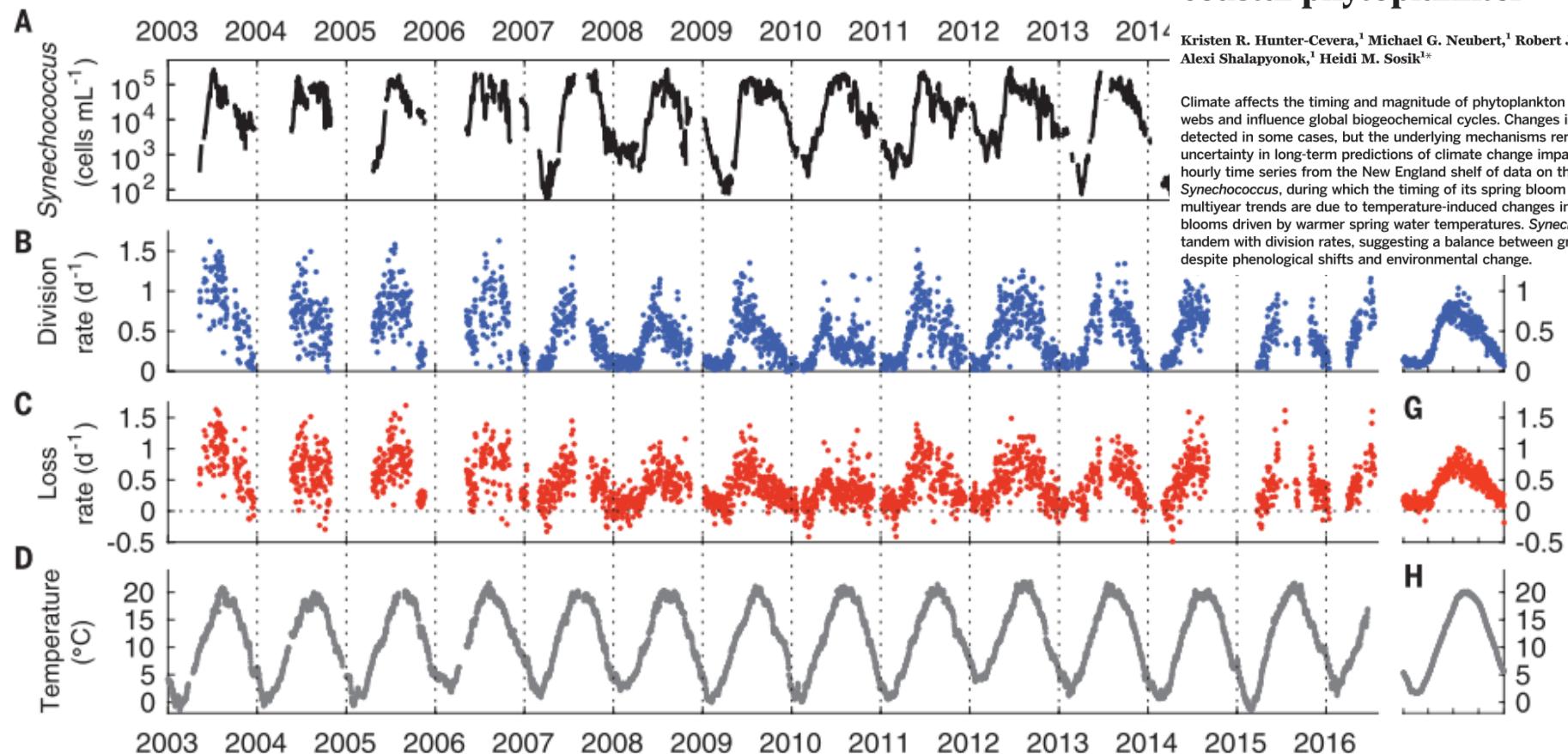
Marine phytoplankton bloom (*Synechococcus*)

PLANKTON DYNAMICS

Physiological and ecological drivers of early spring blooms of a coastal phytoplanktoner

Kristen R. Hunter-Cevera,¹ Michael G. Neubert,¹ Robert J. Olson,¹ Andrew R. Sollow,² Alexi Shalapyonok,¹ Heidi M. Sosik^{1*}

Climate affects the timing and magnitude of phytoplankton blooms that fuel marine food webs and influence global biogeochemical cycles. Changes in bloom timing have been detected in some cases, but the underlying mechanisms remain elusive, contributing to uncertainty in long-term predictions of climate change impacts. Here we describe a 13-year hourly time series from the New England shelf of data on the coastal phytoplanktoner *Synechococcus*, during which the timing of its spring bloom varied by 4 weeks. We show that multiyear trends are due to temperature-induced changes in cell division rate, with earlier blooms driven by warmer spring water temperatures. *Synechococcus* loss rates shift in tandem with division rates, suggesting a balance between growth and loss that has persisted despite phenological shifts and environmental change.



Marine phytoplankton bloom (*Synechococcus*)

Synechococcus

- Discovered in 1979 - Epifluorescence microscopy

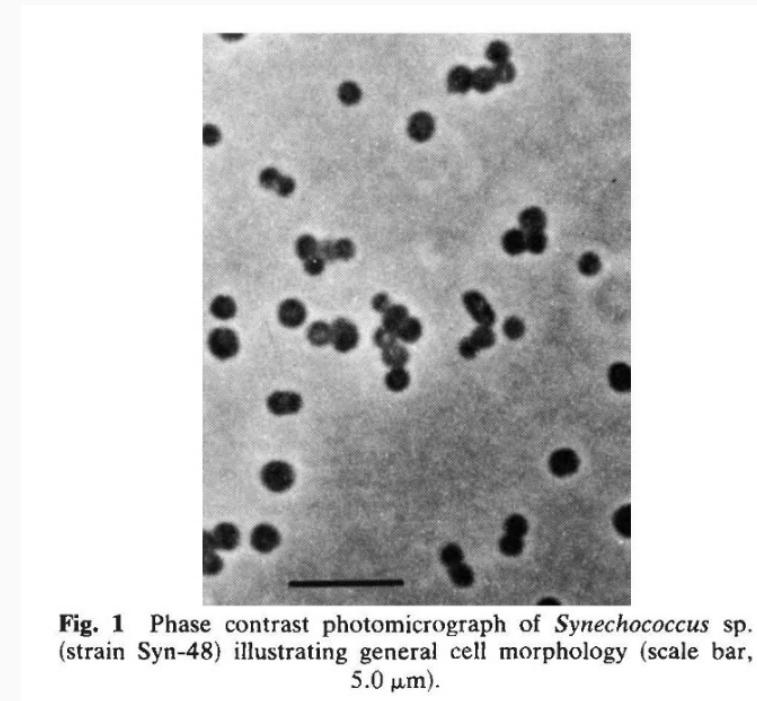
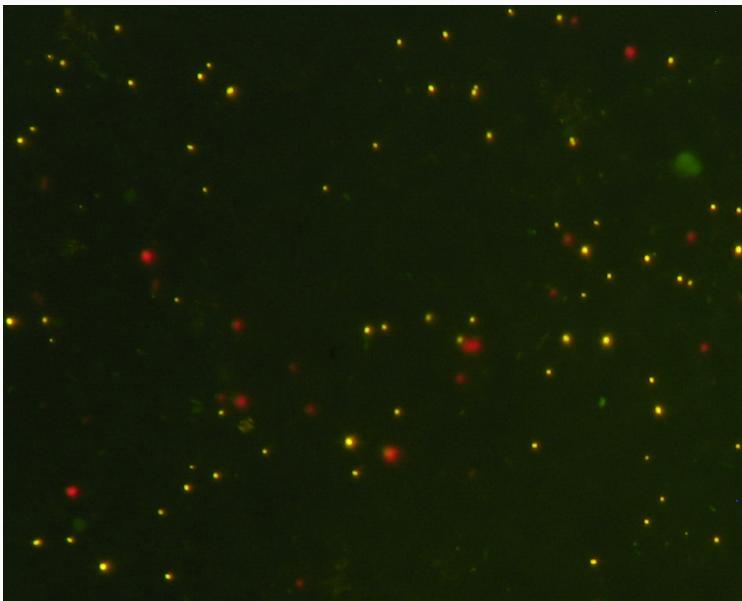
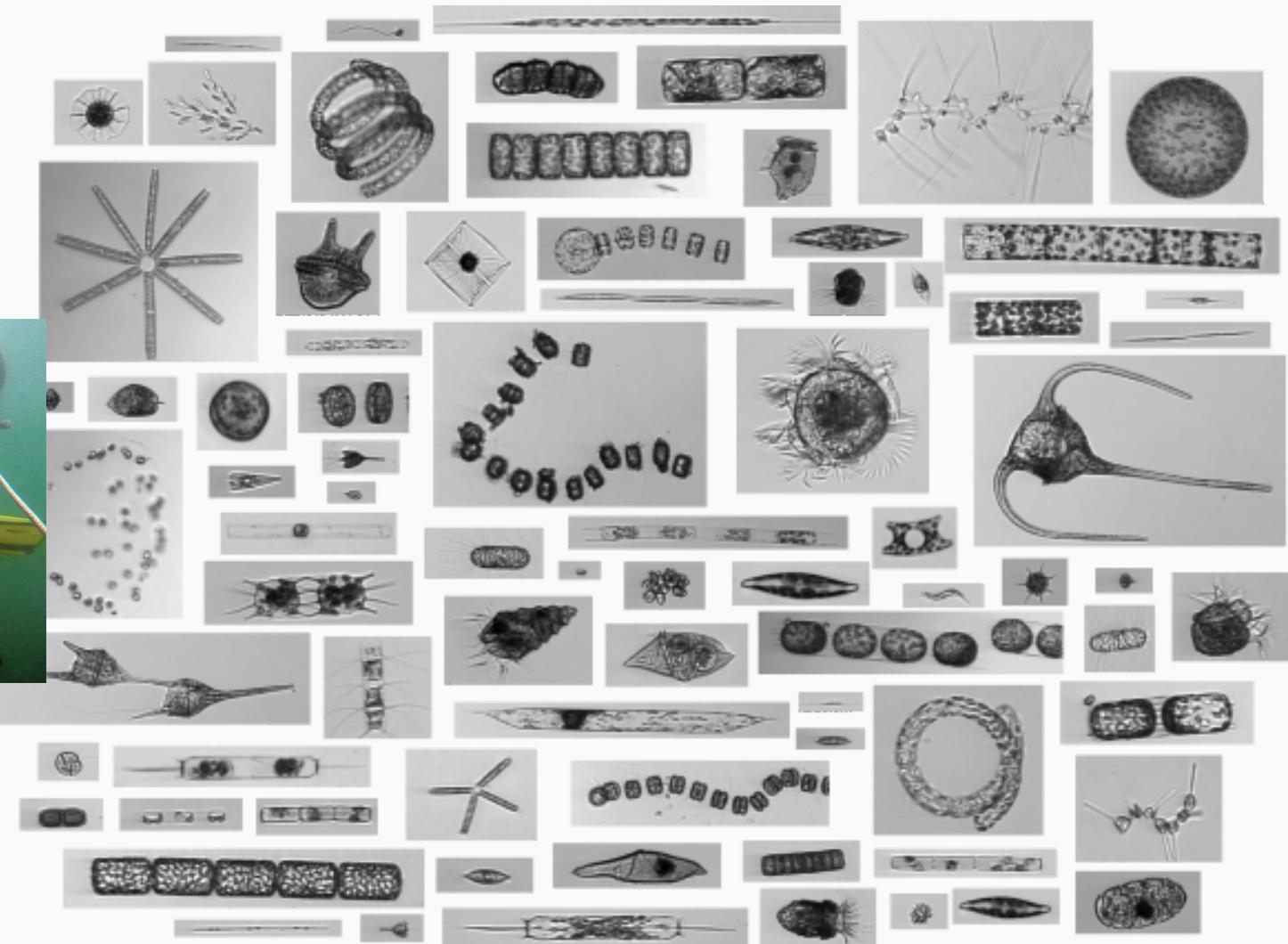


Fig. 1 Phase contrast photomicrograph of *Synechococcus* sp. (strain Syn-48) illustrating general cell morphology (scale bar, 5.0 μm).

Marine phytoplankton bloom (*Synechococcus*)

Flow Cytobot

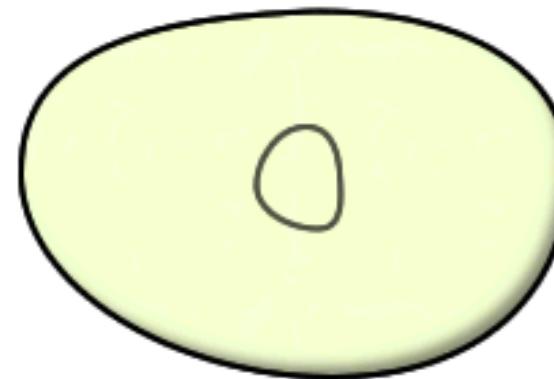
- Imaging and flow cytometry



Marine phytoplankton bloom (*Synechoccus*)

Cell multiplication

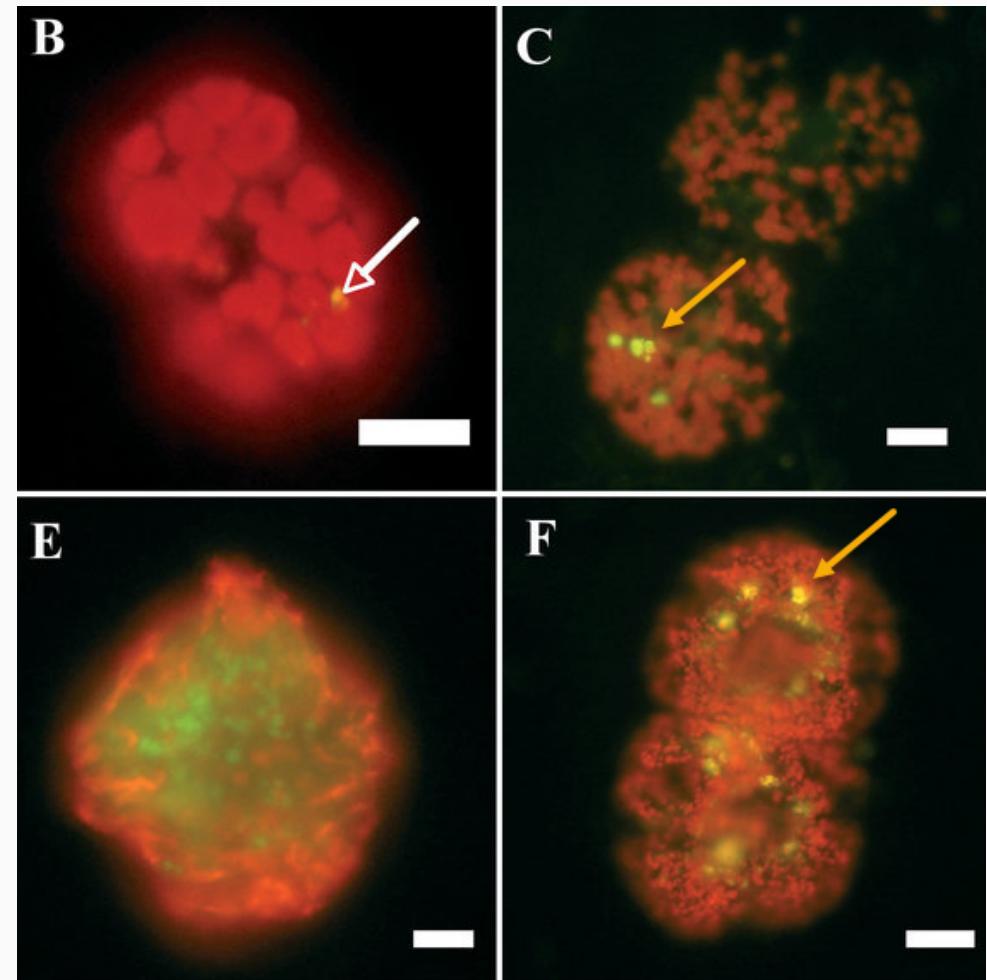
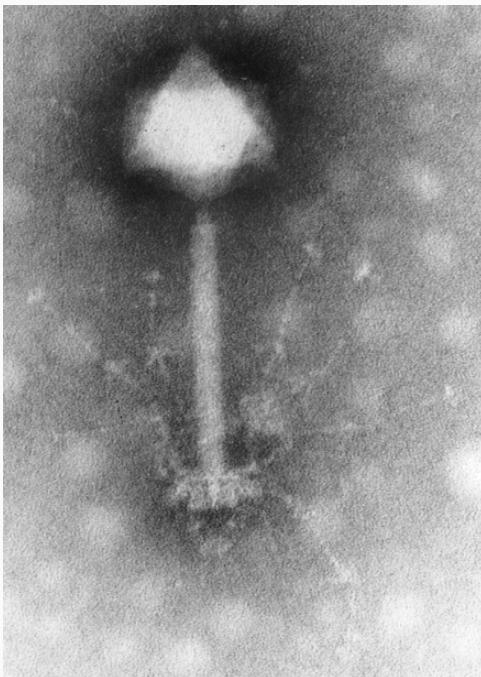
- Binary fission
- Typically once every day



Marine phytoplankton bloom (*Synechococcus*)

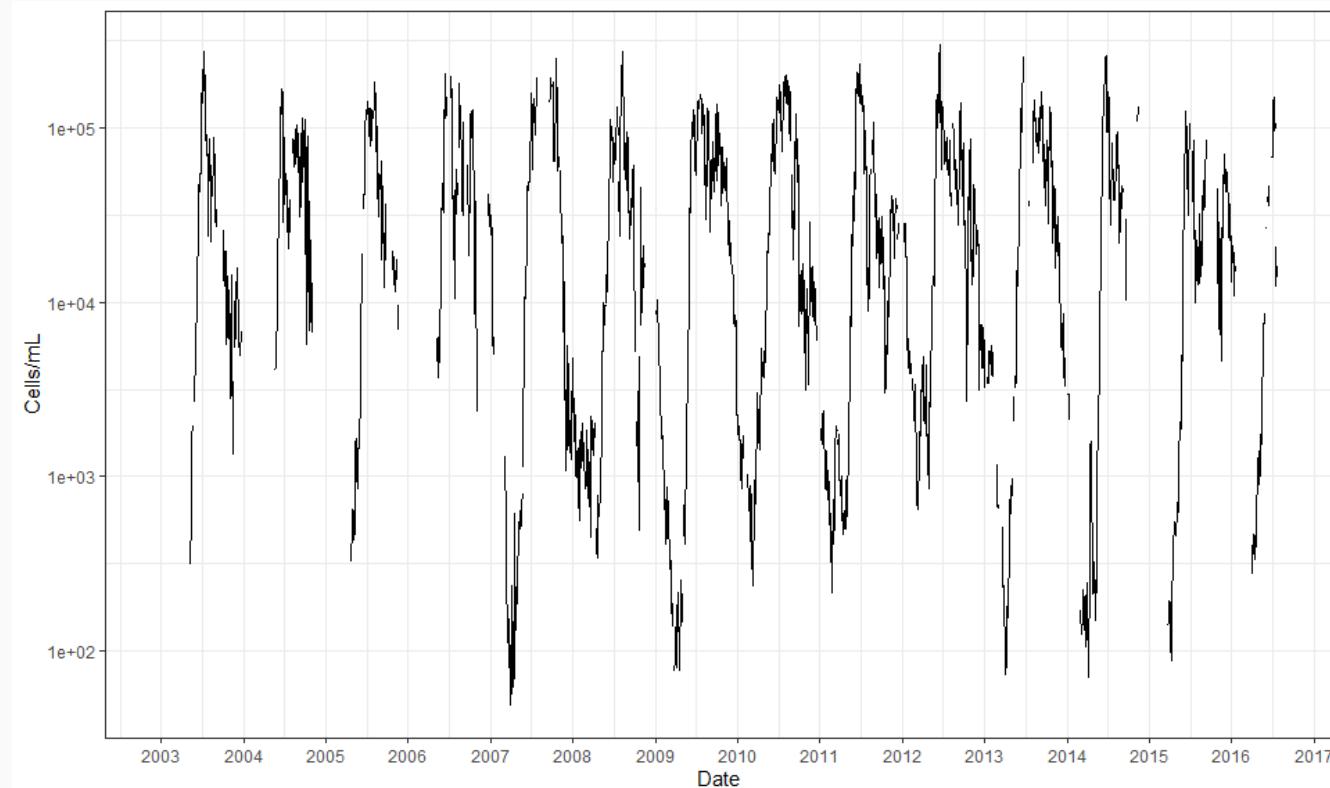
Cell disappearance

- Virus
- Predation
- Cell death (UV, nutrient deprivation)



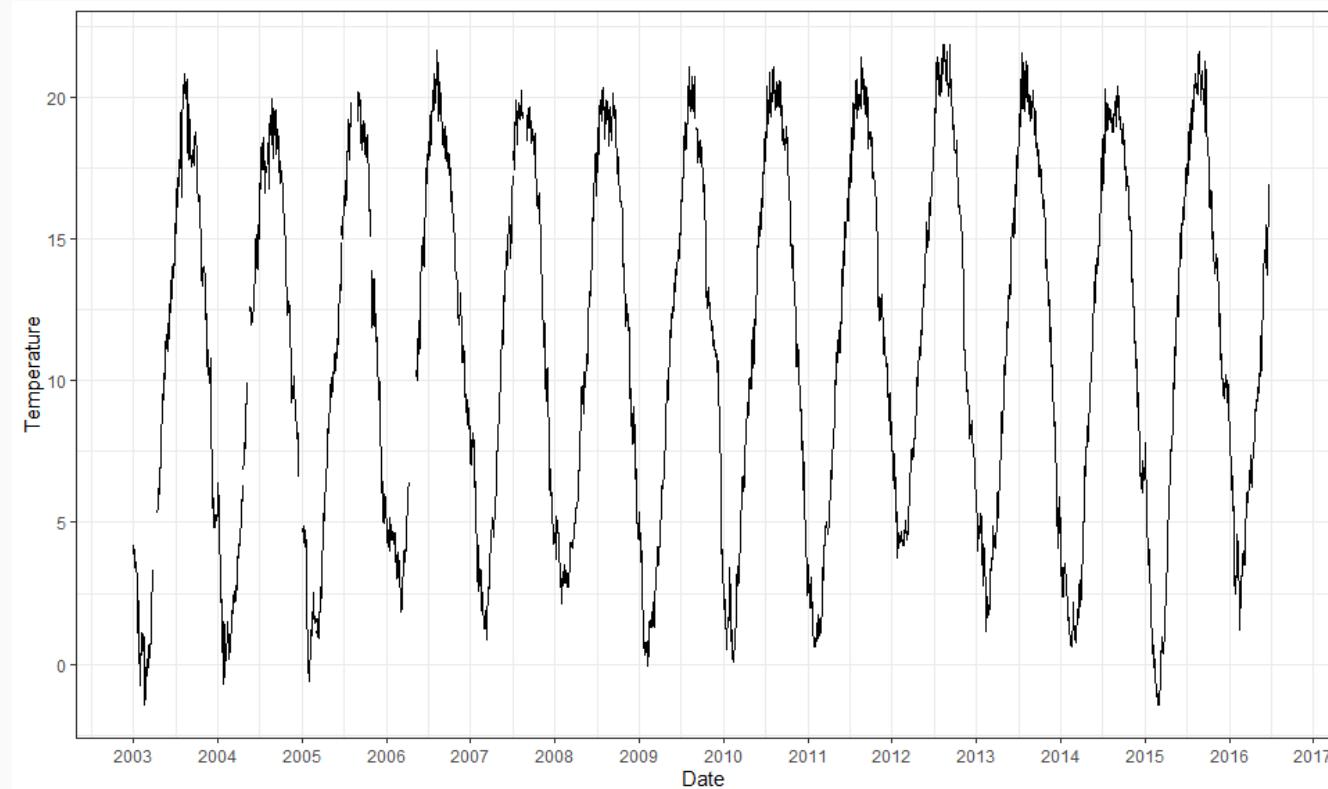
Marine phytoplankton bloom (*Synechococcus*)

Synechococcus abundance



Marine phytoplankton bloom (*Synechoccus*)

Temperature



Manipulating dates: lubridate package

Dates and times with lubridate :: CHEAT SHEET



Date-times



PARSE DATE-TIMES (Convert strings or numbers to date-times)

- Identify the order of the year (y), month (m), day (d), hour (h), minute (m) and second (s) elements in your data.
- Use the function below whose name replicates the order. Each accepts a wide variety of input formats.

`2017-11-28T14:02:00` `ymd_hms()`, `ymd_hm()`, `ymd_h()`.
`ymd_hms("2017-11-28T14:02:00")`

`2017-22-12 10:00:00` `ymd_hms()`, `ymd_hm()`, `ymd_h()`.
`ymd_hms("2017-22-12 10:00:00")`

`11/28/2017 1:02:03` `mdy_hms()`, `mdy_hm()`, `mdy_h()`.
`mdy_hms("11/28/2017 1:02:03")`

`1 Jan 2017 23:59:59` `dmy_hms()`, `dmy_hm()`, `dmy_h()`.
`dmy_hms("1 Jan 2017 23:59:59")`

`20170131` `ymd()`, `ymd_hm()`, `ymd_h()`.
`ymd("20170131")`

`July 4th, 2000` `mdy()`, `mdy_hm()`, `mdy_h()`.
`mdy("July 4th, 2000")`

`4th of July '99` `dmy()`, `dmy_hm()`, `dmy_h()`.
`dmy("4th of July '99")`

`2001: Q3` `yq()` Q for quarter. `yq("2001: Q3")`

`2:01` `hms:hms()` Also `lubridate::hms()`, `hm()` and `ms()`, which return periods.* `hms:hms(sec = 0, min = 1, hours = 2)`

`2017.5` `date_decimal(decimal, tz = "UTC")`
`date_decimal(2017.5)`

`now(tzone = "")` Current time in tz
(defaults to system tz). `now()`

`today(tzone = "")` Current date in a tz
(defaults to system tz). `today()`

`fast_strptime()` Faster strptime.
`fast_strptime("%9/1/01", "%y/%m/%d")`

`parse_date_time()` Easier strptime.
`parse_date_time("%9/1/01", "ymd")`

`2017-11-28 12:00:00`
A date-time is a point on the timeline, stored as the number of seconds since 1970-01-01 00:00:00 UTC

`dt <- as_datetime(1511870400)`
`## "2017-11-28 12:00:00 UTC"`

`2017-11-28`
A date is a day stored as the number of days since 1970-01-01

`d <- as_date(17498)`
`## "2017-11-28"`

`12:00:00`
An hms is a time stored as the number of seconds since 00:00:00

`t <- hms(as.hms(85))`
`## "00:01:25"`

GET AND SET COMPONENTS

Use an accessor function to get a component. Assign into an accessor function to change a component in place.

`d ## "2017-11-28"`
`day(d) ## 28`
`day(d) <- 1`
`d ## "2017-11-01"`

`2018-01-31 11:59:59` `date(x)` Date component. `date(dt)`

`2018-01-31 11:59:59` `year(x)` Year. `year(dt)`
`isoyear(x)` The ISO 8601 year.
`epiyear(x)` Epidemiological year.

`2018-01-31 11:59:59` `month(x, label, abbr)` Month. `month(dt)`

`2018-01-31 11:59:59` `day(x)` Day of month. `day(dt)`
`wday(x, label, abbr)` Day of week. `wday(dt)`
`qday(x)` Day of quarter.

`2018-01-31 11:59:59` `hour(x)` Hour. `hour(dt)`
`minute(x)` Minutes. `minute(dt)`

`2018-01-31 11:59:59` `second(x)` Seconds. `second(dt)`

`2018-01-31 11:59:59` `week(x)` Week of the year. `week(dt)`
`isowk(x)` ISO 8601 week.
`epiweek(x)` Epidemiological week.

`2018-01-31 11:59:59` `quarter(x, with_year = FALSE)` Quarter. `quarter(dt)`

`2018-01-31 11:59:59` `semester(x, with_year = FALSE)` Semester. `semester(dt)`

`2018-01-31 11:59:59` `am(x)` Is it in the am? `am(dt)`
`pm(x)` Is it in the pm? `pm(dt)`

`2018-01-31 11:59:59` `dst(x)` Is it daylight savings? `dst(dt)`

`2018-01-31 11:59:59` `leap_year(x)` Is it a leap year?
`leap_year(dt)`

`2018-01-31 11:59:59` `update(object, ..., simple = FALSE)`
`update(dt, mday = 2, hour = 1)`

Round Date-times

`floor_date(x, unit = "second")`
Round down to nearest unit.
`floor_date(dt, unit = "month")`

`round_date(x, unit = "second")`
Round to nearest unit.
`round_date(dt, unit = "month")`

`ceiling_date(x, unit = "second")`
`change_on_boundary = NULL`
Round up to nearest unit.
`ceiling_date(dt, unit = "month")`

`rollback(dates, roll_to = first = FALSE, preserve_hms = TRUE)`
Roll back to last day of previous month. `rollback(dt)`

Stamp Date-times

`stamp()` Derive a template from an example string and return a new function that will apply the template to date-times. Also `stamp_date()` and `stamp_time()`.

- Derive a template, create a function
`sf <- stamp("Created Sunday, Jan 17, 1999 3:34")`
- Apply the template to dates
`sf(ymd("2010-04-05"))`
`## [1] "Created Monday, Apr 05, 2010 00:00"`

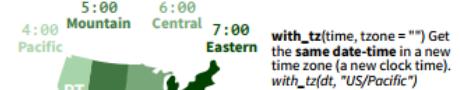
Tip: use a date with day > 12

Time Zones

R recognizes ~600 time zones. Each encodes the time zone, Daylight Savings Time, and historical calendar variations for an area. R assigns one time zone per vector.

Use the UTC time zone to avoid Daylight Savings.

`OlsonNames()` Returns a list of valid time zone names. `OlsonNames()`


`5:00` Mountain
`6:00` Central
`7:00` Eastern
`4:00` Pacific
`PT` PT
`MT` MT
`CT` CT
`ET` ET
`with_tz(time, tzname = "")` Get the same date-time in a new time zone (a new clock time). `with_tz(dt, "US/Pacific")`


`7:00` Pacific
`7:00` Mountain
`7:00` Central
`7:00` Eastern
`7:00` Eastern
`force_tz(time, tzname = "")` Get the same clock time in a new time zone (a new date-time). `force_tz(dt, "US/Pacific")`



Manipulating dates: lubridate package

Parse date

Dates are often read as character from files. In order to be recognized in R as dates, they must be parsed

```
library(lubridate)  
(bdy ← ymd(19530822))
```

```
[1] "1953-08-22"
```

```
(bdy ← dmy("22-08-1953"))
```

```
[1] "1953-08-22"
```

```
(bdy ← dmy("22 aug 1953"))
```

```
[1] "1953-08-22"
```

Manipulating dates: lubridate package

Parse date

```
bdy <- dmy(22-08-1953)
```

Warning: All formats failed to parse. No formats found.

| do not forget the quotes

Parse date and time

```
(bdy_time <- dmy_hm("22-08-1953 16:00"))
```

[1] "1953-08-22 16:00:00 UTC"

Manipulating dates: lubridate package

Extract information from dates

```
bdy <- dmy("22-08-1953")  
year(bdy)
```

```
[1] 1953
```

```
month(bdy)
```

```
[1] 8
```

```
day(bdy)
```

```
[1] 22
```

```
wday(bdy, label=TRUE, abbr = FALSE, week_start = 1)
```

```
[1] samedi
```

```
7 Levels: lundi < mardi < mercredi < jeudi < vendredi < ... < dimanche
```

Manipulating dates: lubridate package

Rounding up dates

```
# Rounding to start of the month  
floor_date(bday, unit="month")
```

```
[1] "1953-08-01"
```

Manipulating dates: lubridate package

Arithmetic

```
# Adding one month  
bday + months(1)
```

```
[1] "1953-09-22"
```

```
# Adding years  
bday + years(66)
```

```
[1] "2019-08-22"
```

Manipulating dates: lubridate package

Intervals

```
# Creating intervals  
(binterval ← lubridate::interval(bday, Sys.Date()))
```

```
[1] 1953-08-22 UTC--2020-04-09 UTC
```

```
# Number of seconds in interval  
int_length(binterval)
```

```
[1] 2102716800
```

```
# Number of days  
seconds_to_period(int_length(binterval))
```

```
[1] "24337d 0H 0M 0S"
```

Manipulating time series: tidyverts packages

tidyverts Home Packages

Tidy tools for time series.

PACKAGES



tsibble
Temporal data frames and tools



fable
Tidy forecasting



feasts
Feature extraction and statistics

Manipulating time series: tidyverts packages

Loading necessary packages

```
library(tidyverse)
library(lubridate)

# Time series manipulation
library(tsibble)

# Time series graphics and statistics
library(feasts)

# Moving computations
library(slidr)

# Forecasting functions
library(fable)

# Interpolation
library(zoo)

theme_set(theme_bw())
```

Manipulating time series: tidyverts packages

Tsibble objects

- Like a dataframe or a tibble but geared for time series
- index : the time variable - here `year` - but can be day, minute etc...
- key : one or several column that corresponding to different time series - here `country`

```
library(tsibbledata)
global_economy
```

```
# A tsibble: 15,150 x 9 [1Y]
# Key:   Country [263]
  Country     Code Year      GDP Growth     CPI Imports Exports Population
  <fct>     <fct> <dbl>    <dbl> <dbl>    <dbl>    <dbl>    <dbl>
  1 Afghanistan AFG  1960 537777811.    NA     NA    7.02    4.13    8996351
  2 Afghanistan AFG  1961 548888896.    NA     NA    8.10    4.45    9166764
  3 Afghanistan AFG  1962 546666678.    NA     NA    9.35    4.88    9345868
  4 Afghanistan AFG  1963 751111191.    NA     NA   16.9     9.17    9533954
  5 Afghanistan AFG  1964 800000044.    NA     NA   18.1     8.89    9731361
  6 Afghanistan AFG  1965 1006666638.    NA     NA   21.4    11.3    9938414
  7 Afghanistan AFG  1966 1399999967.    NA     NA   18.6     8.57   10152331
  8 Afghanistan AFG  1967 1673333418.    NA     NA   14.2     6.77   10372630
```

```
key(global_economy)
```

```
[[1]]
```

```
Country
```

Manipulating time series: tidyverts packages

Tsibble objects

- A series with 2 keys

```
olympic_running
```

```
# A tsibble: 312 x 4 [4Y]
# Key:      Length, Sex [14]
  Year Length Sex     Time
  <dbl> <fct>  <chr> <dbl>
1 1896 100m   men    12
2 1900 100m   men    11
3 1904 100m   men    11
4 1908 100m   men    10.8
5 1912 100m   men    10.8
6 1916 100m   men    NA
7 1920 100m   men    10.8
8 1924 100m   men    10.6
9 1928 100m   men    10.8
10 1932 100m  men    10.3
# ... with 302 more rows
```

```
key(olympic_running)
```

```
[[1]]
Length
[[2]]
Sex
```

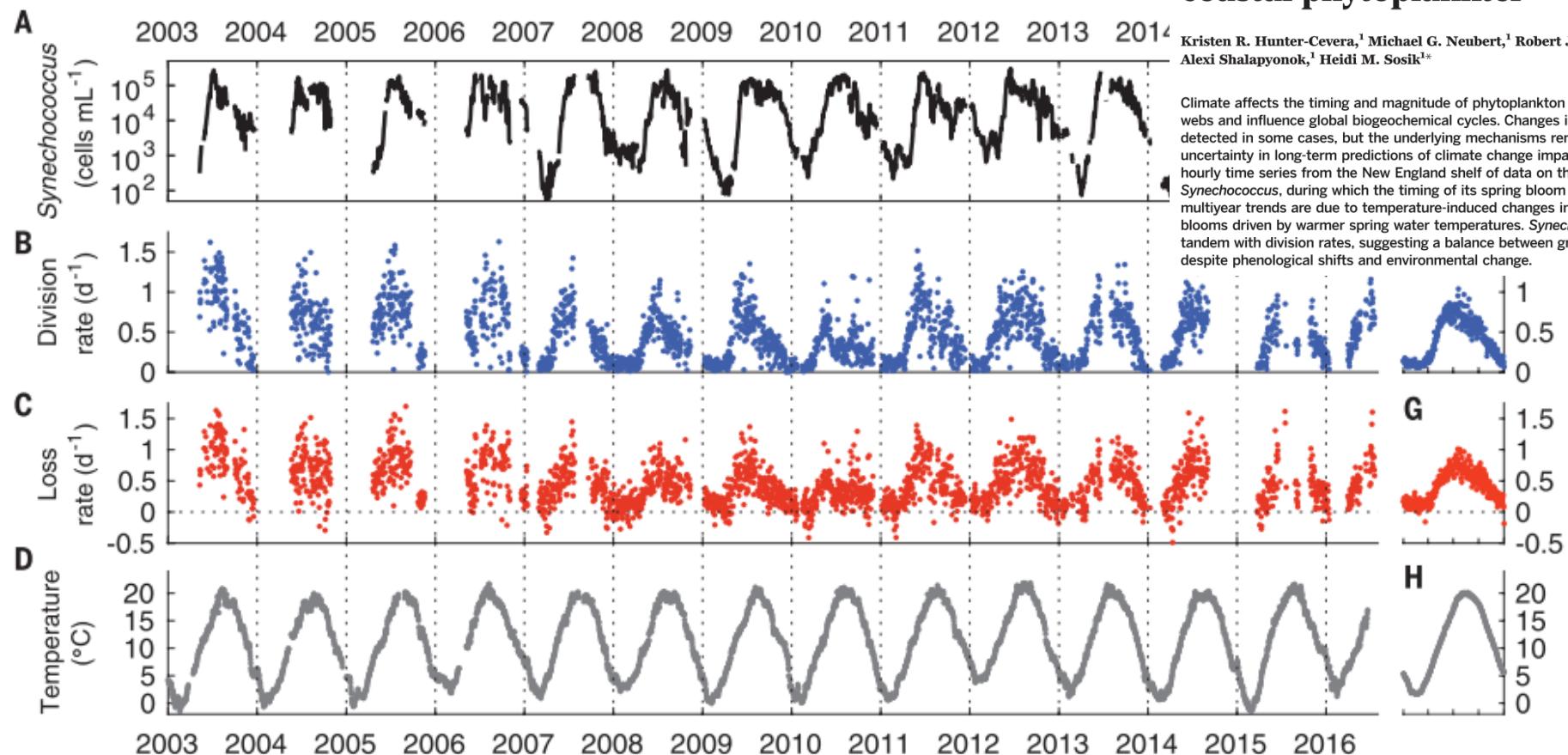
Marine phytoplankton bloom (*Synechococcus*)

PLANKTON DYNAMICS

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Create a tsibble

Read file

```
syn ← read_tsv("data/Syn_temp_light_data.txt", na = c("", "NaN"))
```

Parsed with column specification:

```
cols(  
  Date = col_character(),  
  `Daily Avg. Synechococcus (cells/mL)` = col_double(),  
  `Division rate (1/d)` = col_double(),  
  `Loss rate (1/d)` = col_double(),  
  `Net growth rate (1/d)` = col_double(),  
  `Daily minimum mode of cell volume (um^3)` = col_double(),  
  `PE fluorescence at dawn` = col_double(),  
  `PE fluorescence at dawn normalized by cell volume at dawn (1/um^3)` = col_double(),  
  `Temperature (degree Celsius)` = col_double(),  
  `Daily incident radiation (MJ/um^2)` = col_double()  
)
```

Create a tsibble

Columns

- Many columns have names not compatible with R
- No data of interest in first rows and last rows
- We are going to concentrate on only 4 columns:
 - temperature
 - light
 - *Synechococcus* concentration

Date	Daily Avg. <i>Synechococcus</i> (cells/mL)	Division rate (1/d)	Loss rate (1/d)	Net growth rate (1/d)	Daily minimum mode of cell volume (μm^3)	PE fluorescence at dawn	PE fluorescence at dawn normalized by cell volume at dawn (1/ μm^3)	Temperature (degree Celsius)	Daily incident radiation (MJ/ μm^2)
01-Jan-2003								4.21	2.11
02-Jan-2003								4.06	1.84
03-Jan-2003								3.68	1.53
04-Jan-2003								3.74	3.38
05-Jan-2003								3.82	8.14

Create a tsibble

Rename and select columns then filter

```
syn ← syn %>%
  mutate(Date = lubridate::dmy(Date)) %>%
  rename(date = Date,
         temperature= `Temperature (degree Celsius)` ,
         syn_ml = `Daily Avg. Synechococcus (cells/mL)` ,
         radiation= `Daily incident radiation (MJ/um^2)` ) %>%
  select(date, syn_ml, temperature, radiation) %>%
  filter(date > lubridate::ymd("2003-05-28") & date < lubridate::ymd("2018-09-04"))
```

date	syn_ml	temperature	radiation
2003-05-29	3344.51	11.95	22.83
2003-05-30	3521.90	12.00	28.28
2003-05-31	3939.43	11.92	19.40
2003-06-01	4796.46	11.70	
2003-06-02	4348.95	11.55	

Create a tsibble

Transform to long form and create tsibble

```
syn_long ← syn %>%
  pivot_longer(-date,
    names_to = "parameter",
    values_to = "value" )

tsyn ← tsibble::as_tsibble(syn_long,
                           index = date,
                           key = parameter,
                           regular = TRUE,
                           validate = TRUE)
```

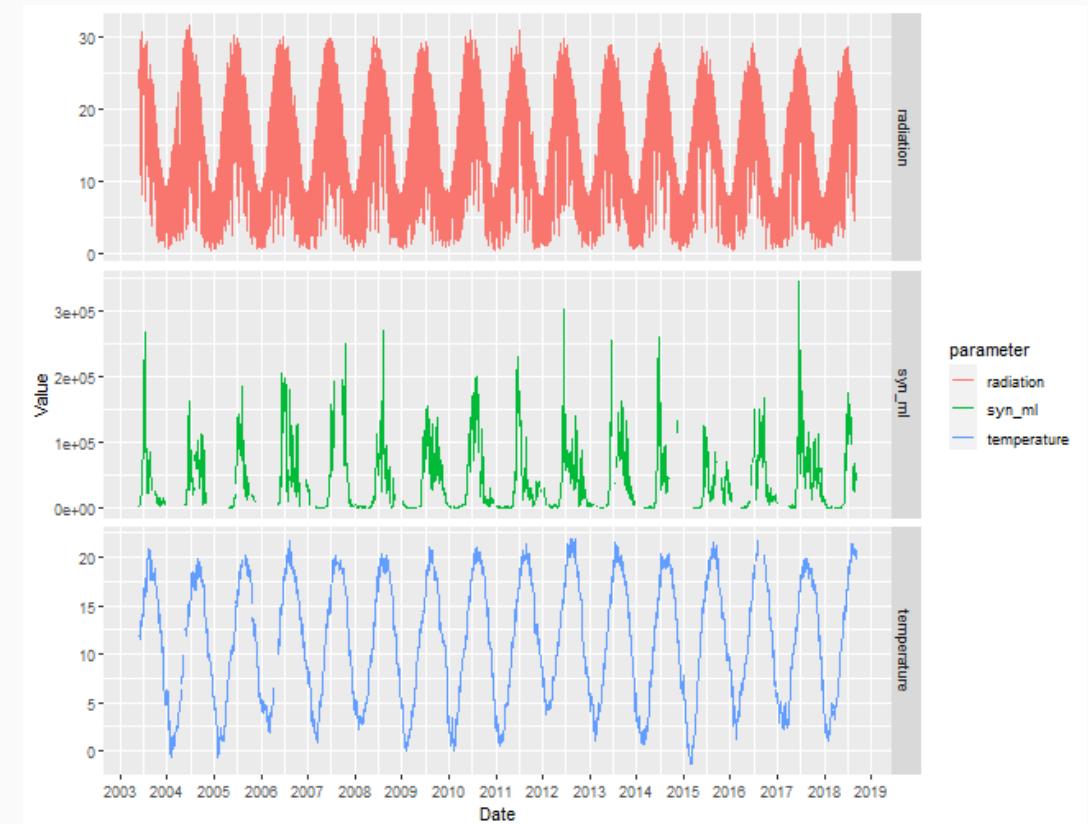
```
# A tsibble: 16,731 x 3 [1D]
# Key:      parameter [3]
#           date      parameter value
#           <date>    <chr>     <dbl>
1 2003-05-29 radiation  22.8
2 2003-05-30 radiation  28.3
3 2003-05-31 radiation  19.4
4 2003-06-01 radiation  NA
5 2003-06-02 radiation  NA
6 2003-06-03 radiation  NA
7 2003-06-04 radiation  NA
8 2003-06-05 radiation  10.6
9 2003-06-06 radiation  29.6
10 2003-06-07 radiation NA
# ... with 16,721 more rows
```

Plot data

Use autoplot

```
autoplot(tsyn) +  
  xlab("Date") + ylab("Value") +  
  scale_x_date(date_breaks="1 year",  
               date_labels = "%Y") +  
  facet_grid(rows = vars(parameter),  
             scales= "free_y")
```

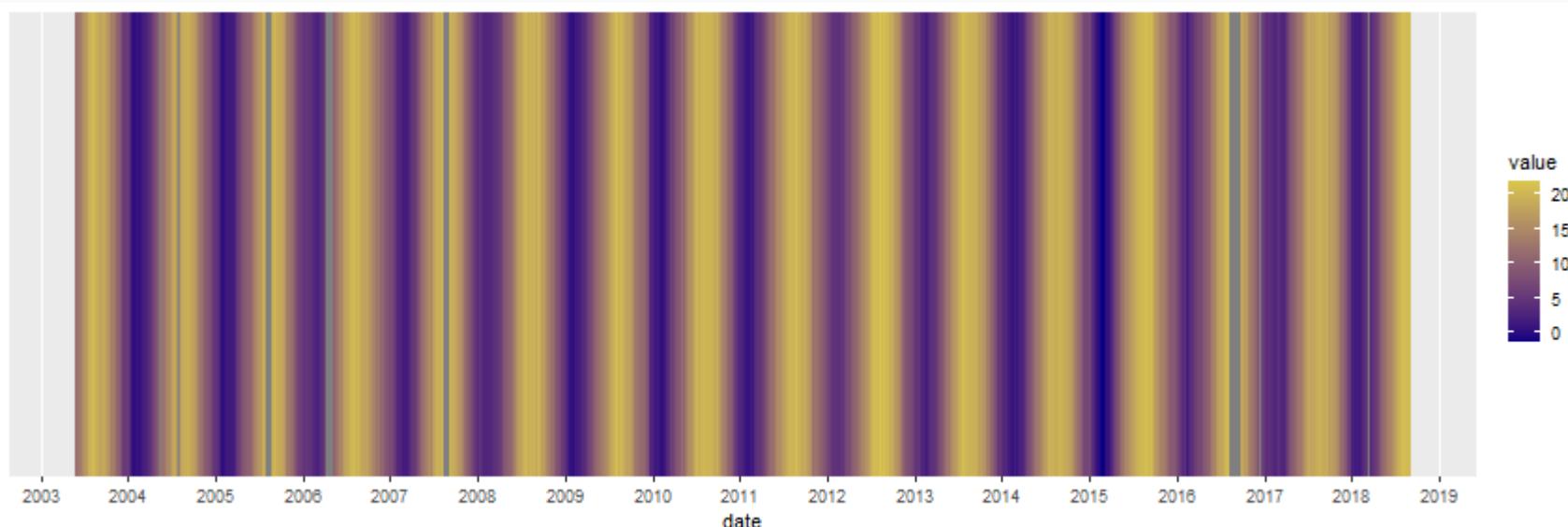
- Can also use ggplot2 of course



Plot data

Tiles

```
tsyn %>%
  filter( parameter = "temperature") %>%
  ggplot(aes(x = date, y = 1)) +
  geom_tile(aes(fill = value)) +
  scale_fill_gradient2(low = "navy", mid = "yellow", high = "red", midpoint = 28) +
  ylab("") + scale_y_discrete(expand = c(0, 0)) +
  scale_x_date(date_breaks="1 year", date_labels = "%Y")
```

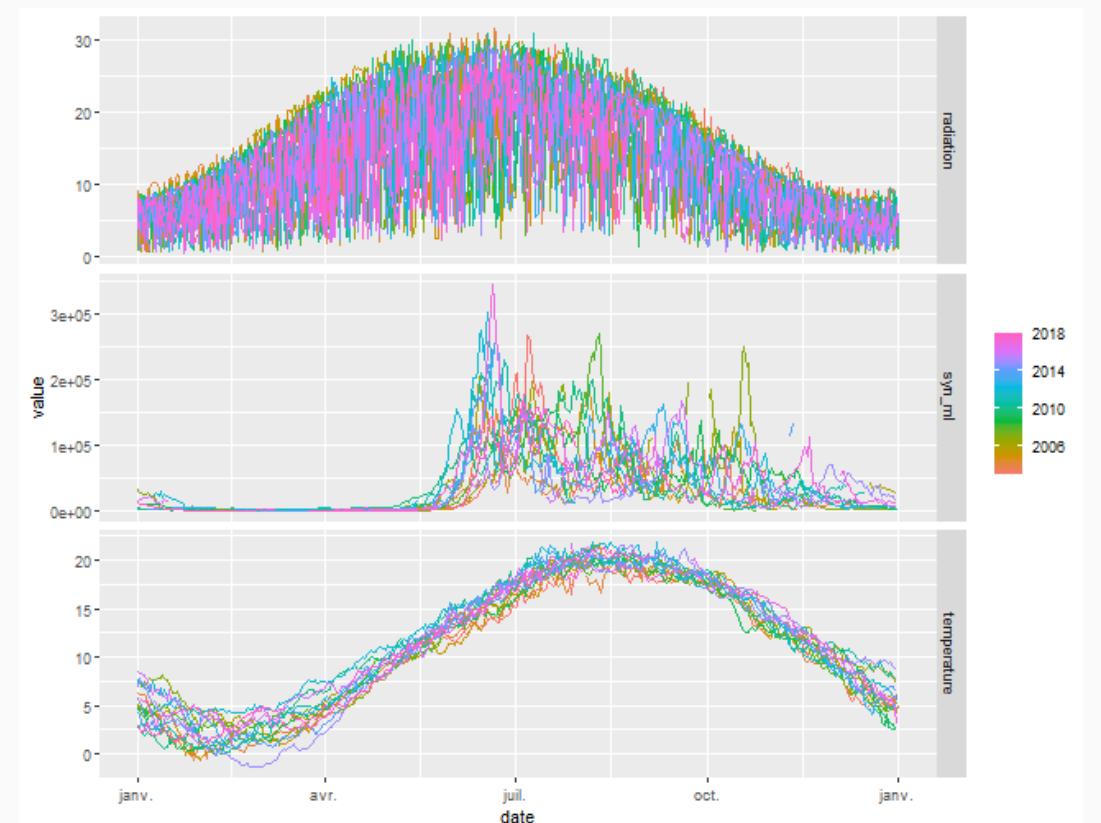


Plot data

Season plots

For all variables

```
tsyn %>%
  feasts::gg_season(y=value, period="year")
```

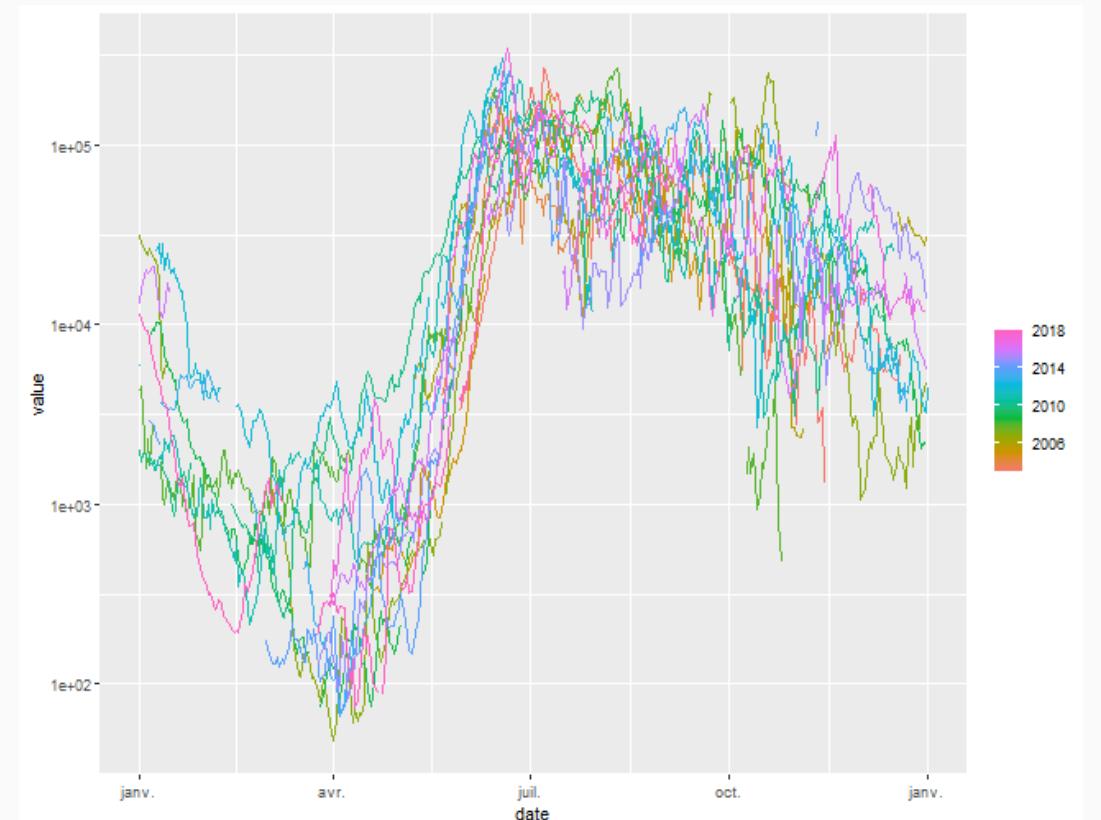


Plot data

Season plots

For cell concentration better to use log scale

```
tsyn %>% filter(parameter = "syn_ml") %>%
  feasts::gg_season(y=value, period="year") +
  scale_y_log10()
```



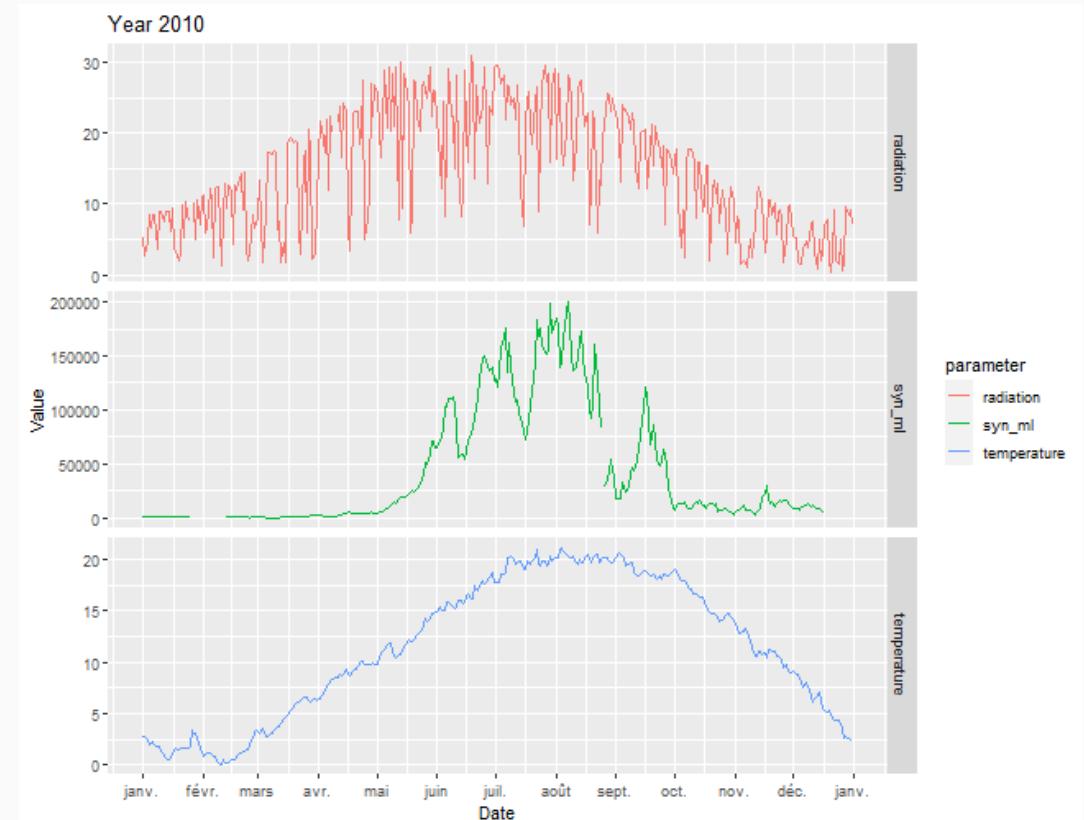
Plot data

Focus on one year

```
tsyn %>%
  filter(year(date) == 2010) %>%
  autoplot() +
  xlab("Date") + ylab("Value") +
  scale_x_date(date_breaks = "1 month",
               date_labels = "%b") +
  facet_grid(rows = vars(parameter),
             scales = "free_y") +
  ggtitle("Year 2010")
```

Note holes in data.

These holes must be filled before time series analysis



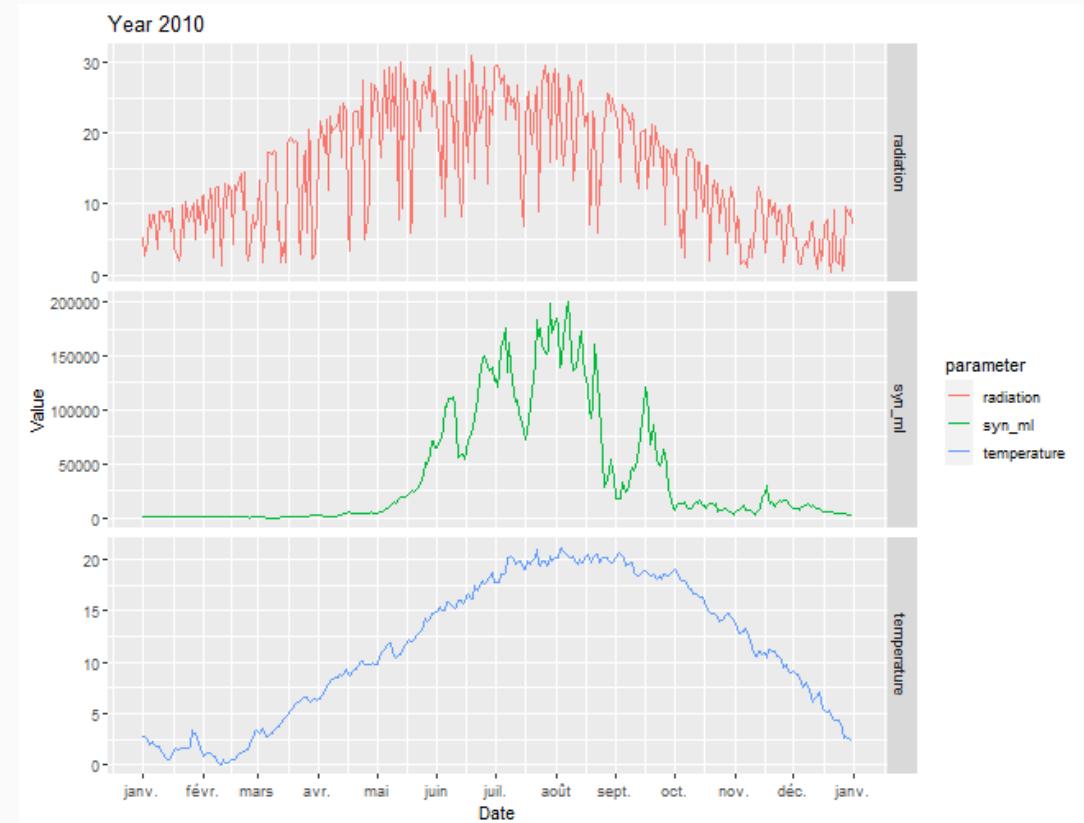
Cleaning and smoothing the data

Estimating missing values

Package `zoo`

- `zoo::na.approx()` - Linear interpolation
- `zoo::na.spline()` - Spline interpolation

```
tsyn_filled <- tsyn %>%
#  filter(parameter = "temperature") %>%
  tsibble::group_by_key()%>%
  mutate(value = zoo::na.approx(value, na.rm = FALSE))
```



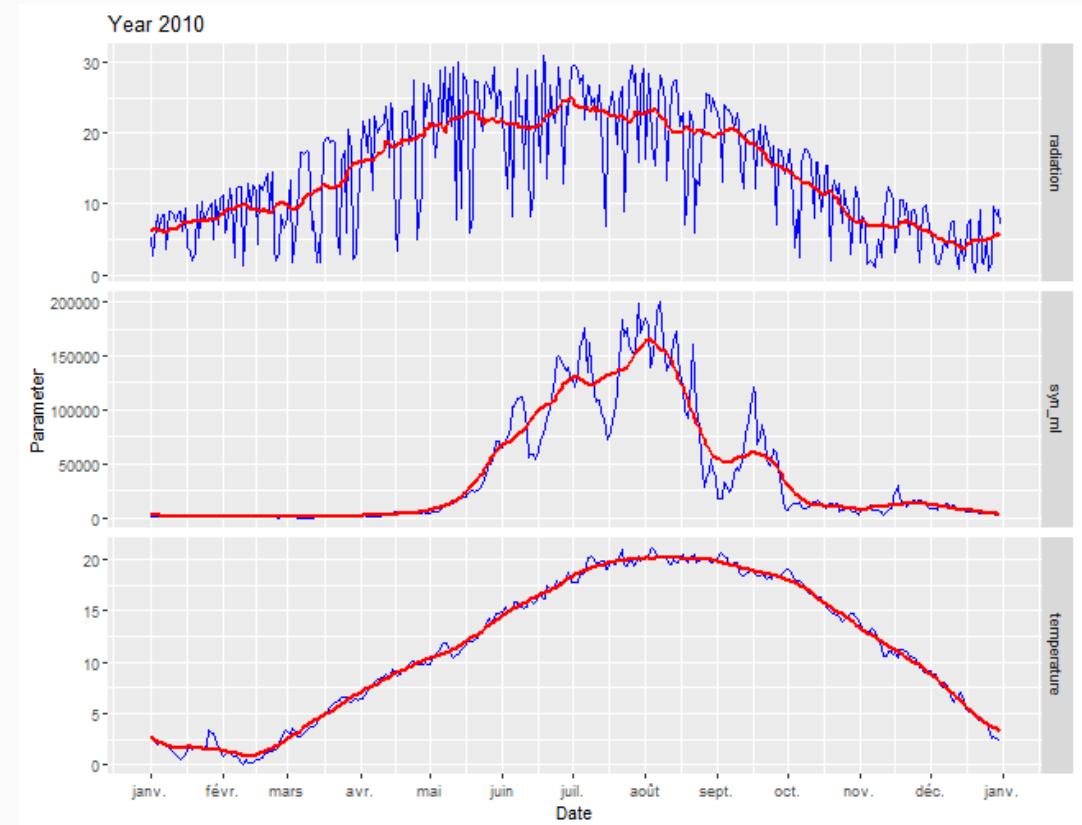
Cleaning and smoothing the data

Moving average

$$\hat{y}_t = \frac{1}{2k+1} \sum_{j=-k}^k y_{t+j}$$

- All points have same weight
- Smoothing increases with k
- Package `slider` is currently developed

```
tsyn_MA ← tsyn_filled %>%
  group_by_key() %>%
  mutate(value_MA = tsibble::slide_dbl(value,
                                         mean, na.rm = TRUE,
                                         .size = 25,
                                         .align = "center"))
```



Cleaning and smoothing the data

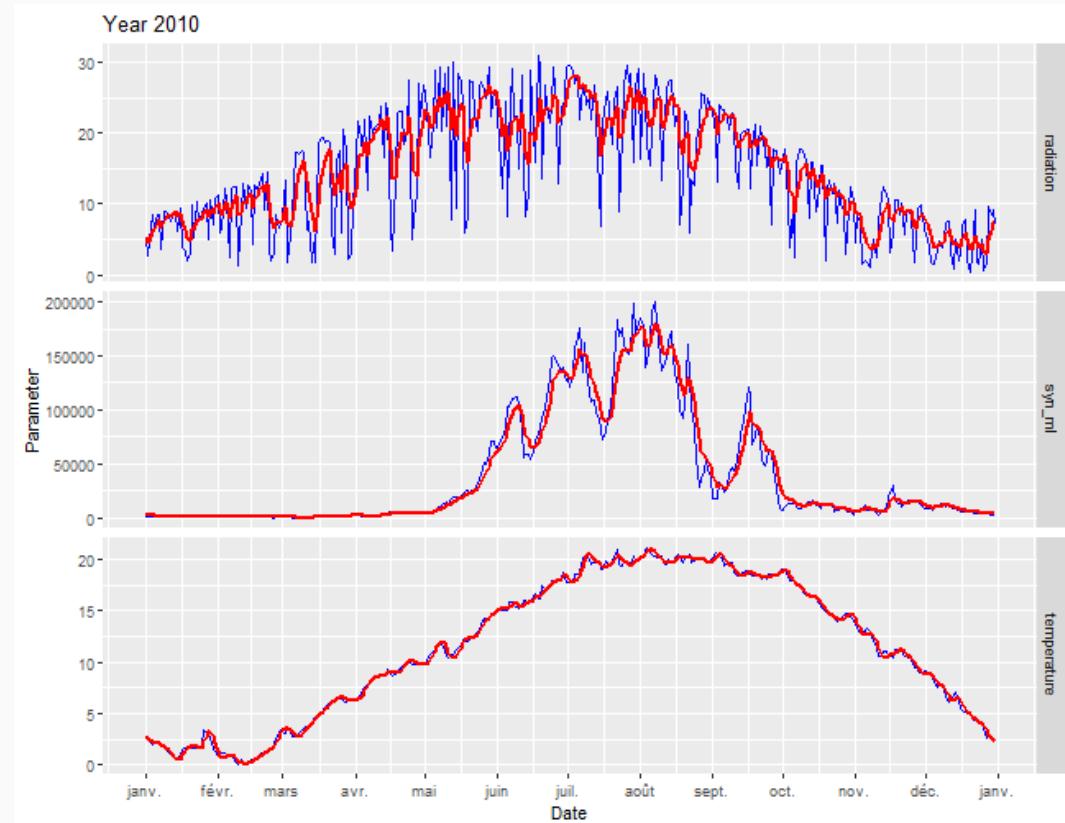
Exponential smoothing

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha) y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \dots \quad (0 \leq \alpha \leq 1)$$

- Forecasting method (use points from past only)
- Recent points have more weight
- Smoothing increases with (α) decreasing

```
tsyn_ETS ← tsyn_filled %>%
  model(fable::ETS(value ~
    season(period = "1 year") +
    trend(alpha = 0.3)))
```

parameter	.model	date	value	level	slope	remainder
radiation	fable::ETS(value ~ season(period = "1 year") + trend(alpha = 0.3))	2003-05-28	19.89920	0.5388970		
radiation	fable::ETS(value ~ season(period = "1 year") + trend(alpha = 0.3))	2003-05-29	22.83	21.15567	0.5391361	0.1170316
radiation	fable::ETS(value ~ season(period = "1 year") + trend(alpha = 0.3))	2003-05-30	28.28	23.67036	0.5397947	0.3035379



Determining periodicity

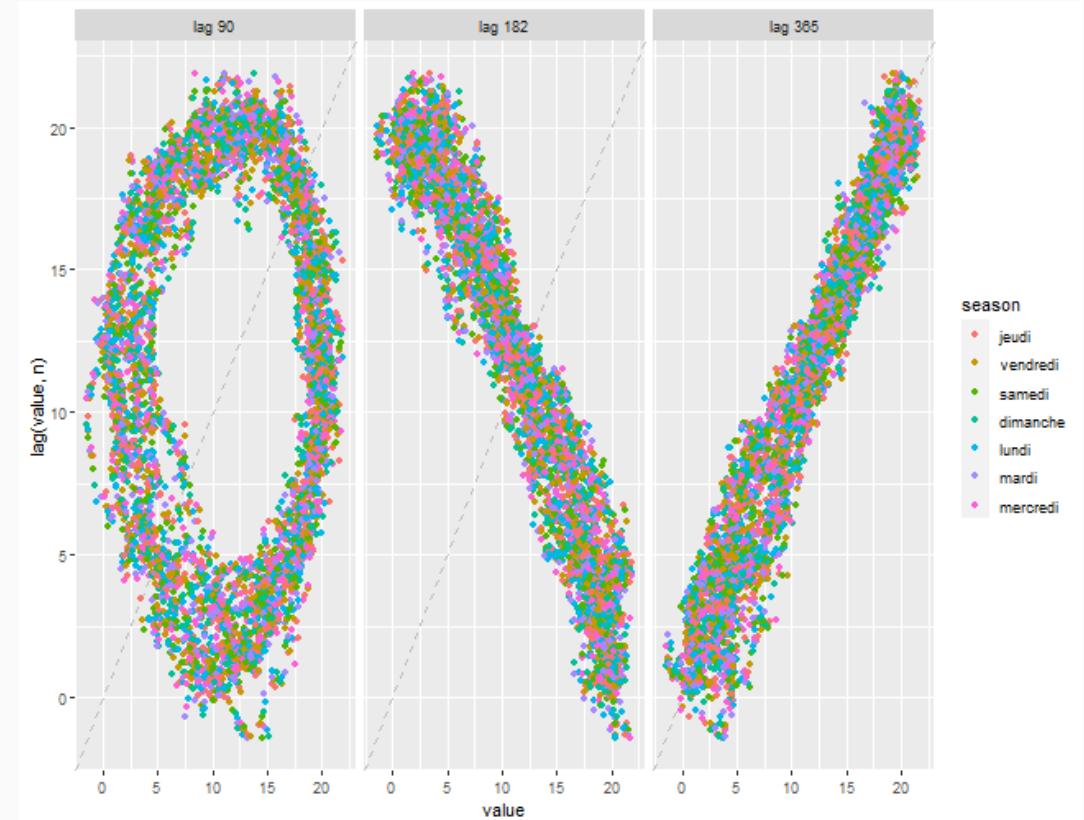
Autocorrelation

$$r_k = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2}$$

Use function `feasts::gg_lag` to visualize

- For temperature

```
tsyn %>%
  filter(parameter = "temperature") %>%
  feasts::gg_lag(lags=c(90, 182, 365), geom = "point")
```

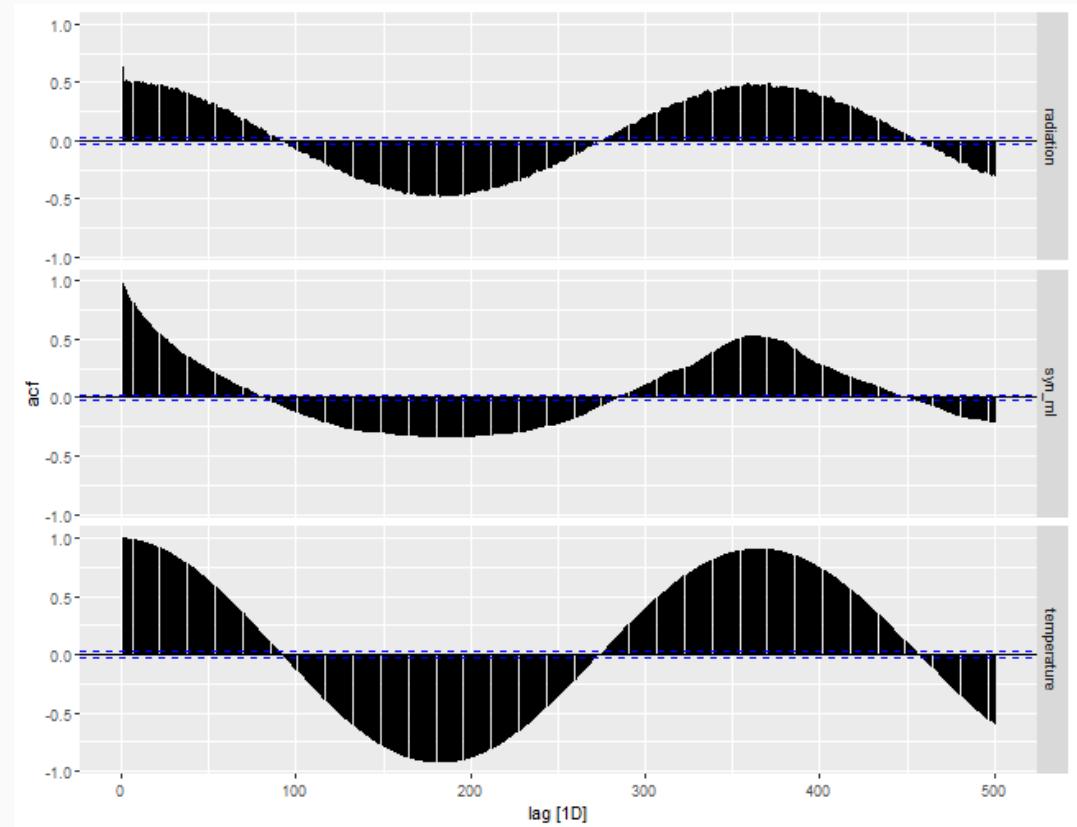


Determining periodicity

Autocorrelation

Use function `feasts::ACF` to compute

```
tsyn_filled %>%  
  feasts::ACF(value, lag_max = 500) %>%  
  autoplot() +  
  scale_x_continuous(breaks=seq(0,500, by=100))
```

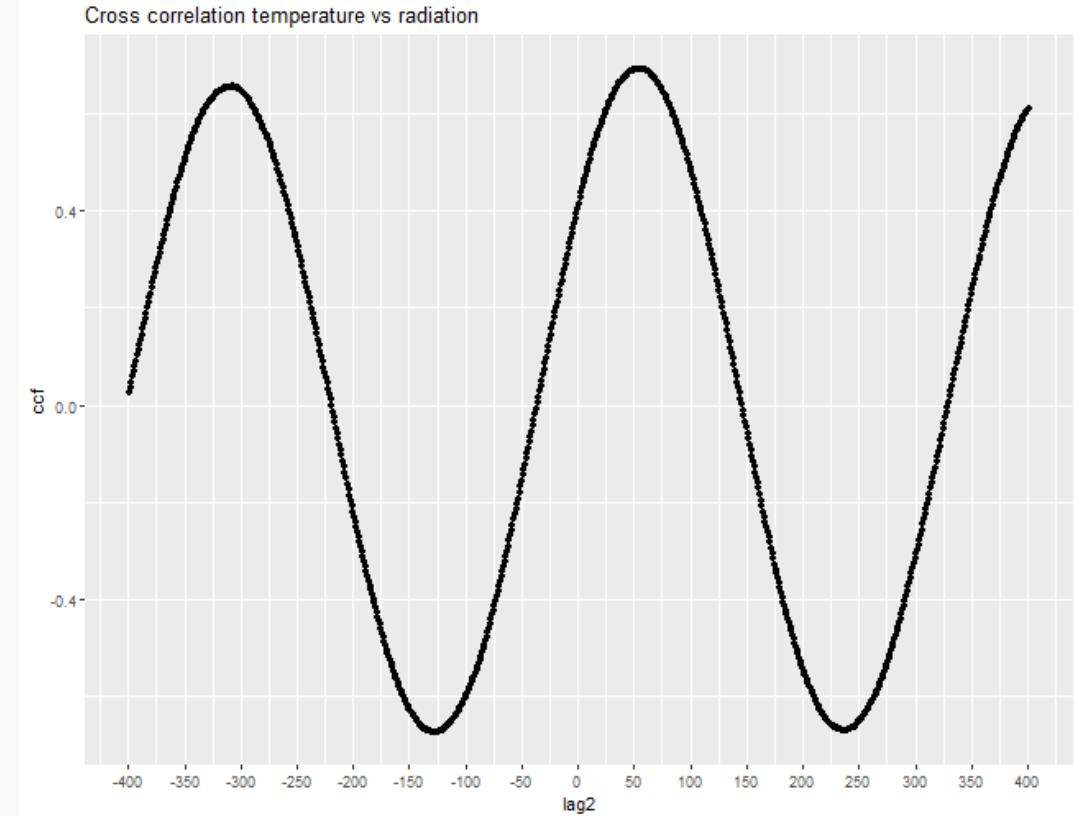


Determining periodicity

Cross correlation

- Same as autocorrelation but now between 2 series (light and temperature)
- Use function `feasts::CCF`
- Go from long form to wide form because variables must be in 2 different columns

```
lag_max = 400
tsyn_filled %>%
  pivot_wider(names_from = "parameter",
              values_from = "value") %>%
  as_tsibble(index = date) %>%
  feasts::CCF(temperature, radiation,
              lag_max = lag_max) %>%
  tibble::rowid_to_column(var = "lag2") %>%
  mutate(lag2 = lag2 - lag_max) %>%
  ggplot() +
  geom_point(aes(x=lag2, y = ccf)) +
  scale_x_continuous(breaks=seq(-lag_max,lag_max, by=50))
  ggtile("Temperature vs radiation")
```



Determining periodicity

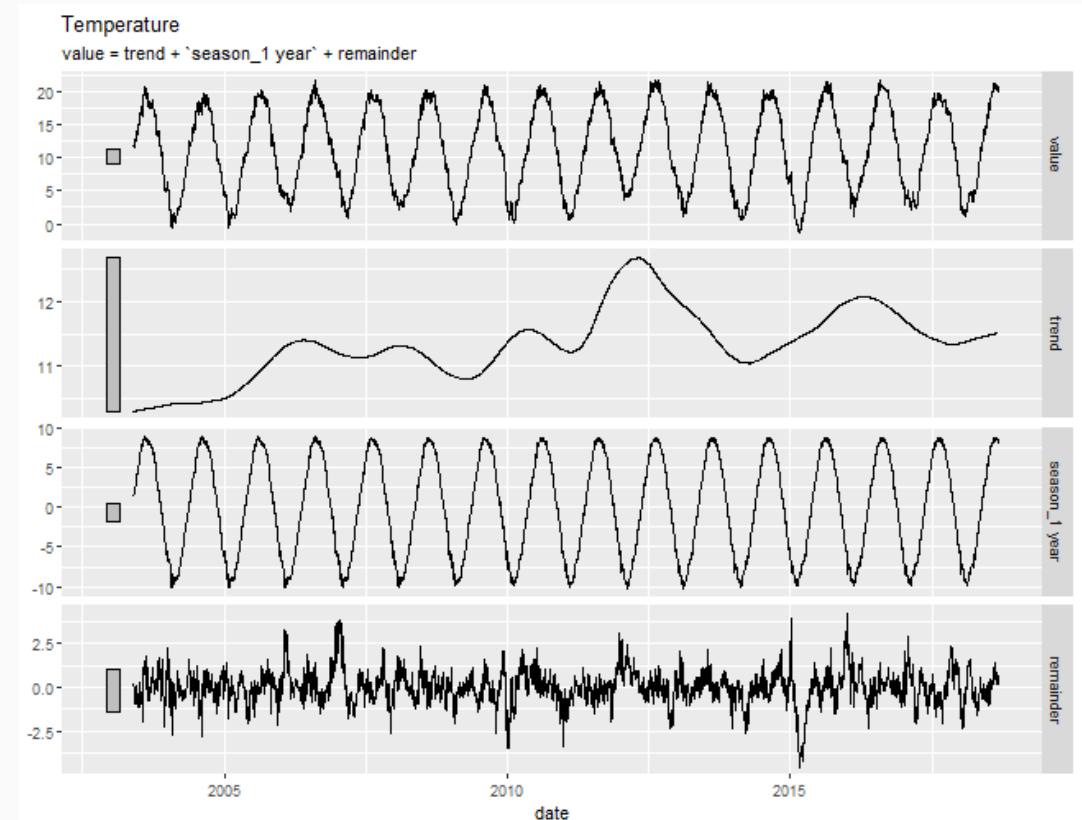
STL decomposition

Three elements: season + trend + error

- Use function `feasts::STL`
- For temperature

```
dcmp_temp <- tsyn_filled %>%
  filter(parameter = "temperature") %>%
  model(stl = feasts::STL(value ~
    season(period= "1 year", wi
    robust = TRUE))
```

parameter	.model	date	value	trend	season_1year	remainder	season_adjust
temperature	stl	2003-05-29	11.95	10.30981	1.482655	0.1575318	10.46735
temperature	stl	2003-05-30	12.00	10.31027	1.726744	-0.0370158	10.27326
temperature	stl	2003-05-31	11.92	10.31073	1.812566	-0.2032953	10.10743



Determining periodicity

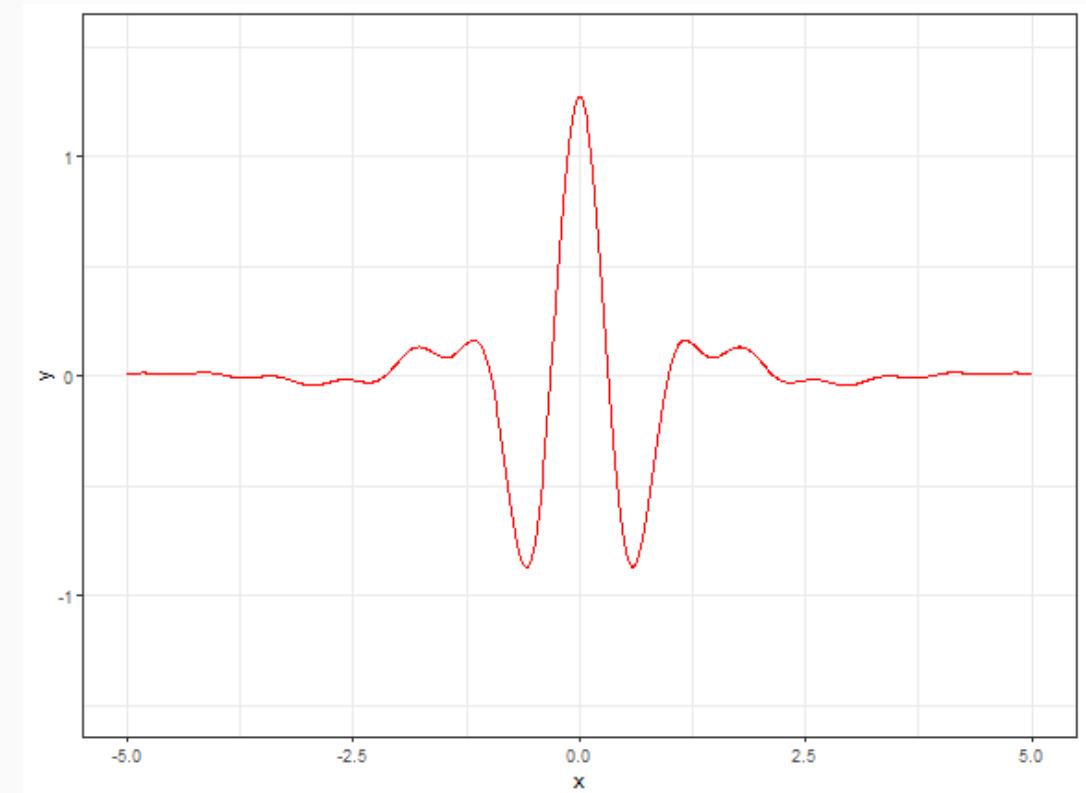
Wavelet analysis

Extension of Fourier analysis

<https://en.wikipedia.org/wiki/Wavelet>

Package `WaveletComp`

[http://www.hs-
stat.com/projects/WaveletComp/WaveletComp_guided_tour.pdf](http://www.hs-stat.com/projects/WaveletComp/WaveletComp_guided_tour.pdf)

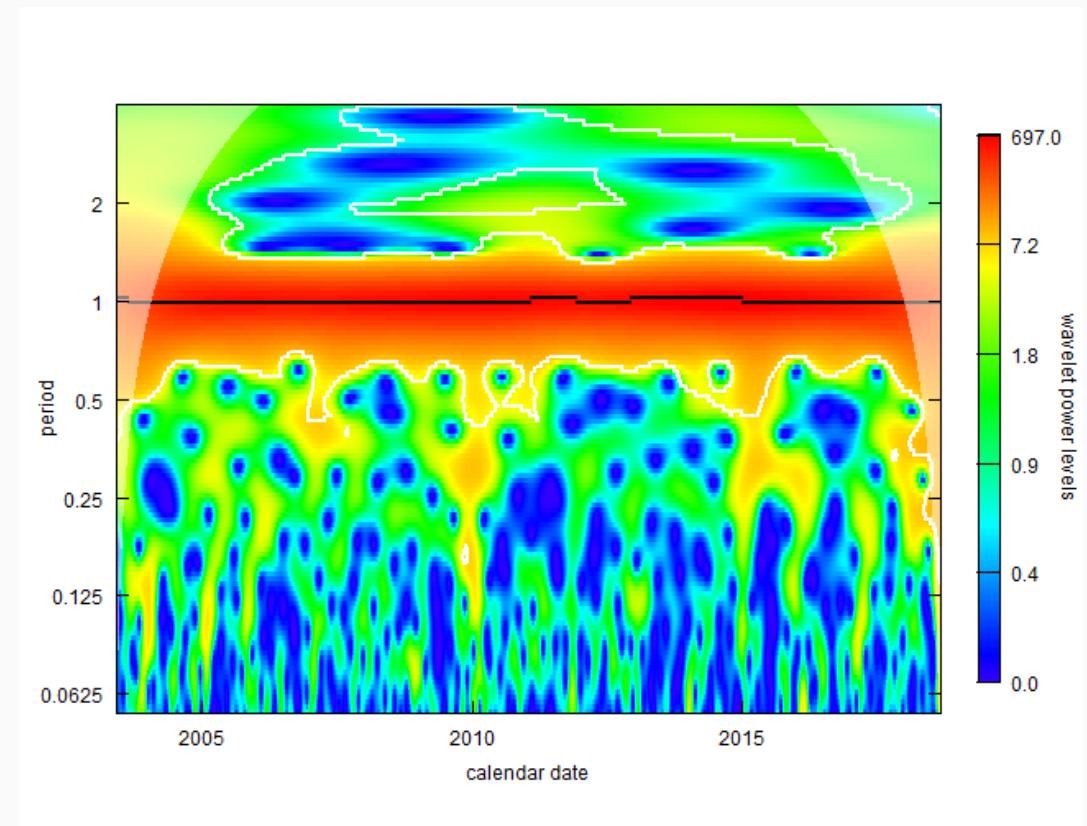


Determining periodicity

Wavelet analysis

For temperature

```
tsyn_wavelet ← tsyn_filled %>%
  filter(parameter = "temperature") %>%
  WaveletComp::analyze.wavelet( my.series = "value",
                                loess.span = 0,
                                dt = 1/365, dj = 1/20,
                                lowerPeriod = 1/18,
                                upperPeriod = 4,
                                make.pval = TRUE,
                                n.sim = 10)
```

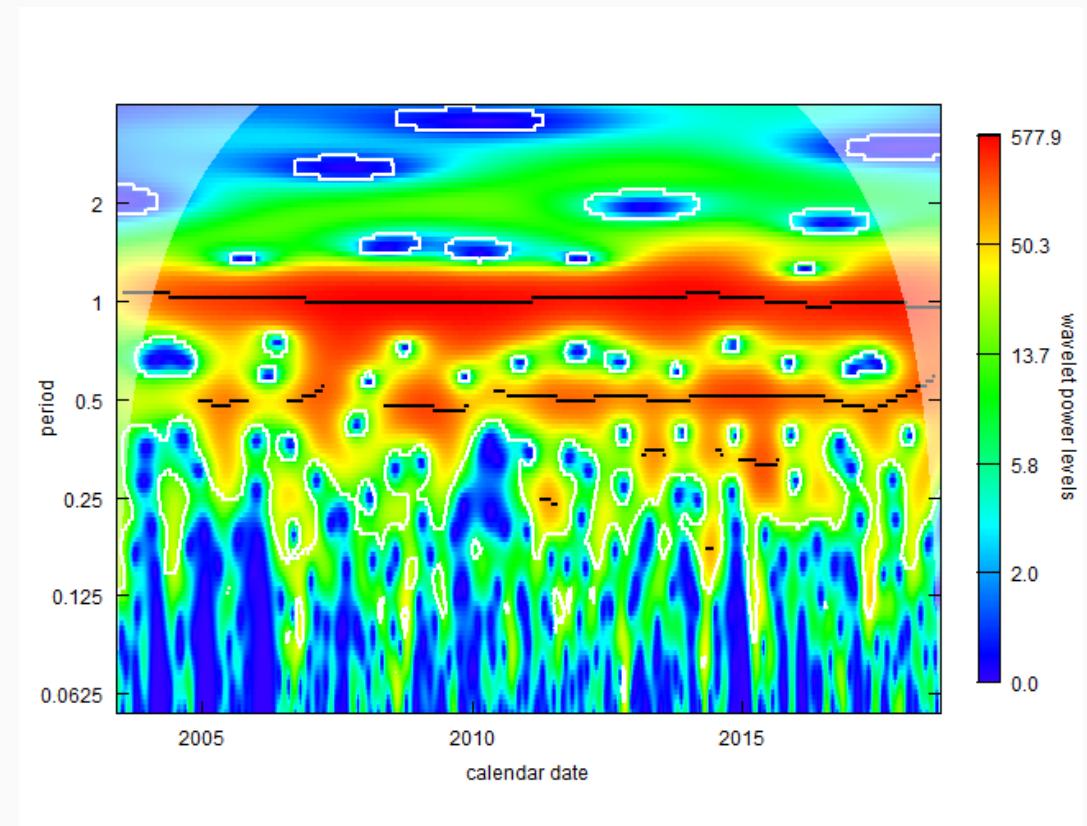


Determining periodicity

Wavelet analysis

For *Synechococcus*

```
tsyn_wavelet ← tsyn_filled %>%
  filter(parameter = "syn_ml") %>%
  mutate(value = log10(value)) %>%
  tidyr::fill(value, .direction = "down") %>%
  WaveletComp::analyze.wavelet( my.series = "value",
                                loess.span = 0,
                                dt = 1/365, dj = 1/20,
                                lowerPeriod = 1/18,
                                upperPeriod = 4,
                                make.pval = TRUE,
                                n.sim = 10)
```



Recap

What we saw today

- Time series in environmental sciences
- Manipulate dates
- Create tsibble objects
- Visualize time series
- Smooth time series
- Determine periodicity and trends

Topics to explore on your own

- Modelling
- Forecasting