Parallel Processing

Data Wrangling, Session 7d

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Code Horizons

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Load the packages, as always

```
library(here)      # manage file paths
library(socviz)    # data and some useful functions
library(tidyverse) # your friend and mine

## Magic new package
# install.packages("furrr")
library(furrr) # Also loads `future`
```

```
Loading required package: future
```

Split, Apply, Combine

A lot of analysis has this pattern

We start with a dataset

We **split** it into pieces, usually according to some feature or categorical variable, or by file or something.

We do something—the *same* thing—to each of those pieces. That is we **apply** a function or procedure to the pieces. That procedure returns some result for each piece. The result will be of the same form: a number, a vector of counts, summary statistics, a model, a list, whatever.

Finally we **combine** those results into a final piece of output, usually a tibble or somesuch.

For example

`dplyr` is all about this.

```
gss_sm ▷
  count(bigregion)
```

```
# A tibble: 4 × 2
  bigregion     n
  <fct>     <int>
1 Northeast   488
2 Midwest     695
3 South      1052
4 West        632
```

We *split* into groups, *apply* the `sum()` function within the groups, and *combine* the results into a new tibble showing the resulting sum per group. The various dplyr functions are oriented to doing this in a way that gives you a consistent set of outputs.

For example: split

We can split, apply, combine in various ways.

Base R has the `split()` function:

```
out ← mtcars ▷
  split(mtcars$cyl)
summary(out) # mtcars split into a list of data frames by the `cyl` variable
```

```
  Length Class      Mode
4 11     data.frame list
6 11     data.frame list
8 11     data.frame list
```

For example: split

Tidyverse has `group_split()`:

```
out ← mtcars ▷
  group_split(cyl)
out
```

```
<list_of<
  tbl_df<
    mpg : double
    cyl : double
    disp: double
    hp  : double
    drat: double
    wt  : double
    qsec: double
    vs  : double
    am  : double
    gear: double
    carb: double
  >
>[3]>
[[1]]
# A tibble: 11 × 11
     mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear  carb
   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
```

For example: apply

The application step is “I want to fit a linear model to each piece”

```
out ← mtcars ▷
  group_split(cyl) ▷
  map(\(df) lm(mpg ~ wt + hp + gear, data = df))
```

For example: apply

The application step is “I want to fit a linear model to each piece” and get a summary

```
mtcars ▷
  group_split(cyl) ▷
  map(\(df) lm(mpg ~ wt + hp + gear, data = df))  ▷
  map(summary) ▷
  map_dbl("r.squared")
```

```
[1] 0.7301860 0.6597413 0.4995237
```

For example: combine

In this case the “combine” step is implicitly at the end: we get a vector of R squareds back, and it’s as long as the number of groups.

```
mtcars ▷
  group_split(cyl) ▷
  map(\(df) lm(mpg ~ wt + hp + gear, data = df))  ▷
  map(summary) ▷
  map_dbl("r.squared")
```

```
[1] 0.7301860 0.6597413 0.4995237
```

For example: apply

This is also what we're doing more elegantly (staying within a tibble structure) if we `nest()` and use `broom` to get a summary out.

```
mtcars ▷
  group_by(cyl) ▷
  nest() ▷
  mutate(model = map(data, \(df) lm(mpg ~ wt + hp + gear, data = df)),
         perf = map(model, broom::glance)) ▷
  unnest(perf)
```

```
# A tibble: 3 × 15
# Groups:   cyl [3]
    cyl data     model  r.squared adj.r.squared sigma statistic p.value    df
  <dbl> <list>   <list>     <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>
1     6 <tibble> <lm>       0.660         0.319  1.20      1.94  0.300      3
2     4 <tibble> <lm>       0.730         0.615  2.80      6.31  0.0211     3
3     8 <tibble> <lm>       0.500         0.349  2.06      3.33  0.0648     3
# ℹ 6 more variables: logLik <dbl>, AIC <dbl>, BIC <dbl>, deviance <dbl>,
#   df.residual <int>, nobs <int>
```

How this happens

In each of these cases, the data is processed *sequentially* or *serially*. R splits the data according to your instructions, applies the function or procedure to each one in turn, and combines the outputs in order out the other side. Your computer's processor is handed each piece in turn.

How this happens

For small tasks that's fine. But for bigger tasks it gets inefficient quickly.

```
## From Henrik Bengtsson's documentation for future/furr
slow_sum ← function(x) {
  sum ← 0
  for (value in x) {
    Sys.sleep(1.0)  ## one-second slowdown per value
    sum ← sum + value
  }
  sum
}

# This takes > ten seconds to run.
tictoc::tic()
slow_sum(1:10)
```

```
[1] 55
```

```
tictoc::toc()
```

```
10.036 sec elapsed
```

If *this* is the sort of task we have to apply to a bunch of things, it's going to take ages.

That's Embarrassing

A feature of many split-apply-combine activities is that it *does not matter* what order the "apply" part happens to the groups. All that matters is that we can combine the results at the end, no matter what order they come back in. E.g. in the `mtcars` example the model being fit to the 4-cylinder cars group doesn't depend in any way on the results of the model being fit to the 8-cylinder group.

This sort of situation is *embarrassingly parallel*.

That's Embarrassing

When a task is embarrassingly parallel, and the number of pieces or groups is large enough or complex enough, then if we can do them at the same time then we should. There is some overhead—we have to keep track of where each piece was sent and when the results come back in—but if that's low enough in comparison to doing things serially, then we should parallelize the task.

Multicore Computing

Parallel computing used to mean “I have a cluster of computers at my disposal”. But modern CPUs are constructed in a semi-modular fashion. They have some number of “cores”, each one of which is like a small processor in its own right. In effect you have a computer cluster already.

Some Terms

Socket: The physical connection on your computer that houses the processor. These days, mostly there's just one.

Core: The part of the processor that actually performs the computation. Most modern processors have multiple cores. Each one can do wholly independent work.

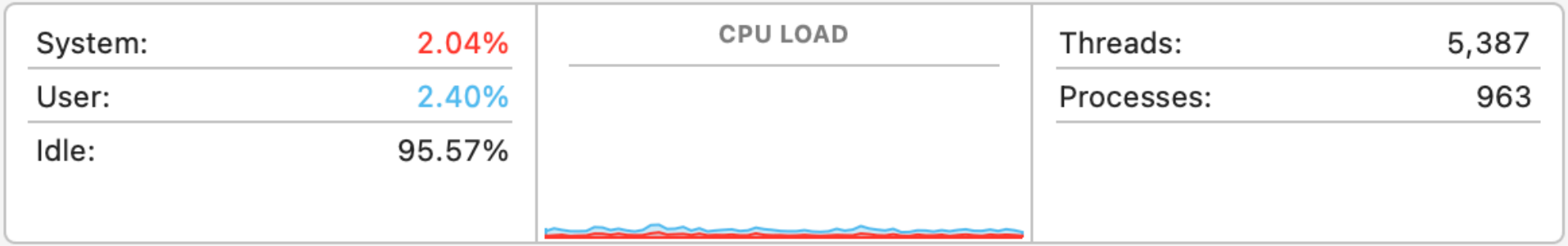
Process: A single instance of a running task or program (R, Slack, Chrome, etc). A core can only run one process at a time. But, cores are *fast*. And so, they can run many *threads*

Thread: A piece of a process that can share memory and resources with other threads. If you have enough power you can do something Intel called **hyperthreading**, which is a way of dividing up a physical core into (usually) two *logical* cores that work on the same clock cycle and share some resources on the physical core.

Cluster: A collection of things that are capable of hosting cores. Might be a single socket (on your laptop) or an old-fashioned room full of many physical computers that can be made to act as if they were a single machine.

Multicore Computing

Most of the time, even when we are using them, our computers sit around doing PRETTY MUCH NOTHING.




```
## How many cores do we have?
parallelly::availableCores()
```

```
system
    16
```

Remember, processor clock cycles are *really fast*. They're measured in billions of cycles per second.

We need to put those cores to work!

Future and furrr

These packages make parallel computing *way* more straightforward than it used to be. In particular, for Tidyverse-centric workflows, `furrr` provides a set of `future_` functions that are drop-in replacements for `map` and friends. So `map()` becomes `future_map()` and so on.

We set things up like this:

```
# library(furrr) # We did this already
plan(multisession) # Default will use the available resources
## Note difference between multisession and multicore
## [tl;dr: the latter is faster, but you can't use it on Windows]
```

Toy Example

```
# Another slow function (from
# Grant McDermott this time)
slow_square ← function(x = 1) {
    x_sq ← x^2
    out ←  tibble(value = x, value_sq = x_sq)
    Sys.sleep(2) # Zzzz
    out
}

tictoc::tic("Serially")
## This is of course way slower than just writing
## slow_square(1:15) but nvm that for now
serial_out ← map(1:15, slow_square) ▷
  list_rbind()
tictoc::toc()
```

```
Serially: 30.099 sec elapsed
```

Toy Example

```
tictoc::tic("Parallelized")
parallel_out ←  future_map_dfr(1:15, slow_square)
tictoc::toc()
```

```
Parallelized: 3.825 sec elapsed
```

```
identical(serial_out, parallel_out)
```

```
[1] TRUE
```

NOAA Data

Data obtained with:

```
mkdir raw
cd raw
wget --no-parent -r -l inf --wait 5 --random-wait 'https://www.ncei.noaa.gov/data/sea-surface-temperature-optimum-interpolation/v2.1/access/avhrr/'
```

This tries to be polite with the NOAA: it enforces a wait time and in addition randomizes it to make it variably longer. Note also no boundary on depth of folder recursion. There are a lot of files (>15,000). Doing it this way will take several *days* in real time (though much much less in actual transfer time of course).

NOAA Temperature Data

Raw data directories:

```
basename(fs::dir_ls(here::here("avhrr")))
```

```
  [1] "198109" "198110" "198111" "198112" "198201" "198202" "198203" "198204"
  [9] "198205" "198206" "198207" "198208" "198209" "198210" "198211" "198212"
 [17] "198301" "198302" "198303" "198304" "198305" "198306" "198307" "198308"
 [25] "198309" "198310" "198311" "198312" "198401" "198402" "198403" "198404"
 [33] "198405" "198406" "198407" "198408" "198409" "198410" "198411" "198412"
 [41] "198501" "198502" "198503" "198504" "198505" "198506" "198507" "198508"
 [49] "198509" "198510" "198511" "198512" "198601" "198602" "198603" "198604"
 [57] "198605" "198606" "198607" "198608" "198609" "198610" "198611" "198612"
 [65] "198701" "198702" "198703" "198704" "198705" "198706" "198707" "198708"
 [73] "198709" "198710" "198711" "198712" "198801" "198802" "198803" "198804"
 [81] "198805" "198806" "198807" "198808" "198809" "198810" "198811" "198812"
 [89] "198901" "198902" "198903" "198904" "198905" "198906" "198907" "198908"
 [97] "198909" "198910" "198911" "198912"
 [ reached getOption("max.print") -- omitted 421 entries ]
```

NOAA Temperature Data

Raw data files, in netCDF (Version 4) format

```
basename(fs::dir_ls(here::here("avhrr", "202402")))
```

```
 [1] "oisst-avhrr-v02r01.20240201.nc" "oisst-avhrr-v02r01.20240202.nc"
 [3] "oisst-avhrr-v02r01.20240203.nc" "oisst-avhrr-v02r01.20240204.nc"
 [5] "oisst-avhrr-v02r01.20240205.nc" "oisst-avhrr-v02r01.20240206.nc"
 [7] "oisst-avhrr-v02r01.20240207.nc" "oisst-avhrr-v02r01.20240208.nc"
 [9] "oisst-avhrr-v02r01.20240209.nc" "oisst-avhrr-v02r01.20240210.nc"
[11] "oisst-avhrr-v02r01.20240211.nc" "oisst-avhrr-v02r01.20240212.nc"
[13] "oisst-avhrr-v02r01.20240213.nc" "oisst-avhrr-v02r01.20240214.nc"
[15] "oisst-avhrr-v02r01.20240215.nc" "oisst-avhrr-v02r01.20240216.nc"
[17] "oisst-avhrr-v02r01.20240217.nc" "oisst-avhrr-v02r01.20240218.nc"
[19] "oisst-avhrr-v02r01.20240219.nc" "oisst-avhrr-v02r01.20240220.nc"
[21] "oisst-avhrr-v02r01.20240221.nc" "oisst-avhrr-v02r01.20240222.nc"
[23] "oisst-avhrr-v02r01.20240223.nc" "oisst-avhrr-v02r01.20240224.nc"
[25] "oisst-avhrr-v02r01.20240225.nc" "oisst-avhrr-v02r01.20240226.nc"
[27] "oisst-avhrr-v02r01.20240227.nc" "oisst-avhrr-v02r01.20240228.nc"
[29] "oisst-avhrr-v02r01.20240229.nc"
```

Some Prep

```
## Seasons for plotting
season <-  function(in_date){
  br = yday(as.Date(c("2019-03-01",
                      "2019-06-01",
                      "2019-09-01",
                      "2019-12-01")))
  x = yday(in_date)
  x = cut(x, breaks = c(0, br, 366))
  levels(x) = c("Winter", "Spring", "Summer", "Autumn", "Winter")
  x
}

season_lab <-  tibble(yrday = yday(as.Date(c("2019-03-01",
                                             "2019-06-01",
                                             "2019-09-01",
                                             "2019-12-01"))),
                      lab = c("Spring", "Summer", "Autumn", "Winter"))
```

NOAA Temperature Data

Raw data files

```
#install.packages("ncdf4")
#install.packages("terra")
library(terra)

## For the filename processing
## This one gives you an unknown number of chunks each with approx n elements
chunk ← function(x, n) split(x, ceiling(seq_along(x)/n))

## This one gives you n chunks each with an approx equal but unknown number of elements
chunk2 ← function(x, n) split(x, cut(seq_along(x), n, labels = FALSE))

## All the daily .nc files:
all_fnames ← as.character(fs::dir_ls(here("avhrr"), recurse = TRUE, glob = "*.nc"))
chunked_fnames ← chunk(all_fnames, 25)

length(all_fnames)
```

```
[1] 15549
```

```
length(chunked_fnames)
```

```
[1] 622
```

NOAA Temperature Data

The data is in netCDF (Version 4) format. An interesting self-documenting format. Read one in with the netCDF reader.

```
tmp ← ncdf4::nc_open(all_fnames[10000])
tmp
```

```
File /Users/kjhealy/Documents/courses/data_wrangling/avhrr/200901/oisst-avhrr-v02r01.20090120.nc
(NC_FORMAT_NETCDF4):

     4 variables (excluding dimension variables):
        short anom[lon,lat,zlev,time]   (Chunking: [1440,720,1,1])  (Compression: shuffle,level 4)
            long_name: Daily sea surface temperature anomalies
            _FillValue: -999
            add_offset: 0
            scale_factor: 0.00999999977648258
            valid_min: -1200
            valid_max: 1200
            units: Celsius
        short err[lon,lat,zlev,time]   (Chunking: [1440,720,1,1])  (Compression: shuffle,level 4)
            long_name: Estimated error standard deviation of analysed_sst
            units: Celsius
            _FillValue: -999
            add_offset: 0
            scale_factor: 0.00999999977648258
            valid_min: 0
```

NOAA Temperature Data

For analysis we are going to use the `terra` package, which understands many GIS type formats. Fundamentally we have a grid or *raster* of data that's 1440 x 720 in size. The data has several *layers*, each one a specific measure, such as sea-surface temperature, sea ice coverage, and so on.

```
tmp ← terra::rast(all_fnames[10000])
tmp
```

```
class       : SpatRaster
dimensions  : 720, 1440, 4  (nrow, ncol, nlyr)
resolution  : 0.25, 0.25  (x, y)
extent      : 0, 360, -90, 90  (xmin, xmax, ymin, ymax)
coord. ref. : lon/lat WGS 84
sources     : oisst-avhrr-v02r01.20090120.nc:anom
              oisst-avhrr-v02r01.20090120.nc:err
              oisst-avhrr-v02r01.20090120.nc:ice
              oisst-avhrr-v02r01.20090120.nc:sst
varnames    : anom (Daily sea surface temperature anomalies)
              err (Estimated error standard deviation of analysed_sst)
              ice (Sea ice concentration)
               ...
names       : anom_zlev=0, err_zlev=0, ice_zlev=0, sst_zlev=0
unit        :    Celsius,    Celsius,          %,    Celsius
time (days) : 2009-01-20
```

Terra can understand rasters that are aggregated into slabs or "bricks" covering

NOAA Temperature Data

Read one in with `terra`. Get the `sst` (Sea Surface Temperature) layer only.

```
tmp ← terra::rast(all_fnames[10000])["sst"]
tmp
```

```
class       : SpatRaster
dimensions  : 720, 1440, 1  (nrow, ncol, nlyr)
resolution  : 0.25, 0.25  (x, y)
extent      : 0, 360, -90, 90  (xmin, xmax, ymin, ymax)
coord. ref. : lon/lat WGS 84
source      : oisst-avhrr-v02r01.20090120.nc:sst
varname     : sst (Daily sea surface temperature)
name        : sst_zlev=0
unit        :    Celsius
time (days) : 2009-01-20
```

NOAA Temperature Data

What reading a *chunk* of filenames (with all their layers) does:

```
tmp2 ← terra::rast(chunked_fnames[[10]])
tmp2
```

```
class       : SpatRaster
dimensions  : 720, 1440, 100  (nrow, ncol, nlyr)
resolution  : 0.25, 0.25  (x, y)
extent      : 0, 360, -90, 90  (xmin, xmax, ymin, ymax)
coord. ref. : lon/lat WGS 84
sources     : oisst-avhrr-v02r01.19820414.nc:anom
              oisst-avhrr-v02r01.19820414.nc:err
              oisst-avhrr-v02r01.19820414.nc:ice
               ... and 97 more source(s)
varnames    : anom (Daily sea surface temperature anomalies)
              err (Estimated error standard deviation of analysed_sst)
              ice (Sea ice concentration)
               ...
names       : anom_zlev=0, err_zlev=0, ice_zlev=0, sst_zlev=0, anom_zlev=0, err_zlev=0, ...
unit        :     Celsius,    Celsius,          %,    Celsius,     Celsius,    Celsius, ...
time (days) : 1982-04-14 to 1982-05-08
```

NOAA Temperature Data

Write a function to get a file, read in the SST raster, and get its area-weighted mean, for the North Atlantic region only.

```
process_raster ← function(fnames, crop_area = c(-80, 0, 0, 60), var = "sst") {

  tdf ← terra::rast(as.character(fnames))[var] ▷
    terra::rotate() ▷    # Fix 0-360 lon
    terra::crop(crop_area) # Manually crop to a defined box. Default is Atlantic lat/lon box

  wts ← terra::cellSize(tdf, unit = "km") # For scaling

  data.frame(
    date = terra::time(tdf),
    # global() calculates a quantity for the whole grid on a particular SpatRaster
    # so we get one weighted mean per file that comes in
    wt_mean_sst = terra::global(tdf, "mean", weights = wts, na.rm=TRUE)$weighted_mean
  )
}
```

NOAA Temperature Data

Try it on one data file:

```
process_raster(all_fnames[1000]) ▷
  as_tibble()
```

```
# A tibble: 1 × 2
  date       wt_mean_sst
  <date>           <dbl>
1 1984-05-27        20.6
```

Try it on one *chunk* of data files:

```
process_raster(chunked_fnames[[500]]) ▷
  as_tibble()
```

```
# A tibble: 25 × 2
   date       wt_mean_sst
   <date>           <dbl>
 1 2015-11-02        22.8
 2 2015-11-03        22.8
 3 2015-11-04        22.8
 4 2015-11-05        22.7
 5 2015-11-06        22.7
 6 2015-11-07        22.7
 7 2015-11-08        22.6
 8 2015-11-09        22.5
 9 2015-11-10        22.5
10 2015-11-11        22.4
# ℹ 15 more rows
```

NOAA Temperature Data

Do it in parallel for all files:

```
# library(furrr) # We did this already
# plan(multisession)

tictoc::tic("Terra Method")
df ← future_map(chunked_fnames, process_raster) ▷
  list_rbind() ▷
  as_tibble() ▷
  mutate(date = ymd(date),
         year = lubridate::year(date),
         month = lubridate::month(date),
         day = lubridate::day(date),
         yrday = lubridate::yday(date),
         season = season(date))
tictoc::toc()
```

```
Terra Method: 30.309 sec elapsed
```

```
dim(df)
```

```
[1] 15549     7
```

NOAA Temperature Data

```
df |>
  slice_sample(n = 10)
```

```
# A tibble: 10 × 7
   date       wt_mean_sst  year month   day yrday season
   <date>           <dbl> <dbl> <dbl> <int> <dbl> <fct>
 1 2000-07-12        22.8  2000     7    12   194 Summer
 2 1991-11-12        21.6  1991    11    12   316 Autumn
 3 2016-06-01        21.6  2016     6     1   153 Summer
 4 2016-08-04        24.1  2016     8     4   217 Summer
 5 2005-04-23        20.3  2005     4    23   113 Spring
 6 2012-01-25        19.7  2012     1    25    25 Winter
 7 2006-11-18        22.3  2006    11    18   322 Autumn
 8 2001-12-22        20.7  2001    12    22   356 Winter
 9 1986-09-20        23.2  1986     9    20   263 Autumn
10 2016-04-01        19.6  2016     4     1    92 Spring
```

NOAA Temperature Data

Make our cores work even harder

```
## Seas of the world polygons
seas ← sf::read_sf(here("seas"))

seas
```

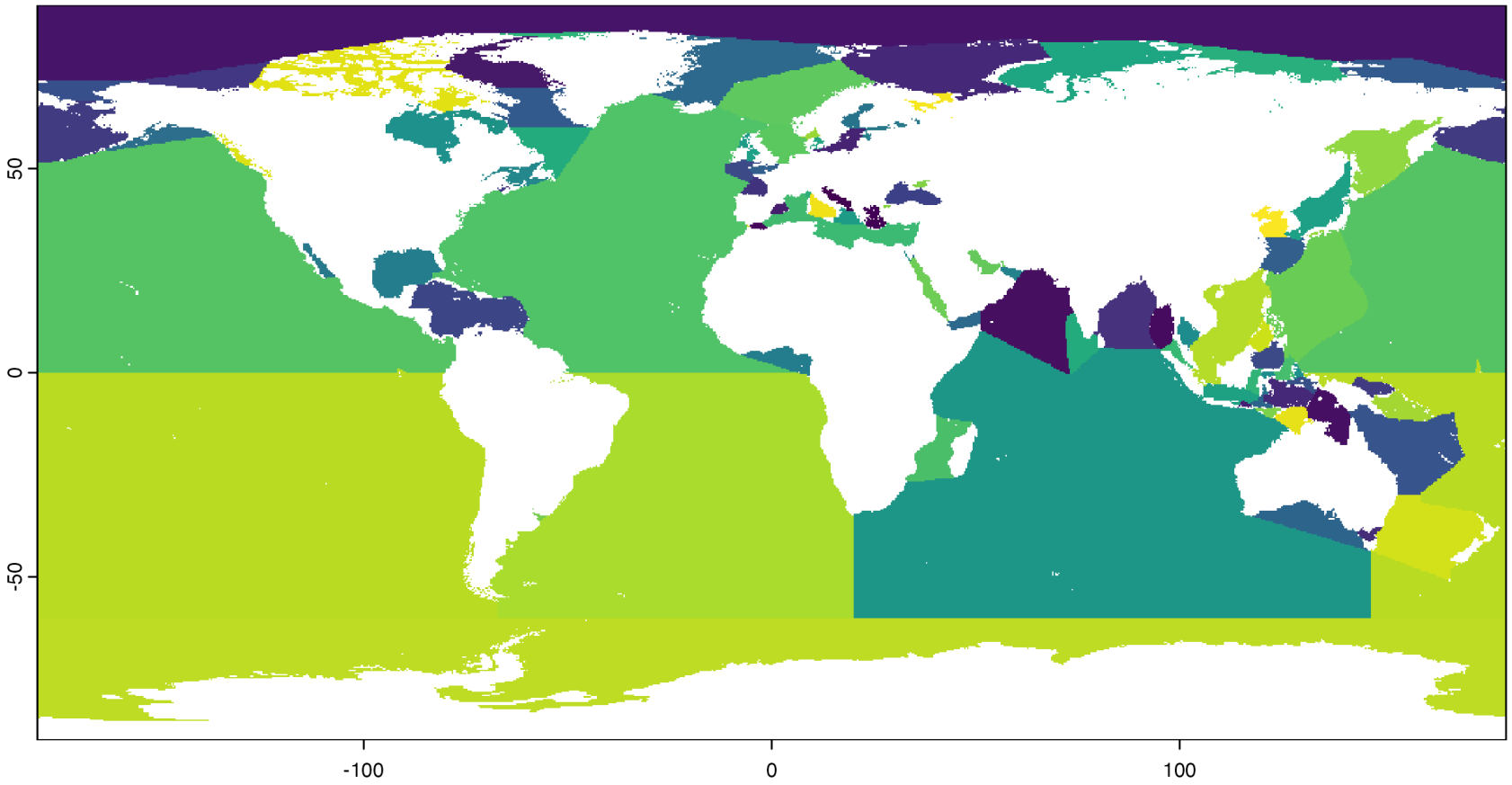
```
Simple feature collection with 101 features and 10 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -180 ymin: -85.5625 xmax: 180 ymax: 90
Geodetic CRS:  WGS 84
# A tibble: 101 × 11
   NAME          ID    Longitude Latitude min_X  min_Y max_X  max_Y   area MRGID
   <chr>         <chr>     <dbl>    <dbl> <dbl>  <dbl> <dbl>  <dbl>  <dbl> <dbl>
 1 Rio de La Pl… 33        -56.8   -35.1  -59.8 -36.4  -54.9 -31.5  3.18e4  4325
 2 Bass Strait   62A       146.    -39.5  144.  -41.4  150.  -37.5  1.13e5  4366
 3 Great Austra… 62        133.    -36.7  118.  -43.6  146.  -31.5  1.33e6  4276
 4 Tasman Sea    63        161.    -39.7  147.  -50.9  175.  -30    3.34e6  4365
 5 Mozambique C… 45A        40.9   -19.3   32.4 -26.8   49.2 -10.5  1.39e6  4261
 6 Savu Sea      48o       122.     -9.48 119.  -10.9  125.   -8.21 1.06e5  4343
 7 Timor Sea     48i       128.    -11.2  123.  -15.8  133.   -8.18 4.34e5  4344
 8 Bali Sea      48l       116.     -7.93 114.   -9.00 117.   -7.01 3.99e4  4340
 9 Coral Sea     64        157.    -18.2  141.  -30.0  170.   -6.79 4.13e6  4364
10 Flores Sea    48j       120.     -7.51 117.   -8.74 123.   -5.51 1.03e5  4341
# ℹ 91 more rows
```

NOAA Temperature Data

```
## Rasterize the seas polygons using one of the nc files
## as a reference grid for the rasterization process
## They're all on the same grid so it doesn't matter which one
one_raster ← all_fnames[1]
seas_vect ← terra::vect(seas)
tmp_tdf_seas ← terra::rast(one_raster)["sst"] ▷
  terra::rotate()
seas_zonal ← terra::rasterize(seas_vect, tmp_tdf_seas, "NAME")
```

NOAA Temperature Data

```
plot(seas_zonal, legend = FALSE)
```



Pointers and wrapping

We'll need to apply this grid of seas and oceans repeatedly — once for each `.nc` file — which means it has to get passed to all our worker cores. But it is stored as a pointer, so we can't do that directly. We need to wrap it:

```
# If we don't do this it can't be passed around
# across the processes that future_map() will spawn
seas_zonal_wrapped ← terra::wrap(seas_zonal)
```

NOAA Temperature Data

Write a function very similar to the other one.

```
process_raster_zonal ← function(fnames, var = "sst") {

  tdf_seas ← terra::rast(as.character(fnames))[var] ▷
    terra::rotate() ▷
    terra::zonal(terra::unwrap(seas_zonal_wrapped), mean, na.rm = TRUE)

  colnames(tdf_seas) ← c("ID", paste0("d_", terra::time(terra::rast(as.character(fnames))[var])))
  tdf_seas ▷
    pivot_longer(-ID, names_to = "date", values_to = "sst_wt_mean")

}
```

NOAA Temperature Data

Try it on one record:

```
process_raster_zonal(all_fnames[10000])
```

```
# A tibble: 101 × 3
   ID                    date         sst_wt_mean
   <chr>                 <chr>              <dbl>
 1 Adriatic Sea          d_2009-01-20       13.5
 2 Aegean Sea            d_2009-01-20       15.9
 3 Alboran Sea           d_2009-01-20       14.8
 4 Andaman or Burma Sea  d_2009-01-20       27.1
 5 Arabian Sea           d_2009-01-20       26.6
 6 Arafura Sea           d_2009-01-20       29.6
 7 Arctic Ocean          d_2009-01-20       -1.74
 8 Baffin Bay            d_2009-01-20       -1.58
 9 Balearic (Iberian Sea) d_2009-01-20      14.0
10 Bali Sea              d_2009-01-20       28.7
# ℹ 91 more rows
```

We'll tidy the date later. You can see we get 101 summary records per day.

NOAA Temperature Data

Try it on one *chunk* of records:

```
process_raster_zonal(chunked_fnames[[1]])
```

```
# A tibble: 2,525 × 3
   ID           date         sst_wt_mean
   <chr>        <chr>              <dbl>
 1 Adriatic Sea d_1981-09-01        23.0
 2 Adriatic Sea d_1981-09-02        23.1
 3 Adriatic Sea d_1981-09-03        22.9
 4 Adriatic Sea d_1981-09-04        22.9
 5 Adriatic Sea d_1981-09-05        22.5
 6 Adriatic Sea d_1981-09-06        22.4
 7 Adriatic Sea d_1981-09-07        22.4
 8 Adriatic Sea d_1981-09-08        22.5
 9 Adriatic Sea d_1981-09-09        22.6
10 Adriatic Sea d_1981-09-10        22.5
# ℹ 2,515 more rows
```

NOAA Temperature Data

Now `future_map()` it:

```
tictoc::tic("Big op")
seameans_df ← future_map(chunked_fnames, process_raster_zonal) ▷
  list_rbind() ▷
  mutate(date = str_remove(date, "d_"),
         date = ymd(date),
         year = lubridate::year(date),
         month = lubridate::month(date),
         day = lubridate::day(date),
         yrday = lubridate::yday(date),
         season = season(date)) ▷
  rename(sea = ID)
tictoc::toc()
```

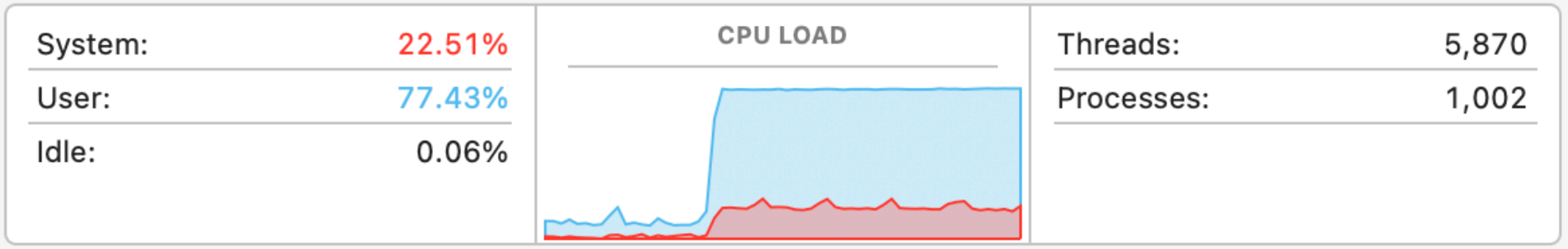
```
Big op: 48.553 sec elapsed
```

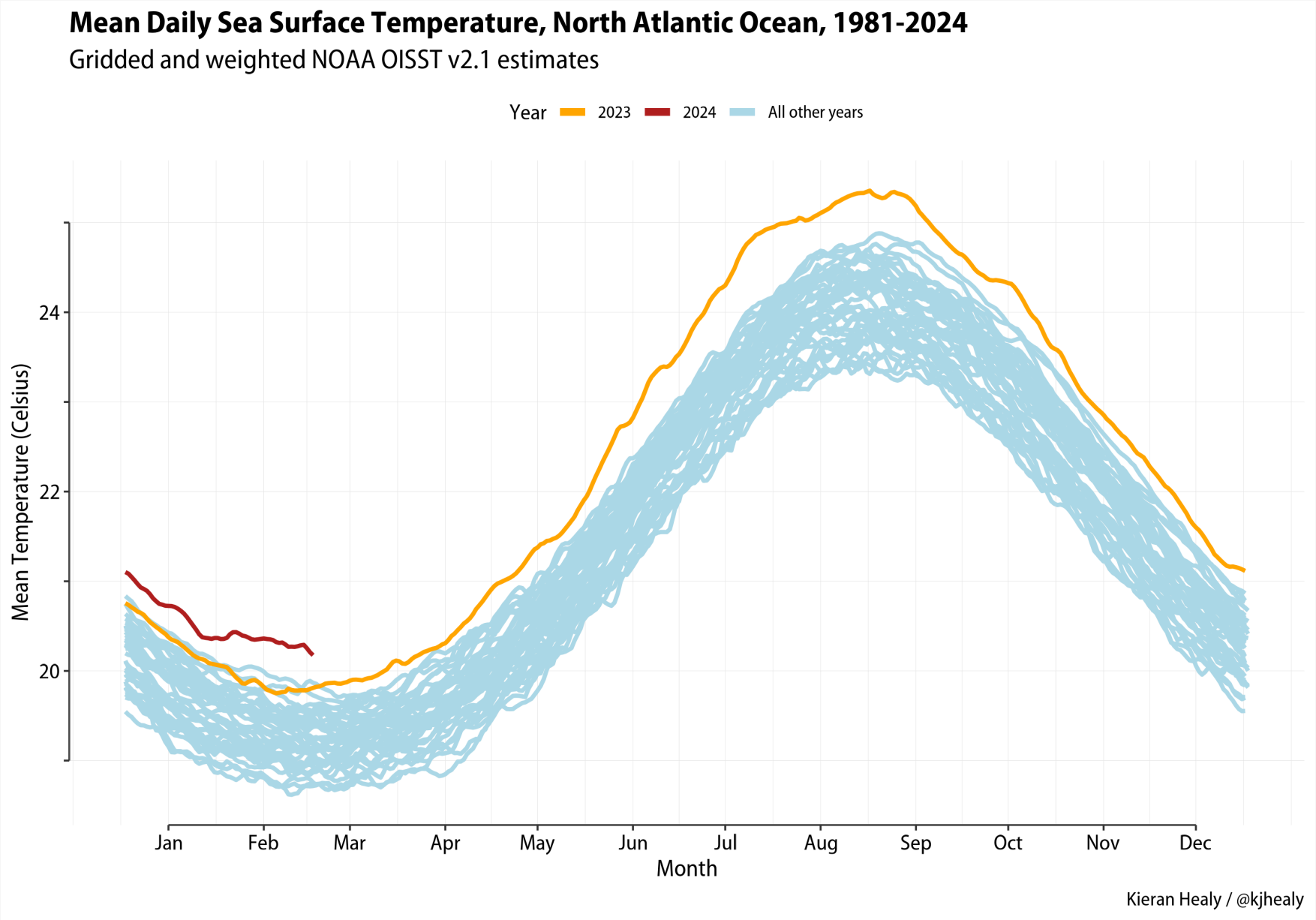
NOAA Temperature Data

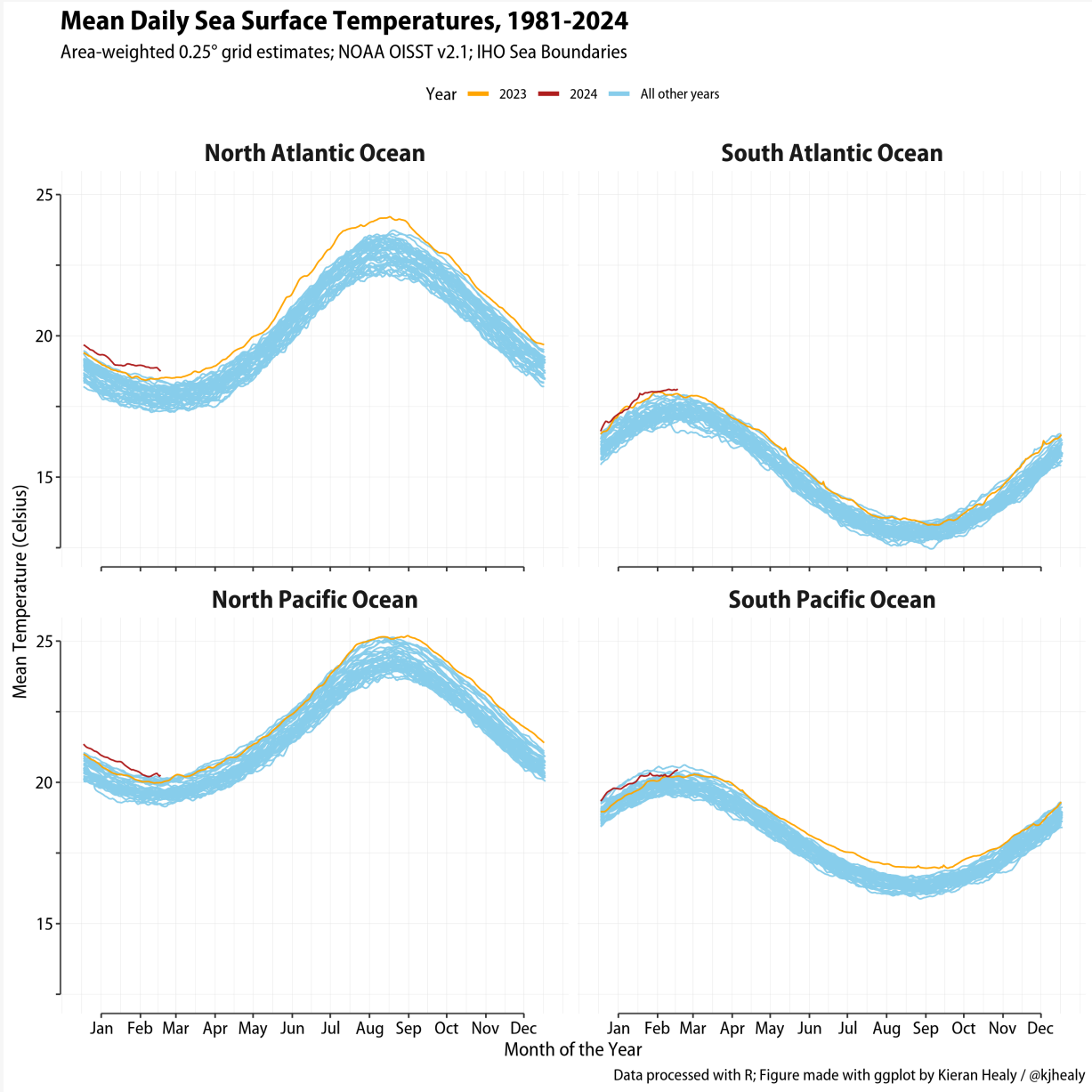
```
seameans_df
```

```
# A tibble: 1,570,449 × 8
   sea          date       sst_wt_mean  year month   day yrday season
   <chr>        <date>           <dbl> <dbl> <dbl> <int> <dbl> <fct>
 1 Adriatic Sea 1981-09-01        23.0  1981     9     1   244 Summer
 2 Adriatic Sea 1981-09-02        23.1  1981     9     2   245 Autumn
 3 Adriatic Sea 1981-09-03        22.9  1981     9     3   246 Autumn
 4 Adriatic Sea 1981-09-04        22.9  1981     9     4   247 Autumn
 5 Adriatic Sea 1981-09-05        22.5  1981     9     5   248 Autumn
 6 Adriatic Sea 1981-09-06        22.4  1981     9     6   249 Autumn
 7 Adriatic Sea 1981-09-07        22.4  1981     9     7   250 Autumn
 8 Adriatic Sea 1981-09-08        22.5  1981     9     8   251 Autumn
 9 Adriatic Sea 1981-09-09        22.6  1981     9     9   252 Autumn
10 Adriatic Sea 1981-09-10        22.5  1981     9    10   253 Autumn
# ℹ 1,570,439 more rows
```

NOAA that's more like it

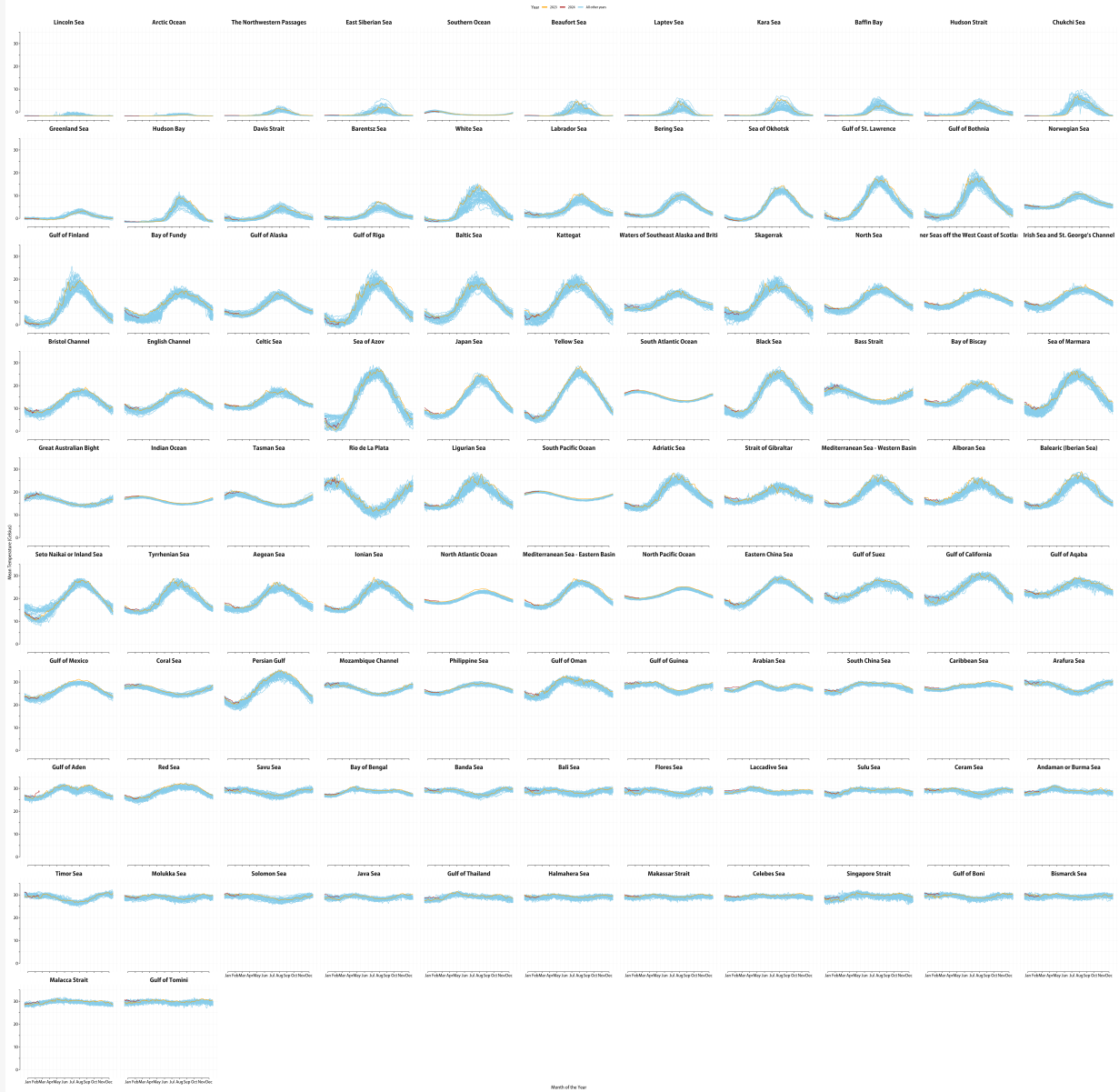



Mean Daily Sea Surface Temperature, North Atlantic Ocean, 1981-2024
Gridded and weighted NOAA OISST v2.1 estimates
Year
2023
2024
All other years
Mean Temperature (Celsius)
24
22
20
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
Kieran Healy / @kjhealy


Mean Daily Sea Surface Temperatures, 1981-2024
Area-weighted 0.25° grid estimates; NOAA OISST v2.1; IHO Sea Boundaries
Year 2023 2024 All other years
North Atlantic Ocean
South Atlantic Ocean
North Pacific Ocean
South Pacific Ocean
Mean Temperature (Celsius)
25
20
15
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Month of the Year
Data processed with R; Figure made with ggplot by Kieran Healy / @kjhealy

Mean Daily Sea Surface Temperatures, 1981-2024

Area-weighted 0.25° grid estimates; NOAA OISST v2.1; IHO Sea Boundaries



Data processed with R; Figure made with ggplot; by Ronan Huds / @jhuds