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R Tools for Observations, Receptors and Footprints (rtorf) for processing atmospheric observations in NOAA-GML

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Summary

In this study, we present a new open-source R package `rtorf`, to read, process, select, and plot NOAA Observation Package (ObsPack) data products. We use a methane ObsPack data product as an example in this code base, but it can be easily modified to analyze ObsPack products for other greenhouse gasses. The R package starts with creating a catalog of all ObsPack files in each product. It then reads all files and creates one database. While reading each ObsPack file, it extracts site elevation and time zone information from the file header and calculates sampling altitude in meters above ground level and local time for individual events. Finally, it processes and selects observations for inverse modeling purposes. This package imports functions from data.table R package, which contains C bindings with parallel implementation via Open-MP (Dowle & Srinivasan, 2021). rtorf provides functions to perform these tasks in a transparent and efficient way, supporting open-source communities in environmental sciences.

The world is experiencing an accelerated global warming due to the accumulation of greenhouse gases (GHG) since the industrial revolution (Reidmiller et al., 2018). Greenhouse gas observations are critical to monitor the state of the atmosphere, quantify present and historical emissions, and understand global climate change. During the 21th Conference of Parties (COP21), it was established the Paris Accord, a multilateral effort reduce greenhouse emissions in order to limit the temperature increment of 1.5 degrees (Rhodes, 2016). Methane is a greenhouse gas responsible for half of the temperature increase since preindustrial levels. Furthermore, methane has a 9 years lifetime and a global warming potential of 30 over 100 years (S.EPA, 2023), with a current global radiative forcing of 0.650 Wm^{-2} (NOAA GML, 2023). Hence, in the 26 version of COP conference (Hunter, Salzman, & Zaelke, 2021), it was signed the Global Methane Pledge aiming reduce at least methane emissions 30% from 2020 levels by 2030, with U.S. as one of the initial parties (U.S. White House, 2021). Therefore, monitoring CH_4 observations, emissions and sinks has become critical. NOAA ObsPack data has been used to support many studies. For instance, the global methane budget for the year 2017 was 596 Tgy^{-1}, in agreement with other studies (Saunois et al., 2016, 2020) Lu et al. (2021), characterized global methane emissions in between 2014 and 2017, including a comparison with Greenhouse gases Observing SATellite (GOSAT) data. Saunois et al. (2016). At regional scale, Lu et al. (2022) and Hu et al. performed another studied focused on north america using as priors local emissions inventories.

The National Oceanic and Atmospheric Administration (NOAA) and its Global Monitoring Laboratory (GML) has the mission of acquire, evaluate and make available long-term records of atmospheric gases[1]. To achieve that goal, GML gather own and other

[1] https://gml.noaa.gov/

laboratories data, releasing observation in a compendium named ObsPack (Masarie, Peters, Jacobson, & Tans, 2014). Specifically, the CH_4 ObsPack GLOBALVIEW+ is a comprehensive product consisting in observations from aircrafts, ships, surface stations, towers and aircores. ObsPack include a descriptor named `datasetid` covering: aircraft-pfp, aircraft-insitu, aircraft-flask, surface-insitu, surface-flask, surface-pfp, tower-insitu, aircore, shipboard-insitu, and shipboard-flask. ObsPack product generally contains hundreds of files, each of which has different sampling frequencies, hours, and attributes. It takes time and effort to develop tools to read and process each ObsPack product and select observations of interest for specific modeling and data analysis purposes.

The NOAA ObsPack data is delivered to the public as NetCDF and text files (Masarie et al., 2014). The structure of the files including descriptor fields depend on the type of file. For instance, the metadata from aircrafts is different than surface stations, but all the files include concentrations and other critical fields. Given the complexity of ObsPack format, reading and analyzing the data can be cumbersome. The `rtorf` package provides the GHG science and research community a transparent and efficient tool to process ObsPack products for GHG modeling and analyses. In this manuscript we present `rtorf`, an R package to read, process and plot NOAA ObsPack data, a software useful and needed for the community (R Core Team, 2024). For this release, we are focused on the CH_4 ObsPack GLOBALVIEW+ product. The general process consists in creating a summary of the ObsPack files, reading them in an iteration process, filtering, and generating another output and plots.

Installation

To install `rtorf`, the user must have installed the R package remotes and run the following script. This process will install all the required dependencies, such as data.table, `cptcity`, an R package with more than 7000 color palettes, and `lubridate`, a package to manage time and dates (Grolemund & Wickham, 2011; Ibarra-Espinosa, 2017). Then, we call the libraries to load the function into the environment. `rtorf` is hosted at GitHub, which allows the implementation of checking the package installation in a variety OS. To have a general view of rtorf, the reader can view the online diagram of the package[2].

```
remotes::install_github("noaa-gml/rtorf")
```

Overview

`rtorf` is a collection of function organized together to read and process ObsPack files. The general process consists in create a summary of the ObsPack files, reading them in an iteration process, filter and generating another output. As CH_4 ObsPACKGLOBALViewplus 5.1, the product used in this manuscript, includes dataid, we produced a guide for each of of them available at https://noaa-gml.github.io/rtorf. Then, in this manuscript we present the processing of `aircraft-insitu`. The obspack product in this case is `obspack_ch4_1_GLOBALVIEWplus_v5.1_2023-03-08`.

Summary

We first call the libraries `rtorf` and `data.table`. Most of objects returned by `rtorf` are of class `data.table`. Then, we define the datasetid to be identified in the name of the files inside the directory with data. This process print a summary of the data and if the logical argument verbose is `TRUE`, print the file being read in each iteration, default is `FALSE`.

[2] https://gitdiagram.com/noaa-gml/rtorfml

```r
library(rtorf)
library(data.table)
cate = c("aircraft-pfp","aircraft-insitu", "aircraft-flask",
         "surface-insitu", "surface-flask", "surface-pfp", "tower-insitu",
         "aircore", "shipboard-insitu","shipboard-flask")

obs <- "Z:/obspack/obspack_ch4_1_GLOBALVIEWplus_v5.1_2023-03-08/data/nc/"
index <- obs_summary(obs = obs,
                     categories = cate)
```

```
## Number of files of index: 429
##               sector     N
##               <char> <int>
##  1:     aircraft-pfp    40
##  2:  aircraft-insitu    15
##  3:    surface-flask   106
##  4:   surface-insitu   174
##  5:   aircraft-flask     4
##  6:          aircore     1
##  7:      surface-pfp    33
##  8:     tower-insitu    51
##  9:  shipboard-flask     4
## 10: shipboard-insitu     1
## 11:    Total sectors   429
## Detected 190 files with agl
## Detected 239 files without agl
```

Once the index of file is built, we can read each file. As we are directing to the nc directory in ObsPack, with NetCDF files inside, we use the function `obs_read_nc`. This function dumps the NetCDF information into a data.table with `long` format (Silge & Robinson, 2016). As the global attributes is attributes in the NetCDF would result in a data.table with too many columns, we used the argument `att` equals to FALSE, which is default. In ground-based datasetid the `solar_time` array is available. This is useful to select specific observations, for more information check the site documentation. At the moment, this array is not available for aircraft observations, hence we select `FALSE`. In this case, we select `verbose` equal to `TRUE`, to see the name of the files being read.

```r
datasetid <- "aircraft-insitu"
df <- obs_read_nc(index = index, categories = datasetid,
                  att = FALSE, solar_time = FALSE, verbose = TRUE)
```

```
## Searching aircraft-insitu...
## 1: ch4_above_aircraft-insitu_1_allvalid.nc
## 2: ch4_act_aircraft-insitu_428_allvalid-b200.nc
## 3: ch4_act_aircraft-insitu_428_allvalid-c130.nc
## 4: ch4_cob2003b_aircraft-insitu_59_allvalid.nc
## 5: ch4_eco_aircraft-insitu_1_allvalid.nc
## 6: ch4_hip_aircraft-insitu_59_allvalid.nc
## 7: ch4_iagos-caribic_aircraft-insitu_457_allvalid.nc
## 8: ch4_korus-aq_aircraft-insitu_428_allvalid-dc8.nc
## 9: ch4_man_aircraft-insitu_1_allvalid.nc
## 10: ch4_orc_aircraft-insitu_3_allvalid-merge10.nc
## 11: ch4_seac4rs_aircraft-insitu_428_allvalid-ER2.nc
## 12: ch4_seac4rs_aircraft-insitu_428_allvalid-dc8.nc
## 13: ch4_start08_aircraft-insitu_59_allvalid.nc
## 14: ch4_tom_aircraft-insitu_1_allvalid.nc
```

```
## 15: ch4_ugd_aircraft-insitu_1_allvalid.nc
```

The resulting `data.table` contains 59 columns and 2041758 observations. Furthermore, the size of `data.table` is 1.4 Gb. The data includes observations between 2003 and 2021. Now we can define some parameters to filter our data, like the year 2020 and spatially data below 8000 meters above sea level (masl) and focused over north America. Nevertheless, it can be modified to any region.

```
df <- df[year == 2020 & altitude_final < 8000 & latitude < 80 &
           latitude > 10 & longitude < -50 & longitude > -170]
```

Now we have a `data.table` that contains 59 columns and 236 observations. The size of `data.table` is 0 Gb. Sometimes the data can be alaready filtered every 20 seconds or for a different period of time. However, raw data can be availab ein a second-by-second basis. Under this case we may need to aggregate datah. In this example, we can add a column of time in format "POSIXct" and cut the seconds every 20 seconds. Usually, aircraft observations every 1 second. Then, We can simplify the data by calculating averages every 20 seconds. We perform this task by cutting time very 20 seconds. Then, we add a new column with the mandatory name `key_time`, which will be used to aggregate data with "POSIXct" class, but every 20 seconds.

```
df <- obs_addtime(df)
```

```
## Adding timeUTC
## Adding timeUTC_start
## Adding timeUTC_end
## Found time_interval
```

```
df$sec2 <- obs_freq(x = df$second,
                    freq = seq(0, 59, 20))
df$key_time <- ISOdatetime(year = df$year, month = df$month, day = df$day,
                           hour = df$hour, min = df$minute, sec = df$sec2,
                           tz = "UTC")
df[1, c("timeUTC", "key_time")]
```

```
##                 timeUTC            key_time
##                  <POSc>              <POSc>
## 1: 2020-01-08 22:59:55 2020-01-08 22:59:40
```

now we can aggregate the data using the function `obs_agg`. The argument cols indicate which columns will be averaged. Then, we add local time with the function `obs_addltime` and we re order the data.table.

```
df2 <- obs_agg(df,
               cols =  c("year", "month", "day", "hour", "minute",
                         "second", "time", "time_decimal",  "value",
                         "latitude", "longitude", "altitude_final",
                         "pressure", "u", "v", "temperature",
                         "type_altitude"))
```

```
## Adding time
```

```
df3 <- obs_addltime(df2)
setorderv(df3, cols = c("site_code", "timeUTC"),
          order = c(-1, 1))
```

Solar or local time

Identifying the local time is important for atmospheric reasons. Sometimes we need observations when the Planetary Boundary Layer is high, so that the concentrations are well distributed, in genera around 2:00pm, when planetary boundary layer is higher. In `rtorf` we use an hierarchical approach based on the availability of critical information. Basically, if the solar time array is available, we use the function `obs_addstime`. In the negative case `rtorf` searches for the metadata `site_utc2lst` to convert UTC time to local. Finally, in the absence of the mentioned data, we calculate an approximation of the local time using the geographical coordinates, as :

$$lt = UTC + longitude/15 * 60 * 60$$

Where lt is the local time, UTC the time, $longitude$ the coordinate.

Plots

Now we have the data processed and ready to be exported. `rtorf` includes a number of functions to save the data as tabulated format in text, csv and CSVY[3] are csv files with a YAML header. This functions can be seen in the documentation. In this last part of the manuscript we will show some visualizations. We included a function named `obs_plot` which plots data in long format using R base functions. Here we see data for the month of March 2020. This useful function allows to plot several sites and prints the x-axis range.

```
obs_plot(df3[month == 3], time = "timeUTC", yfactor = 1e9,
         type = "b", xlab = "UTC time", ylab = expression(CH[4]~ppb))
```

Finally, we show some vertical profiles for the months of January and March of 2020. We can see how during March of 2020 methane concentrations are lower than January. This may be due the implementation of Lockdowns (Espinosa et al., 2023). A manuscript focused on the impact of COVID-19 on methane emissions will be submitted soon.

```
x <- df3
x$ch4 <- x$value*1e+9
obs_plot(x, time = "ch4",  y = "altitude_final",  colu = "month",
         type = "b",  xlab = expression(CH[4]~ppb),  ylab = "altitude (m)")
```

HYSPLIT

`rtorf` also provides functions to run HYSPLIT (Hybrid Single-Particle Lagrangian Integrated Trajectory) model (Stein et al., 2015), through `obs_hysplit_control`, `obs_hysplit_ascdata` and `obs_hysplit_setup`. These function were designed to be used inside programs and run using `rslurm` for parallel processing[4]. This capability is particularly valuable for in-depth analysis of atmospheric observations, helping to interpret measurement data in the context of air mass histories and contributing to more robust emission quantifications and atmospheric model evaluations.

Future work

We are currently porting `rtorf` to python into a package named `pytorf`[5].

[3] https://csvy.org/
[4] https://noaa-gml.github.io/rtorf/articles/hysplit.ht
[5] https://github.com/noaa-gml/pytorf

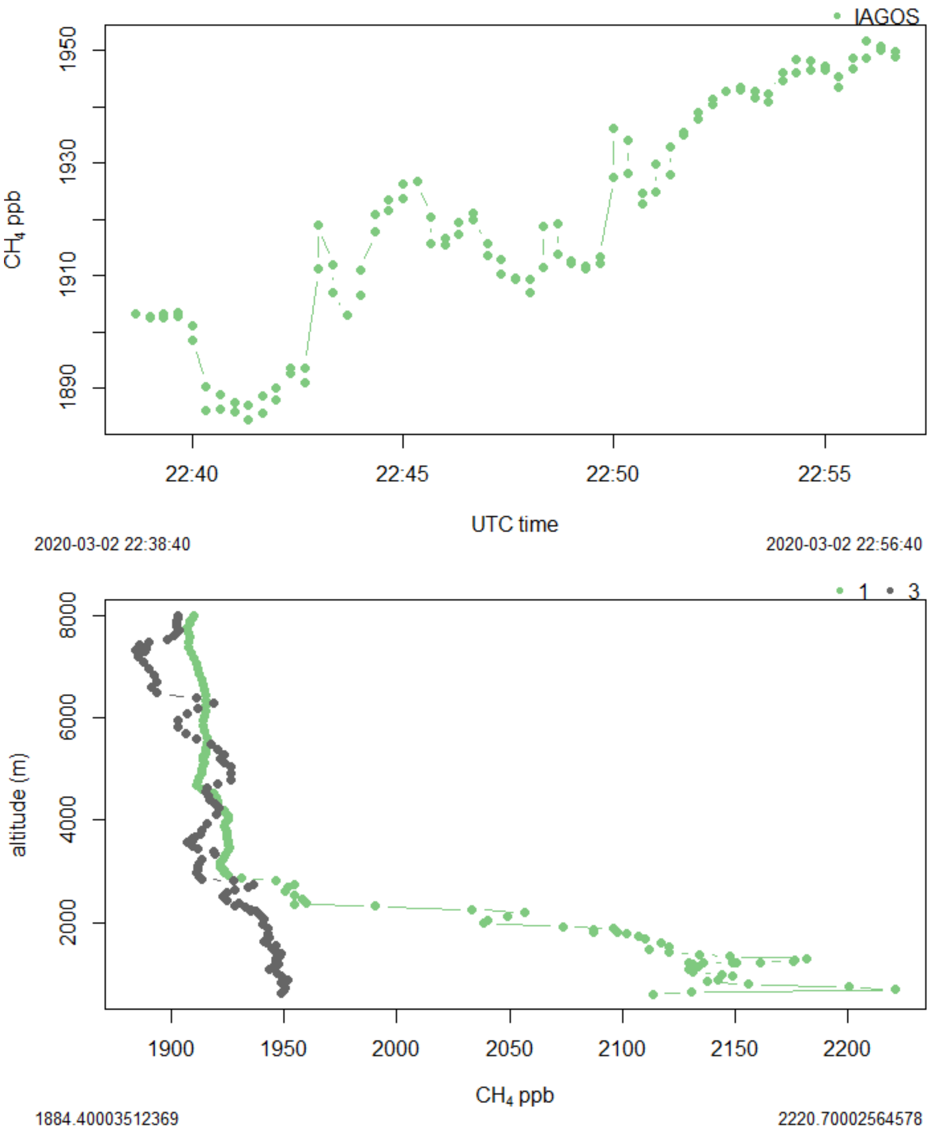

Figure 1: a) Time series, b) Monthly observations by altitude

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References

Dowle, M., & Srinivasan, A. (2021). *Data.table: Extension of 'data.frame'*. Retrieved from https://CRAN.R-project.org/package=data.table

Espinosa, S. I., Hu, L., Miller, S., Harkins, C., McDonald, B. C., Oh, Y., Bruhwiler, L., et al. (2023). COVID-19 impacts on the US methane emissions. *AGU23*.

Grolemund, G., & Wickham, H. (2011). Dates and times made easy with lubridate. *Journal of Statistical Software*, *40*(3), 1–25. Retrieved from https://www.jstatsoft.org/v40/i03/

Hu, L., Andrews, A. E., Montzka, S. A., Miller, S. M., Bruhwiler, L., Oh, Y., Sweeney, C., et al. An unexpected seasonal cycle in u.s. Oil and gas methane emissions. *Environmental Science & Technology*, *0*(0), null. doi:10.1021/acs.est.4c14090

Hunter, D. B., Salzman, J. E., & Zaelke, D. (2021). Glasgow climate summit: Cop26. *UCLA School of Law, Public Law Research Paper*, (22-02).

Ibarra-Espinosa, S. (2017). *Cptcity: Incorporating the cpt-city archive into r*. Retrieved from https://CRAN.R-project.org/package=cptcity

Lu, X., Jacob, D. J., Wang, H., Maasakkers, J. D., Zhang, Y., Scarpelli, T. R., Shen, L., et al. (2022). Methane emissions in the united states, canada, and mexico: Evaluation of national methane emission inventories and 2010–2017 sectoral trends by inverse analysis of in situ (GLOBALVIEWplus CH< sub> 4</sub> ObsPack) and satellite (GOSAT) atmospheric observations. *Atmospheric Chemistry and Physics*, *22*(1), 395–418.

Lu, X., Jacob, D. J., Zhang, Y., Maasakkers, J. D., Sulprizio, M. P., Shen, L., Qu, Z., et al. (2021). Global methane budget and trend, 2010–2017: Complementarity of inverse analyses using in situ (GLOBALVIEWplus CH< sub> 4</sub> ObsPack) and satellite (GOSAT) observations. *Atmospheric Chemistry and Physics*, *21*(6), 4637–4657.

Masarie, K., Peters, W., Jacobson, A., & Tans, P. (2014). ObsPack: A framework for the preparation, delivery, and attribution of atmospheric greenhouse gas measurements. *Earth System Science Data*, *6*(2), 375–384.

NOAA GML. (2023). THE NOAA ANNUAL GREENHOUSE GAS INDEX (AGGI). *NOAA*. GML. Retrieved from https://gml.noaa.gov/aggi/aggi.html

R Core Team. (2024). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Reidmiller, D. R., Avery, C. W., Easterling, D. R., Kunkel, K. E., Lewis, K. L., Maycock, T. K., & Stewart, B. C. (2018). Impacts, risks, and adaptation in the united states: Fourth national climate assessment, volume II. doi:doi: 10.7930/NCA4.2018

Rhodes, C. J. (2016). The 2015 paris climate change conference: COP21. *Science progress*, *99*(1), 97–104.

Saunois, M., Bousquet, P., Poulter, B., Peregon, A., Ciais, P., Canadell, J. G., Dlugokencky, E. J., et al. (2016). The global methane budget 2000–2012. *Earth System Science Data*, *8*(2), 697–751.

Saunois, M., Stavert, A. R., Poulter, B., Bousquet, P., Canadell, J. G., Jackson, R. B., Raymond, P. A., et al. (2020). The global methane budget 2000–2017. *Earth system science data*, *12*(3), 1561–1623.

S.EPA, U. (2023). Understanding global warming potentials. *EPA*. Environmental Protection Agency. Retrieved from https://www.epa.gov/ghgemissions/understanding-global-warming-potentials#:~:text=Methane%20(CH4)%20is%20estimated,more%20energy%20than%20CO2.

Silge, J., & Robinson, D. (2016). Tidytext: Text mining and analysis using tidy data principles in r. *Journal of Open Source Software*, *1*(3), 37. doi:10.21105/joss.00037

Stein, A. F., Draxler, R. R., Rolph, G. D., Stunder, B. J., Cohen, M. D., & Ngan, F. (2015). NOAA's HYSPLIT atmospheric transport and dispersion modeling system. *Bulletin of the American Meteorological Society*, *96*(12), 2059–2077.

U.S. White House. (2021, September). Joint US-EU press release on the global methane pledge. *The White House*. The United States Government. Retrieved from https://www.whitehouse.gov/briefing-room/statements-releases/2021/09/18/joint-us-eu-press-release-on-the-global-methane-pledge/