EarthArXiv coversheet

Title: 360-day to Gregorian calendar climate model output conversion

Author: Dr Jonny Williams, The National Institute of Water and Atmospheric Research, jonny.williams@niwa.co.nz

360-day to Gregorian calendar climate model output conversion

Jonny Williams*[1]

[1]The National Institute of Water and Atmospheric Research
Wellington, New Zealand

July 5, 2023

Abstract

Data from some climate model simulations is in a 360 days per year format, that is, every month is 30 days long. The main reason for this is analytical convenience in creating seasonal, annual and multi-annual means which are an integral part of climate model development and evaluation. This work illustrates a method to convert daily-mean, 360-day calendar climate model data into 'real', Gregorian calendar format. The method includes randomisation of the interpolation dates to avoid spurious artefacts in the output data, support for leap years and the ability to be run in in parallel so that multiple variables and years can be processed simultaneously. Future work to generalise this software to allow for sub-daily output frequency is encouraged and it is hoped that this work facilitates easier inter-model comparisons and knowledge transfer.

1 Introduction

Climate model output from the UK Met Office led Unified Model Partnership frequently have a 360-day calendar, for example the UK Earth System Model, version 1.0 – UKESM1.0 [4]. This simplification allows for straightforward creation of seasonal, annual and multi-annual means because the differing length of the months and leap years are irrelevant. These means are the backbone of climate model development and evaluation.

This convenience becomes a problem however in the following situations:

- Comparing daily time series with observational data or with other models with Gregorian calendars.
- Using the data as input for other models – e.g. hydrological studies – which require Gregorian calendar input.

In this work we use daily minimum temperature data, `tasmin`, from the r1i1p1f2 ensemble member in the 1950HC experiment from the Aerosol and Chemistry Intercomparison Project, AerChemMIP [2][1]. The data is on its native grid which has a regular latitude-longitude spacing of 1.25° × 1.875°. The method we present here however is generic and only relies on the input data being in 360-day calendar format and could therefore be used for other horizontal resolutions – including – unevenly-spaced grids, and indeed for other models such as those of the ocean circulation and sea-ice extent.

*Corresponding Author: jonny.williams@niwa.co.nz

[1]Filename `tasmin_day_UKESM1-0-LL_histSST-1950HC_r1i1p1f2_gn_19500101-20141230.nc`.

2 Method

The work described here is written entirely in the Python programming language and is implented through an interactive `Jupyter` notebook, `360day2greg.ipynb` [5]. The `Jupyter` environment enables interactive 'point and click' coding plus the ability to parallelize the variables and years being processed with the `papermill` package.

2.1 Non-leap years

The scheme used here is described in the documentation of the Localized Constructed Analogs project, LOCA (https://loca.ucsd.edu/loca-calendar/). This LOCA description is qualitative however and does not provide details on how this method would be done in practice. This work fills that gap by providing an open-source method for implementation and future extension.

Fundamentally, the scheme adds either 5 or 6 days' worth of data to the input depending if the year in question is a leap year or not. More specifically:

1. Read in each year of data to give 360 individual data points.
2. Split the data into 5 sections of 72 days such that in each 72 day period, the placement of the extra day is randomly assigned. This ensures that each year of the potentially multi-year dataset will differ in its location of extra days and hence will not introduce spurious artefacts.
3. The extra days are assigned the mean value of the preexisting days either side.
4. A check is performed to see if it is a leap year.
5. If 4 is true, insert another extra day – February 29th – as the mean of the newly calculated February 28th and March 1st.

As is often the case with computational algorithms, the theory is considerably more straightforward than the practice and this is described in the next section.

3 Python implementation

All code necessary to reproduce the examples presented here is open-source. The input file used to generate the examples here is also freely available to download from the Earth System Grid Federation, ESGF [1].

The code uses the `papermill` package to parallelize the running of the analysis by variable – `var` – and year (https://papermill.readthedocs.io/, version 2.3.4). In the examples used here, we use:

```
>>> var = 'air_temperature'
>>> year = 1972
```

We use the `Iris` package, version 3.2.1 [3] to read in the NetCDF data as follows:

```
>>> cube = iris.load_cube(filename,
    var &
    iris.Constraint(time=lambda cell: cell.point.year == year)).\
    intersection(latitude = (latmin,latmax),
    longitude = (lonmin,lonmax))
```

The basic data structure of `Iris` is the `cube` and describes the latitude-longitude-time temperature data read in to the Python interpreter. We use 'constraint loading' to only load the year and variable of interest and the `intersection` method of `Iris`' to load a particular region defined by latitude and longitude bounds. In the case used here, the region describes New Zealand, Figure 1, in which the horizontal resolution of the grid-scale example data is clearly visible.

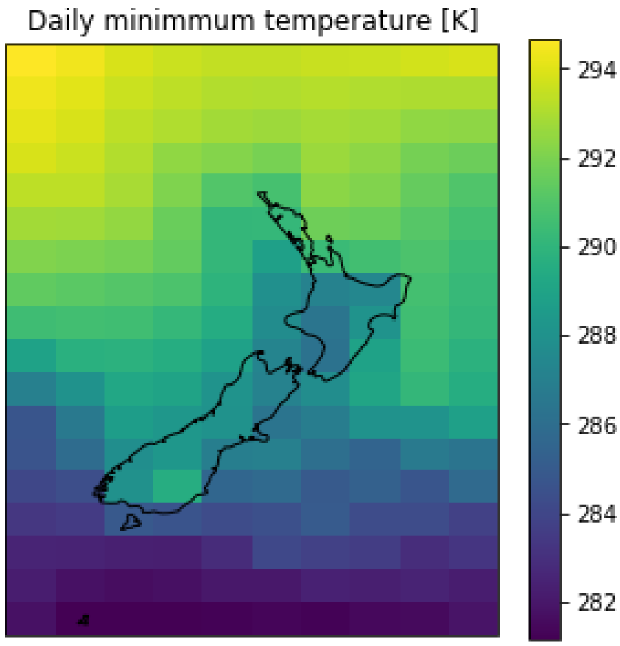

Figure 1: The area considered in this work. The data is daily minimum temperature at the grid scale for January 1st 1972.

Next, the 360 days' worth of data in the `cube` are split into a Python dictionary with one entry – 'key' – per day:

```
>>> split_cube = {}
>>> for i in tqdm(range(360)):
    split_cube[str(i)] = copy.deepcopy(cube[i])
>>> split_cube.keys()
    dict_keys(['0', '1', '2', ..., '359'])
```

Note the use of the `tqdm` package to give a progress bar in the `for` loop, https://github.com/tqdm/tqdm.

The random numbers are generated using:

```
>>> random.seed(year)
>>> rands = []
>>> for i in range(5):
    myrand = random.randrange(0 + i * 72, 72 + i * 72)
    if myrand == 359:
        myrand -= 1
    rands.append(myrand)
```

This ensures that a different random seed is used for each year and that if the final day of the year is chosen, to go back 1 day so that a mean of the final two days can be used; otherwise an error occurs.

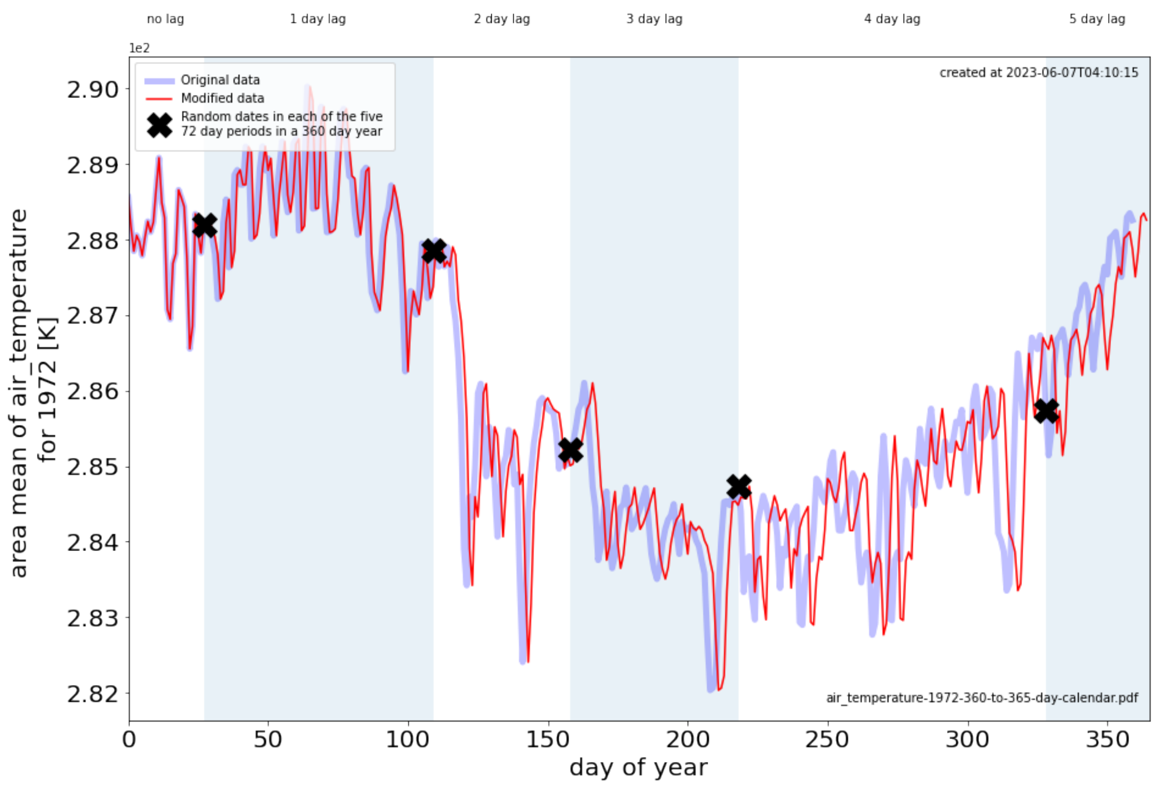

Figure 2: Raw 360-day data (thick blue line) and the postprocessed 365-day output (thin red line). The black crosses indicate the positions of the randomly assigned extra days. The alternating blue and white bands further illustrate the positions of the extra days, showing the extent of the lag between the 365-day and 360-day calendar types.

To ensure that the final dataset conforms to the correct format, the `proleptic_gregorian` calendar is used (see release notes for the `datettime` Python package and the ISO-8601 date and time format standard).

At this point, the new days are appended to the end of each 72 day period and then reordered to give 365 days of data, Figure 2. With the addition of each extra day throughout the year, the lag between the new 365-day calendar and the original 360-day one is increased, as indicated by the black crosses and alternating blue and white bands in Figure 2. One can also see this in the progressing distance between the thick blue and thin red lines as the year goes on. The annual cycle is clearly preserved without any nonphysical discontinuities.

3.1 Leap year extension

Following on the previous section, which is carried out for all years, the Python `calendar` module is used to test whether the year in question is a leap year or not:

```
>>> if calendar.isleap(year) == True:
        ...
```

Then all days from March 1st in the resulting array of data from the previous section are shifted forward 1 day, and the new February 29th day is simply the mean of the old February 28th and March 1st. This gives the result shown in Figure 4.

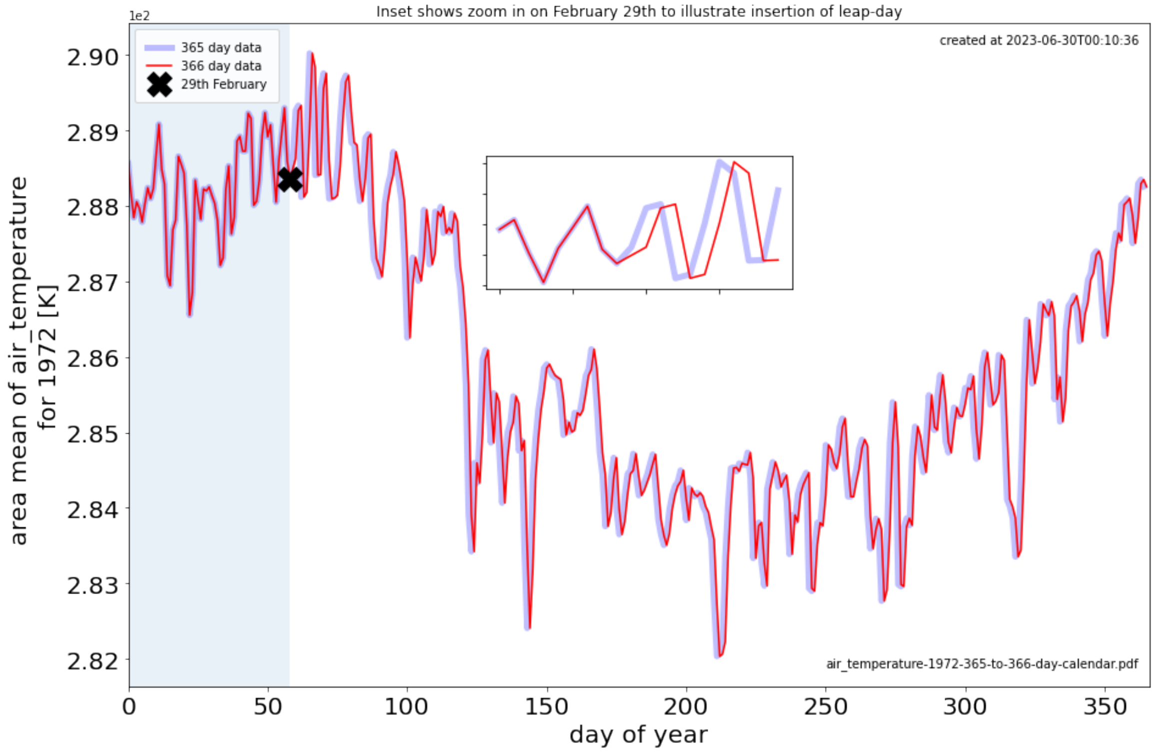

Figure 3: Conversion of 365-day to leap year data. The black cross and alternating blue and white bands show the presence of the shifted data after February 28th and the preservation of the annual cycle is clearly visible. The inset is a close-up of the data around Feburary 28th.

3.2 Parallisation with `papermill`

The amount of data being read in can be such that the input/output sections, 'IO', of the code can be prohibitively slow. This will be even more apparent for higher spatial resolution datasets. To address this, the code is written in such a way so it can be run in parallel for each year and variable using the `papermill` package. From a standard Linux terminal, the syntax is, for example:

```
> papermill ./360day2greg.ipynb
            ./360day2greg-air_temperature-1972.ipynb
            -p year 1972 -r var air_temperature
```

where the input `Jupyter` notebook is `360day2greg.ipynb`, the output notebook is `360day2greg-air_temperature-1972.ipynb`. The `-p` and `-r` flags indicate the passing of parameters and raw text to `papermill` respectively. In practice these different flags are used because the variable name is a Python string (i.e. to be surrounded by quotation marks in the code) and the year is an integer.

An advantage of running the different years and variables like this is that an archive of the data analysis performed is kept. In addition the figures shown here are saved as PDFs.

Depending on the software stack and resource constraints available to the user at runtime, the `papermill` commands can be run as 'background' jobs or with a scheduler such as `Slurm` [6].

4 Conclusions and future extensions

We have implemented the algorithm presented in the documentation of the LOCA project to convert 360-day calendar climate model data to use a Gregorian date format. This transformation is often needed when using data from the suite of models run by the UK Met Office led Unified Model Partnership. Example applications are when daily data timeseries from different climate models – with differing native calendar types – are compared to one another, or when model data is used to force downstream models such as basin-scale hydrological flow simulations.

At the time of writing, this work has not been applied to sub-daily situations. However, this would undoubtedly be useful and worthwhile due to the importance of higher-time-resolution parameters such as tidal processes. The software described here is open-source, as is the example driving data and extensions to this work are encouraged.

5 Acknowledgements

The author was funded through the Ministry of Business Innovation and Employment of the New Zealand Government, Deep South National Science Challenge project number C01X1412.

References

[1] Luca Cinquini et al. "The Earth System Grid Federation: An open infrastructure for access to distributed geospatial data". In: *Future Generation Computer Systems* 36 (2014), pp. 400–417. ISSN: 0167-739X. DOI: https://doi.org/10.1016/j.future.2013.07.002.

[2] W. J. Collins et al. "AerChemMIP: quantifying the effects of chemistry and aerosols in CMIP6". In: *Geoscientific Model Development* 10.2 (2017), pp. 585–607. DOI: 10.5194/gmd-10-585-2017. URL: https://gmd.copernicus.org/articles/10/585/2017/.

[3] Met Office. *Iris: A powerful, format-agnostic, and community-driven Python package for analysing and visualising Earth science data*. v3.6. Exeter, Devon, 2010 - 2023. DOI: 10.5281/zenodo.7948293. URL: http://scitools.org.uk/.

[4] Alistair A. Sellar et al. "Implementation of U.K. Earth System Models for CMIP6". In: *Journal of Advances in Modeling Earth Systems* 12.4 (2020), e2019MS001946. DOI: https://doi.org/10.1029/2019MS001946.

[5] Jonny Williams. *jonnyhtw/360day2greg: For EarthArXiv*. Version v5. July 2023. DOI: 10.5281/zenodo.8115395. URL: https://doi.org/10.5281/zenodo.8115395.

[6] Andy B. Yoo, Morris A. Jette, and Mark Grondona. "SLURM: Simple Linux Utility for Resource Management". In: *Job Scheduling Strategies for Parallel Processing*. Ed. by Dror Feitelson, Larry Rudolph, and Uwe Schwiegelshohn. Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 44–60. ISBN: 978-3-540-39727-4.