GCAM Annual Meeting 2023 - unofficial user's guide

The purpose of this tutorial is to demonstrate how `stitches` can be used as an emulator. While `stitches` can emulate a number of CMIP6 models, this example will focus on emulating CanESM5 SSP245 results.

This tutorial also assumes that the user has either seen a talk on `stitches` or read the paper published in *Earth System Dyanmics* (Tebaldi et al 2022). This tutorial is aimed at highlighting the flexibility of functions in `stitches`.

A simpler quickstart notebook comes in every stitches download and includes installation instructions:

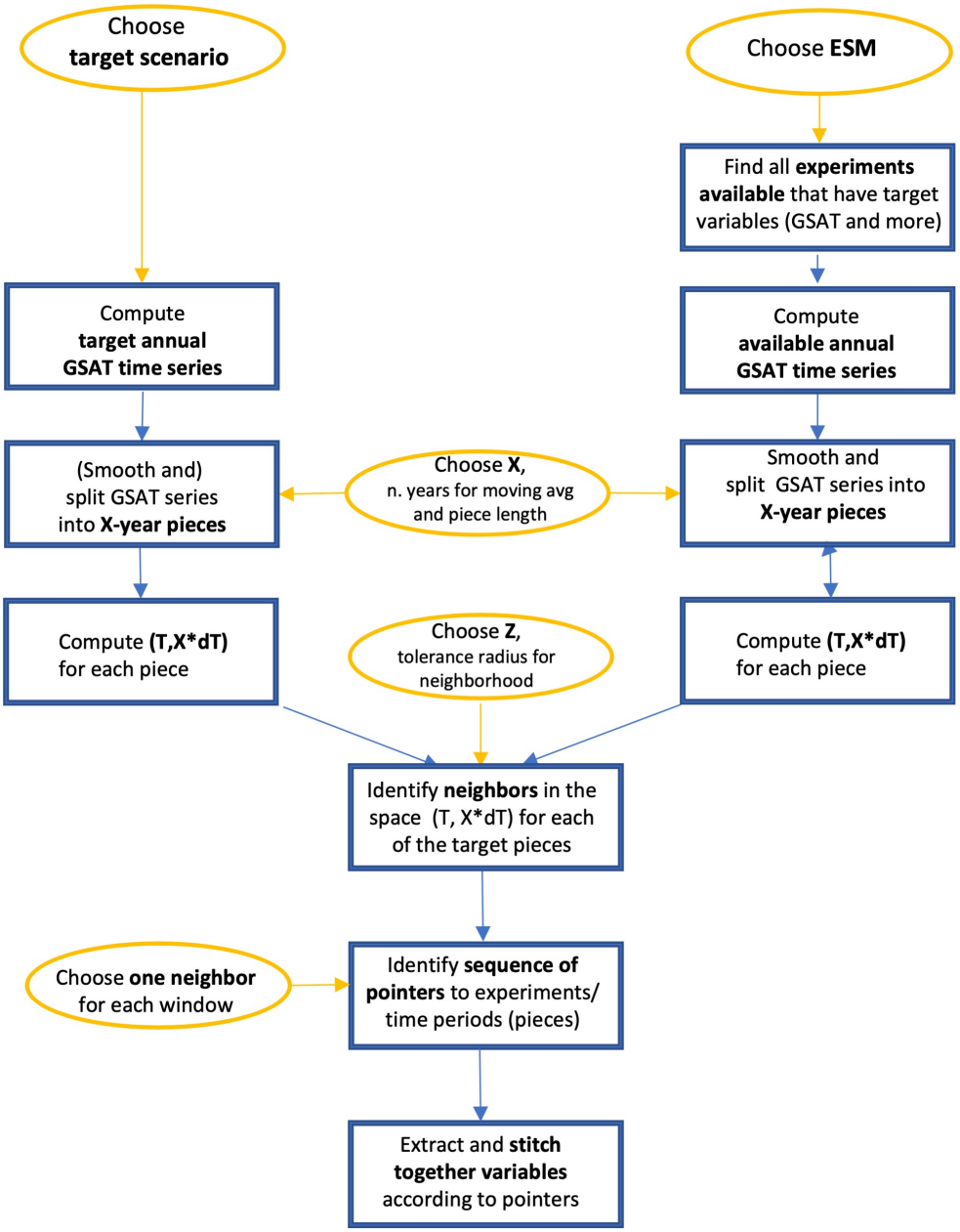
https://github.com/JGCRI/stitches/blob/main/notebooks/stitches-quickstart.ipynb

Both notebooks assume a familiarity with CMIP-style data.

To use `stitches`, there are a number of decisions users have to make, perhaps the most important being:

- Which ESM will `stitches` emulate?
- What archive data will be used? These are values of global temperature (in the following referred to as GSAT, or Tgav, or tas) for experiments/time periods (e.g., historical and SSP realizations) that the target data will be matched to. It should only contain data for the specific ESM that is being emulated. Since the match occurs in terms of annual GSAT but the ultimate purpose is to emulate other variables at possibly higher temporal frequencies (e.g., monthly or daily precipitation, winds, humidity) it will be important for the users to make sure that the archive data represents experiments/time windows for which those variables have been saved/made available by the ESM that they want to emulate. `stitches` includes checks on this but pre-filtering data is always safe.
- What target data will be used? This data frame represents the temperature pathway the stitched product will follow. The contents of this data frame may come from computing GSAT from CMIP6 ESM temperature output (as we do in this tutorial) according to a standard SSP scenario, or it may follow some arbitrary pathway that a simple model like Hector or FaIR has produced.

A diagram illustrating the `stitches` process is included for reference:

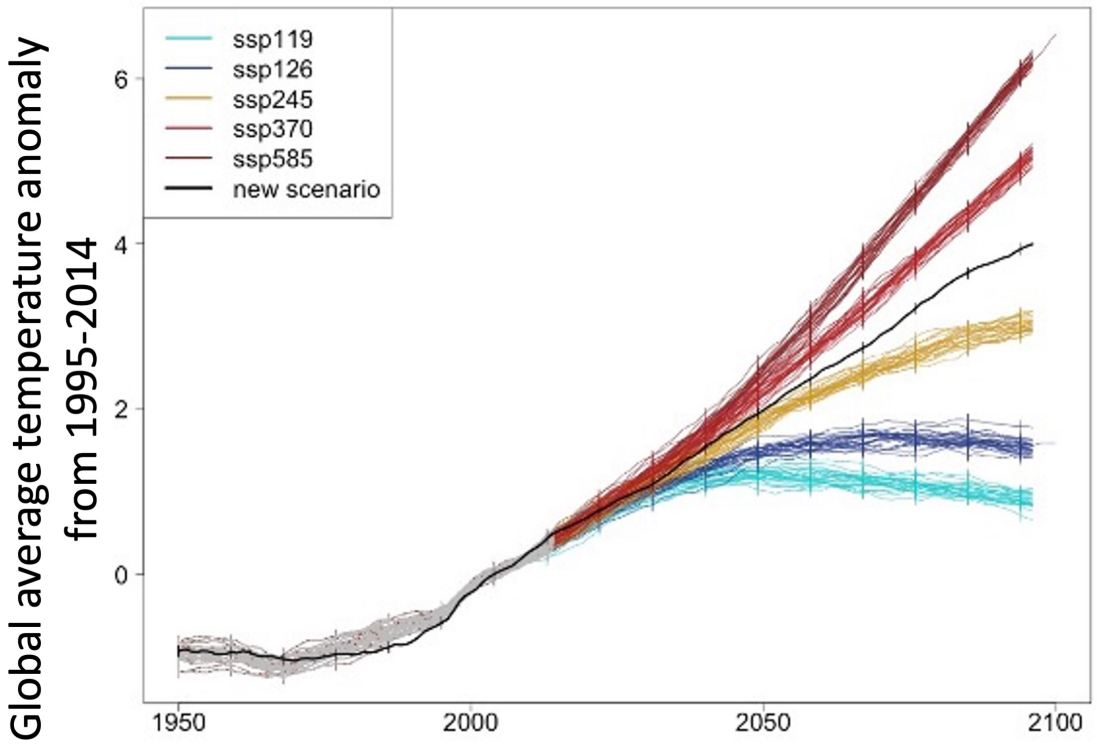


- `stitches` defaults to $X = 9$ year windows.

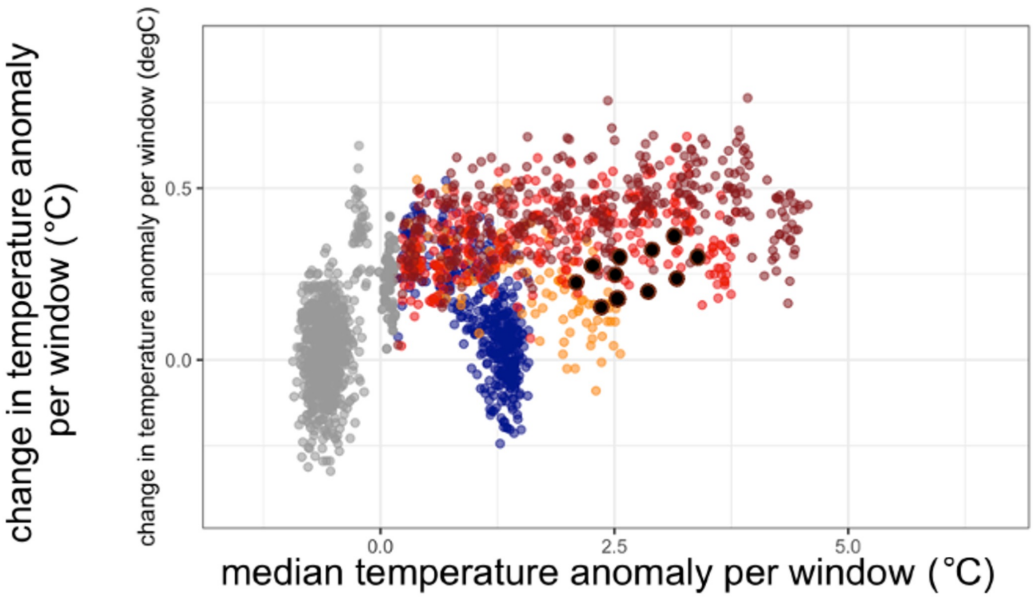
In essence STITCHES works by matching X-year segments of a target GSAT trajectory to X-year segments of available GSAT trajectories, computed from the archived output of an ESM that has been run according to SSP scenarios. The choice of X balances the need to maintain temporal consistency with the need to have flexibility in matching GSAT anomalies and rates of change. STITCHES uses X=9 year windows.

So, if one were to take ESM data for many scenarios and plot the corresponding global average temperature trajectoriesafter smoothing, the vertical lines drawn here represents a potential segmenting of the data into those 9-year windows of both available simulations

(colored lines) and a target trajectory (the back line, here as an example, the new trajectory intermediate to those available).



For each segment, the median temperature value and the change in value per segment can be plotted in a two-dimensional space where now the windows of the available scenarios are the colored dots, and those of the target scenario are the black dots:



This two dimensional space is where matching between target points (black) and available archive points (colorful) occurs, using a nearest neighbor approach.

Getting Started

```
import stitches
```

Load the additional python libraries that will be used in this example. These packages are installed as `stitches` dependencies.

```
import os
import pkg_resources
import warnings

import numpy as np
import pandas as pd
from matplotlib import pyplot as plt



# For help with plotting
%matplotlib inline
%config InlineBackend.figure_format = 'retina'
plt.rcParams['figure.figsize'] = 12, 6
```

Install the package data from Zenodo

The package data is all data that has been processed from raw Pangeo data and is generated with package functions. For convenience and rapid cloning of the github repository, the package data is also minted on Zenodo and can be quickly downloaded for using the package.

```
# stitches.install_package_data()
```

Example Set Up

In this example, we will use `stitches` to emulate CanESM5 SSP245 results (an experiment run under CMIP6). This is our *Target Data*. Then we will compare the `stitches` results with actual CanESM5 SSP245 output data.

For CMIP6 results, Earth system model data runs from 1850-2100 (or 2099, depending on the ESM). This tutorial will focus on emulating that entire period.

Decide on the target data

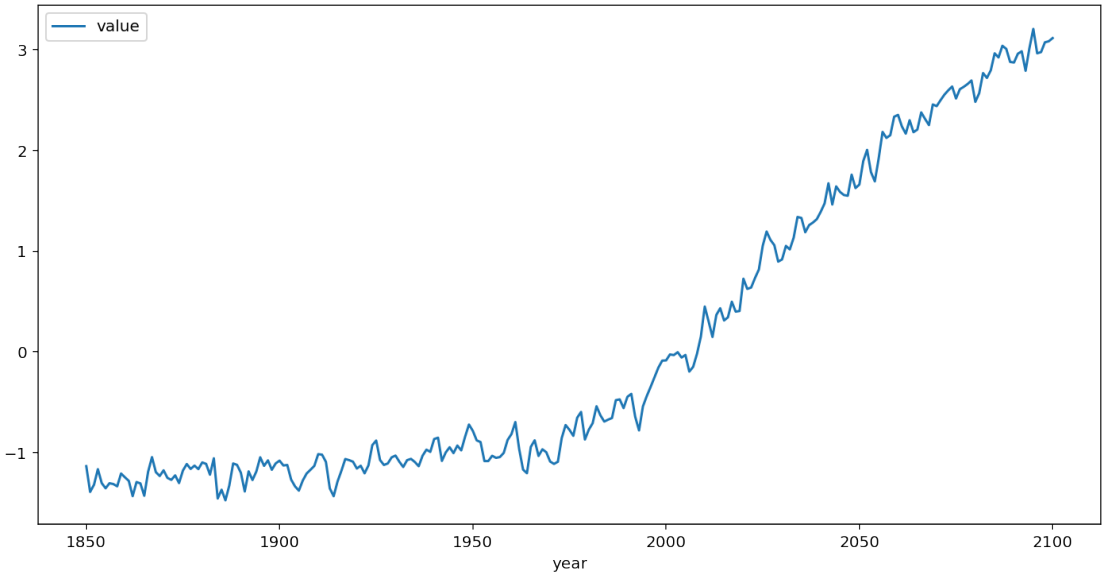
- The primary input to `stitches` functions that most users will adjust is the target data.
- The target data is the temperature pathway the stitched (emulated) product will follow. This data can come from an ESM or another class of climate models, for a specific SSP scenario or an arbitrarily defined scenario. Similarly to the archive data, the target data should contain the mean temperature anomaly and rate of temperature change for every X-year window into which the target GSAT trajectory has been subdivided.
- The target data window and the archive window must be the same length, `stitches` uses a X=9-year window by default. `stitches` includes functions for processing raw ESM Tgav data into the structure it needs for matching.
- In this example, we will use CanESM5 SSP245 results for a single ensemble member to use as our target data.

```
# Load time series and subset to target time series if needed:
data_directory = pkg_resources.resource_filename('stitches', "data")
targ = pd.read_csv(os.path.join(data_directory, "tas-data",
"CanESM5_tas.csv"))
target_data = targ.loc[(targ["model"] == "CanESM5")
                       & (targ["experiment"] == 'ssp245')].copy()

target_data  = target_data[target_data["ensemble"].isin(['r1i1p1f1'])].copy()

target_data = target_data.drop(columns='zstore').reset_index(drop=True)
```

Take a look at the structure and a plot of the time series we will be targeting:

```
print(target_data.head())
target_data.plot(x='year', y='value')
plt.show()
plt.close()
```

```
  variable experiment  ensemble    model  year     value
0      tas     ssp245  r1i1p1f1  CanESM5  1850 -1.133884
1      tas     ssp245  r1i1p1f1  CanESM5  1851 -1.389375
2      tas     ssp245  r1i1p1f1  CanESM5  1852 -1.318175
3      tas     ssp245  r1i1p1f1  CanESM5  1853 -1.163771
4      tas     ssp245  r1i1p1f1  CanESM5  1854 -1.302066
```



- Critically, these time series are *global average temperature anomaly from 1995-2014 average*.
- Note that Hector outputs are in terms of anomaly from pre-industrial average, so Hector outputs will need a shift before being used as targets for stitching.
- Any time series of global average temperature anomalies can be used as a target. However, the data frame containing this time series must be structured as above: a `variable` column containing entries of 'tas', `year` and `value` columns containing the data, and `experiment`, `ensemble`, `model` columns with identifying information of the source of this target data.
- The actual entries in the `experiment`, `ensemble`, `model` columns are only used for generating identifying strings for generated ensemble members.
- In this demonstration, we will specifically be targeting ensemble member 1 of the CanESM5 SSP245 simulations. The entire SSP245 ensemble may be jointly targeted

by omitting the line `target_data = target_data[target_data["ensemble"].isin(['r1i1p1f1'])].copy()`

Decide on the archive data

- Limit the archive matching data to the model we are trying to emulate, CanESM5 in this case.
- In this example, we treat SSP245 as a novel scenario rather than one run by the ESM and available, so we exclude it from the archive data.
- The internal package data called `matching_archive` contains the temperature results for all the ESMs-Scenarios-ensemble members that are available for `stitches` to use in its matching process. In this file monthly, tas output has been processed to compute annual global mean temperature anomaly and the temperature change over each window that the trajectory is subdivided into. By default `stitches` uses a 9-year window.
- `stitches` actually provides two files in its pacakge data.
- `matching_archive.csv` can be considered the default (for now). Starting in 1850, nine year windows are sliced forward and don't overlap.
- The final window ends up beginning in 2093, and is only 8 years long to terminate in 2100 (7 years if the ESM ends in 2099).
- When an 8 year archive window gets matched to a 9 year target window, `stitches` repeats the final archive window year to get to 9 years.
- For ESMs that end in 2099, the 2093-2099 seven-year window must be omitted
- That means that we lose some of the most interesting differences between scenarios.
- Therefore, `stitches` includes `matching_archive_staggered.csv` as package data as well. The difference is that this file does every possible full 9-year chunk, not just slicing sequentially from the starting point.
- We have to do a little more pre-processing for the archive data, but it offers more flexibility and robustness.
- The `stitches_quickstart` notebook that ships with the package uses the default `matching_archive.csv` and is generally a shorter version of this tutorial.

```
# read in the package data of all ESMs-Scenarios-ensemble members avail.
data_directory = pkg_resources.resource_filename('stitches', "data")
path = os.path.join(data_directory, 'matching_archive_staggered.csv')
data = pd.read_csv(path)
```

Extra preprocessing for `matching_archive_staggered.csv`

Let's start from the final ESM year, 2100 for CanESM5, and prioritize getting that as a full 9 year window. Short windows can be on the front end.

- if the final year for an ESM is 2099, you'd just do `end_yr_vector = end_yr_vector-1` to shift everything up a year.

```
staggered_archive = data.copy()

end_yr_vector = [1857, 1866, 1875,1884, 1893,
                 1902, 1911, 1920, 1929, 1938, 1947,
                 1956,  1965, 1974, 1983, 1992, 2001,
                 2010, 2019, 2028, 2037, 2046, 2055,
                 2064, 2073, 2082, 2091, 2100]

tmp = staggered_archive.loc[(data["experiment"].isin(['ssp126', 'ssp370',
'ssp585']))
                      & (data["model"] == "CanESM5")].copy()
archive_data = stitches.fx_processing.subset_archive(staggered_archive = tmp,
                            end_yr_vector = end_yr_vector)

print(archive_data)
```

```
     experiment variable    model   ensemble  start_yr  end_yr  year  \
0        ssp126      tas  CanESM5  r10i1p1f1      1858    1866  1862
1        ssp126      tas  CanESM5  r10i1p1f1      1867    1875  1871
2        ssp126      tas  CanESM5  r10i1p1f1      1876    1884  1880
3        ssp126      tas  CanESM5  r10i1p1f1      1885    1893  1889
4        ssp126      tas  CanESM5  r10i1p1f1      1894    1902  1898
...         ...      ...      ...        ...       ...     ...   ...
2020     ssp585      tas  CanESM5   r9i1p1f1      2056    2064  2060
2021     ssp585      tas  CanESM5   r9i1p1f1      2065    2073  2069
2022     ssp585      tas  CanESM5   r9i1p1f1      2074    2082  2078
2023     ssp585      tas  CanESM5   r9i1p1f1      2083    2091  2087
2024     ssp585      tas  CanESM5   r9i1p1f1      2092    2100  2096

            fx        dx
0    -1.299509 -0.001848
1    -1.225040  0.010931
2    -1.205325 -0.012385
3    -1.299790  0.004692
4    -1.219588  0.003027
...        ...       ...
2020  3.250968  0.080163
2021  4.020579  0.088755
2022  4.731989  0.076436
2023  5.508628  0.089533
2024  6.249420  0.058199
```

```
[2025 rows x 9 columns]
```

The staggered archive ONLY has 9 year windows, no short windows. So no window from 1850-1857 exists to get pulled for that `end_yr`. The historical period is so consistent, there are plenty of other full sized (9year) windows that have similar properties and can make for a good match, so we aren't really losing anything by not having archive points representing 1850-1857. If we really want, we can go ahead and have an 1850-1858 window in the archive by just replacing 1857 with 1858 in the above. There will be one year (1858) in common between that new window and the one ending in 1866 but that's not an amount of similarity that would lead to unrealistic behavior like if we used all of the entries in the staggered archive.

And that would look like:

```
end_yr2 = [1858, 1866, 1875,1884, 1893,
           1902, 1911, 1920, 1929, 1938, 1947,
           1956,  1965, 1974, 1983, 1992, 2001,
           2010, 2019, 2028, 2037, 2046, 2055,
           2064, 2073, 2082, 2091, 2100]
archive_data = stitches.fx_processing.subset_archive(staggered_archive = tmp,
                                end_yr_vector =
end_yr2).sort_values(by=['experiment', 'ensemble', 'end_yr'])
print(archive_data)
```

```
     experiment variable    model   ensemble  start_yr  end_yr  year  \
0         ssp126      tas  CanESM5  r10i1p1f1      1850    1858  1854
75        ssp126      tas  CanESM5  r10i1p1f1      1858    1866  1862
76        ssp126      tas  CanESM5  r10i1p1f1      1867    1875  1871
77        ssp126      tas  CanESM5  r10i1p1f1      1876    1884  1880
78        ssp126      tas  CanESM5  r10i1p1f1      1885    1893  1889
...          ...      ...      ...        ...       ...     ...   ...
2095      ssp585      tas  CanESM5   r9i1p1f1      2056    2064  2060
2096      ssp585      tas  CanESM5   r9i1p1f1      2065    2073  2069
2097      ssp585      tas  CanESM5   r9i1p1f1      2074    2082  2078
2098      ssp585      tas  CanESM5   r9i1p1f1      2083    2091  2087
2099      ssp585      tas  CanESM5   r9i1p1f1      2092    2100  2096

             fx        dx
0    -1.360399  0.016472
75   -1.299509 -0.001848
76   -1.225040  0.010931
77   -1.205325 -0.012385
78   -1.299790  0.004692
...        ...       ...
2095  3.250968  0.080163
2096  4.020579  0.088755
2097  4.731989  0.076436
2098  5.508628  0.089533
2099  6.249420  0.058199
```

```
[2100 rows x 9 columns]
```

This is what we will go ahead and use for our archive data.

- There is one year of data (1858) that gets shared between two archive windows.
- Therefore it is possible to get a year of data repeated in the stitched outputs.
- This is no worse than the default archive, and possibly better to have it happen in the period before the SSPs really diverge.
- In general, you don't want many shared years between archive windows, or unrealistic behavior can occur.

Target data pre-processing

- We had decided to target SSP245 realization 1 to emulate
- Our archive is set up with 9 year chunks, and we prioritized having a full 9 year window ending in 2100 and working backward for that data.
- We can do the same thing for our target data.
- The target data doesn't necessarily have to have the same length as the archive trajectory.
- It does benefit, however, from being a multiple of 9 long, although having an 8 year window in the target is fine as well.
- Shorter windows in the target are also fine from the perspective of the method, we just haven't coded it cleanly yet.

Regardless, the first step of pre-processing any target data is to smooth it.

- even Hector outputs, which are already quite smooth, require this.

```
target_data = stitches.fx_processing.calculate_rolling_mean(target_data,
                                                            size=31).copy()
```

The default chunking, starting with 1850 and cutting every 9 years after that. This results in the final window only being 8 years. That is fine, a target window that is only 1 year short is not a problem.

```
target_data1 = stitches.fx_processing.get_chunk_info(
    stitches.fx_processing.chunk_ts(df = target_data,  n=9)).copy()
print(target_data1)
```

```
    ensemble variable experiment    model  start_yr  end_yr  year        fx
\
0   r1i1p1f1      tas     ssp245  CanESM5      1850    1858  1854 -1.272611
1   r1i1p1f1      tas     ssp245  CanESM5      1859    1867  1863 -1.250102
2   r1i1p1f1      tas     ssp245  CanESM5      1868    1876  1872 -1.243684
3   r1i1p1f1      tas     ssp245  CanESM5      1877    1885  1881 -1.204998
```

4	r1i1p1f1	tas	ssp245	CanESM5	1886	1894	1890	-1.197851
5	r1i1p1f1	tas	ssp245	CanESM5	1895	1903	1899	-1.213103
6	r1i1p1f1	tas	ssp245	CanESM5	1904	1912	1908	-1.170853
7	r1i1p1f1	tas	ssp245	CanESM5	1913	1921	1917	-1.145708
8	r1i1p1f1	tas	ssp245	CanESM5	1922	1930	1926	-1.086683
9	r1i1p1f1	tas	ssp245	CanESM5	1931	1939	1935	-1.012161
10	r1i1p1f1	tas	ssp245	CanESM5	1940	1948	1944	-0.986856
11	r1i1p1f1	tas	ssp245	CanESM5	1949	1957	1953	-0.953562
12	r1i1p1f1	tas	ssp245	CanESM5	1958	1966	1962	-0.937034
13	r1i1p1f1	tas	ssp245	CanESM5	1967	1975	1971	-0.867323
14	r1i1p1f1	tas	ssp245	CanESM5	1976	1984	1980	-0.736610
15	r1i1p1f1	tas	ssp245	CanESM5	1985	1993	1989	-0.481056
16	r1i1p1f1	tas	ssp245	CanESM5	1994	2002	1998	-0.239006
17	r1i1p1f1	tas	ssp245	CanESM5	2003	2011	2007	0.064410
18	r1i1p1f1	tas	ssp245	CanESM5	2012	2020	2016	0.456957
19	r1i1p1f1	tas	ssp245	CanESM5	2021	2029	2025	0.831730
20	r1i1p1f1	tas	ssp245	CanESM5	2030	2038	2034	1.189269
21	r1i1p1f1	tas	ssp245	CanESM5	2039	2047	2043	1.515511
22	r1i1p1f1	tas	ssp245	CanESM5	2048	2056	2052	1.855482
23	r1i1p1f1	tas	ssp245	CanESM5	2057	2065	2061	2.160776
24	r1i1p1f1	tas	ssp245	CanESM5	2066	2074	2070	2.443211
25	r1i1p1f1	tas	ssp245	CanESM5	2075	2083	2079	2.659419
26	r1i1p1f1	tas	ssp245	CanESM5	2084	2092	2088	2.842125
27	r1i1p1f1	tas	ssp245	CanESM5	2093	2100	2097	2.956517

	dx
0	0.004091
1	0.003794
2	0.000281
3	0.004243
4	-0.001675
5	0.001456
6	0.004645
7	0.003106
8	0.005930
9	0.007817
10	0.004842
11	-0.000143
12	0.005436
13	0.014498
14	0.019400
15	0.026402
16	0.032784
17	0.042232
18	0.037038
19	0.041484
20	0.039982
21	0.037994
22	0.034255
23	0.032611

```
24  0.030718
25  0.024061
26  0.011227
27  0.014718
```

For consistency with how we set up the archive, however, we will have the target window ending in 2100 be a complete 9 years and work back.

You can use the `base_chunk=8` argument to do that. The previous call starting in 1850 and cutting every 9 years aftere that uses the default `base_chunk=0`. `base_chunk=8` means the target starts in 1850+8 = 1858 and cuts every 9 years after that, ending in 2100.

If the ESM data ends in 2099 and you wanted the target window ending in 2099 to be a complete 9 year window, you'd use `base_chunk=7`. It's a little clunky and we could certainly make it more interpretable/flexible, but it's not too bad to figure out for now hopefully.

```
target_data2 = stitches.fx_processing.get_chunk_info(
    stitches.fx_processing.chunk_ts(df = target_data,  n=9,
                                    base_chunk=8)).copy()
print(target_data2)
```

```
    ensemble variable experiment    model  start_yr  end_yr  year        fx
\
0   r1i1p1f1      tas     ssp245  CanESM5      1858    1866  1862 -1.254450
1   r1i1p1f1      tas     ssp245  CanESM5      1867    1875  1871 -1.242954
2   r1i1p1f1      tas     ssp245  CanESM5      1876    1884  1880 -1.214581
3   r1i1p1f1      tas     ssp245  CanESM5      1885    1893  1889 -1.195424
4   r1i1p1f1      tas     ssp245  CanESM5      1894    1902  1898 -1.200969
5   r1i1p1f1      tas     ssp245  CanESM5      1903    1911  1907 -1.172773
6   r1i1p1f1      tas     ssp245  CanESM5      1912    1920  1916 -1.145221
7   r1i1p1f1      tas     ssp245  CanESM5      1921    1929  1925 -1.091947
8   r1i1p1f1      tas     ssp245  CanESM5      1930    1938  1934 -1.022043
9   r1i1p1f1      tas     ssp245  CanESM5      1939    1947  1943 -0.994382
10  r1i1p1f1      tas     ssp245  CanESM5      1948    1956  1952 -0.955606
11  r1i1p1f1      tas     ssp245  CanESM5      1957    1965  1961 -0.945947
12  r1i1p1f1      tas     ssp245  CanESM5      1966    1974  1970 -0.879419
13  r1i1p1f1      tas     ssp245  CanESM5      1975    1983  1979 -0.761327
14  r1i1p1f1      tas     ssp245  CanESM5      1984    1992  1988 -0.506838
15  r1i1p1f1      tas     ssp245  CanESM5      1993    2001  1997 -0.268266
16  r1i1p1f1      tas     ssp245  CanESM5      2002    2010  2006  0.030355
17  r1i1p1f1      tas     ssp245  CanESM5      2011    2019  2015  0.420281
18  r1i1p1f1      tas     ssp245  CanESM5      2020    2028  2024  0.791804
19  r1i1p1f1      tas     ssp245  CanESM5      2029    2037  2033  1.149695
20  r1i1p1f1      tas     ssp245  CanESM5      2038    2046  2042  1.481969
21  r1i1p1f1      tas     ssp245  CanESM5      2047    2055  2051  1.819203
22  r1i1p1f1      tas     ssp245  CanESM5      2056    2064  2060  2.127866
23  r1i1p1f1      tas     ssp245  CanESM5      2065    2073  2069  2.402196
24  r1i1p1f1      tas     ssp245  CanESM5      2074    2082  2078  2.636278
25  r1i1p1f1      tas     ssp245  CanESM5      2083    2091  2087  2.832238
26  r1i1p1f1      tas     ssp245  CanESM5      2092    2100  2096  2.937192
```

```
          dx
0   0.003499
1   0.000194
2   0.004563
3  -0.001245
4   0.000351
5   0.004305
6   0.002159
7   0.005531
8   0.008648
9   0.003807
10  0.001086
11  0.006385
12  0.013736
13  0.016582
14  0.028356
15  0.032369
16  0.038950
17  0.037003
18  0.041818
19  0.039828
20  0.036774
21  0.034212
22  0.033031
23  0.030943
24  0.023368
25  0.012831
26  0.014289
```

if you really don't want to sacrifice the 1850-1857 years in the stitched outputs, you can get kind of clunky and play around with the `chunk_ts` arguments to get an 1850-1857 chunk and just append that to the target data

```
short_target_window = stitches.fx_processing.get_chunk_info(
    stitches.fx_processing.chunk_ts(df = target_data,  n=8,
                                    base_chunk=0)).copy()

short_target_window = short_target_window[short_target_window['end_yr'] ==
1857].copy()

print(short_target_window)
```

```
   ensemble variable experiment    model  start_yr  end_yr  year        fx  \
0  r1i1p1f1      tas     ssp245  CanESM5      1850    1857  1854 -1.272611

        dx
0  0.00468
```

```
target_data3 = pd.concat([short_target_window,
target_data2]).reset_index(drop=True).copy()
print(target_data3)
```

```
    ensemble variable experiment    model  start_yr  end_yr  year        fx
\
0   r1i1p1f1      tas     ssp245  CanESM5      1850    1857  1854 -1.272611
1   r1i1p1f1      tas     ssp245  CanESM5      1858    1866  1862 -1.254450
2   r1i1p1f1      tas     ssp245  CanESM5      1867    1875  1871 -1.242954
3   r1i1p1f1      tas     ssp245  CanESM5      1876    1884  1880 -1.214581
4   r1i1p1f1      tas     ssp245  CanESM5      1885    1893  1889 -1.195424
5   r1i1p1f1      tas     ssp245  CanESM5      1894    1902  1898 -1.200969
6   r1i1p1f1      tas     ssp245  CanESM5      1903    1911  1907 -1.172773
7   r1i1p1f1      tas     ssp245  CanESM5      1912    1920  1916 -1.145221
8   r1i1p1f1      tas     ssp245  CanESM5      1921    1929  1925 -1.091947
9   r1i1p1f1      tas     ssp245  CanESM5      1930    1938  1934 -1.022043
10  r1i1p1f1      tas     ssp245  CanESM5      1939    1947  1943 -0.994382
11  r1i1p1f1      tas     ssp245  CanESM5      1948    1956  1952 -0.955606
12  r1i1p1f1      tas     ssp245  CanESM5      1957    1965  1961 -0.945947
13  r1i1p1f1      tas     ssp245  CanESM5      1966    1974  1970 -0.879419
14  r1i1p1f1      tas     ssp245  CanESM5      1975    1983  1979 -0.761327
15  r1i1p1f1      tas     ssp245  CanESM5      1984    1992  1988 -0.506838
16  r1i1p1f1      tas     ssp245  CanESM5      1993    2001  1997 -0.268266
17  r1i1p1f1      tas     ssp245  CanESM5      2002    2010  2006  0.030355
18  r1i1p1f1      tas     ssp245  CanESM5      2011    2019  2015  0.420281
19  r1i1p1f1      tas     ssp245  CanESM5      2020    2028  2024  0.791804
20  r1i1p1f1      tas     ssp245  CanESM5      2029    2037  2033  1.149695
21  r1i1p1f1      tas     ssp245  CanESM5      2038    2046  2042  1.481969
22  r1i1p1f1      tas     ssp245  CanESM5      2047    2055  2051  1.819203
23  r1i1p1f1      tas     ssp245  CanESM5      2056    2064  2060  2.127866
24  r1i1p1f1      tas     ssp245  CanESM5      2065    2073  2069  2.402196
25  r1i1p1f1      tas     ssp245  CanESM5      2074    2082  2078  2.636278
26  r1i1p1f1      tas     ssp245  CanESM5      2083    2091  2087  2.832238
27  r1i1p1f1      tas     ssp245  CanESM5      2092    2100  2096  2.937192

          dx
0   0.004680
1   0.003499
2   0.000194
3   0.004563
4  -0.001245
5   0.000351
6   0.004305
7   0.002159
8   0.005531
9   0.008648
10  0.003807
11  0.001086
12  0.006385
13  0.013736
```

```
14  0.016582
15  0.028356
16  0.032369
17  0.038950
18  0.037003
19  0.041818
20  0.039828
21  0.036774
22  0.034212
23  0.033031
24  0.030943
25  0.023368
26  0.012831
27  0.014289
```

Emulate

- now that you are empowered to process almost any data into an archive and a target, we can emulate.
- This occurs with two functions:
- `stitches.make_recipe()` does the matching between a target and archive, and gives the pointers to all of the pangeo-hosted netcdf files of data.
- `stitches.gmat_stitching()` or `stitches.gridded_stitching()` then stitch either global average temperature anomaly trajectories or gridded, multivariate netcdfs from those recipes.

Matching and making the recipe.

The arguments for making recipes are relatively simple. You specify the target data, the archive data, how many matches you want to try to make for each realization of the target data, and whether you want your results to be reproducible.

Two other optional variables include

- `non_tas_variables` - which variables in addition to tas do you think you want to have gridded results for? The default is to only provide tas recipes.
- `res` - do you want to stitch monthly (`'mon'`) or daily (`'day'`) gridded results? The default is to monthly as daily files are very large to work with and create.

Within `make_recipe`, two steps are happening:

1. matching - identifying possible archive window matches for each target window
2. permuting - random combinations of those potential matches are drawn to create stitched time series. These draws control for 'envelope collapse', where the same

archive window gets used in the same place for many generated ensemble members.

The remaining argument, `tol` specifies the matching tolerance - for each target window, how far out away in the archive are we willing to look for similar points?

- `stitches` prioritizes providing a nearest neighbor match, which dictates how it currently uses `tol`
- `tol=0.0` corresponds to providing the nearest neighbor match.
- Each target window gets its own, custom nearest neighbor match that is some distance away, `dist_nn`.
- For each target window, we center a circular matching neighborhood on the target point. In a radius of `dist_nn`, we know the nearest neighbor is the only available point by definition.
- Therefore, we expand the matching neighborhood for each target point to search for matches up to a distance of `dist_nn + tol` away.
- So if target window A has a nearest neighbor 0.1degC away, and `tol=0.01`, then a circle centered on A with radius 0.11degC contains all possible matches. If target window B has a nearest neighbor 0.05degC away, then its matching neighborhood is a circle centered on B with a radius of 0.06degC.
- We do this because when doing random draws of all possible combinations of collapse-free ensembles from a set of potential matches, formatting the matching in this way turns finding a cutoff tolerance value for each ESM into a min-max problem that's a little easier to calculate.
- In the paper, we provide `z_cutoff` values that are 'safe' maximum tolerances to use for every ESM examined. We will be adding more ESMs in the future.

```
# the nearest neighbor recipes
nn_recipes = stitches.make_recipe(target_data = target_data3,
                                  archive_data=archive_data,
                                  tol=0.0,
                                  N_matches=4,
                                  reproducible=True)
print(nn_recipes.head())
```

```
You have requested more recipes than possible for at least one target
trajectories, returning what can
The following target windows have a nearest neighbor in T, dT space
that is more than 0.25degC away. This may or may not result in poor
matches and we recommend validation.
  target_variable target_experiment target_ensemble target_model  \
0             tas            ssp245        r1i1p1f1      CanESM5
```

```
   target_start_yr  target_end_yr  target_year  target_fx  target_dx  \
0             2083           2091         2087   2.832238   0.012831

  archive_experiment  ... archive_model archive_ensemble archive_start_yr  \
0             ssp370  ...       CanESM5        r17i1p1f1             2056

   archive_end_yr  archive_year  archive_fx  archive_dx   dist_dx   dist_fx
\
0            2064          2060    2.815717    0.045724  0.263149  0.016521

    dist_l2
0  0.263667

[1 rows x 21 columns]
--------------------------------------------------------------------------
------------
  target_start_yr target_end_yr archive_experiment archive_variable  \
0            1850          1857         historical              tas
1            1858          1866         historical              tas
2            1867          1875         historical              tas
3            1876          1884         historical              tas
4            1885          1893         historical              tas

  archive_model archive_ensemble       stitching_id archive_start_yr  \
0       CanESM5        r16i1p1f1  ssp245~r1i1p1f1~1             1885
1       CanESM5         r3i1p1f1  ssp245~r1i1p1f1~1             1858
2       CanESM5        r19i1p1f1  ssp245~r1i1p1f1~1             1858
3       CanESM5         r1i1p1f1  ssp245~r1i1p1f1~1             1867
4       CanESM5        r17i1p1f1  ssp245~r1i1p1f1~1             1903

  archive_end_yr                                           tas_file
0           1892  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
1           1866  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
2           1866  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
3           1875  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
4           1911  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
```

Depending on the version of stitches being used, you might get a print statement saying

```
The following target windows have a nearest neighbor in T, dT space that is
more than 0.25degC away. This may or may not result in poor matches and we
recommend validation.
```

This is a flat check we are implementing on our development branch - if any the nearest neighbor matches for any target window are more than 0.25degC away, then this statement is printed with the target window's details.

This does not necessarily mean anything is wrong and this flag can be printed in runs that have been validated extremely well.

Iit just means that the target trajectory may not be similar enough for the selected archive of data points, and validation is warranted. `stitches` is a constructive method and generally any generated ensemble should be validated against the training data. This is why we pre-calculate the tolerance cutoff values for each ESM in the ESD paper, to save effort validating future generated ensembles.

```
# additional recipes
my_recipes = stitches.make_recipe(target_data = target_data3,
                                  archive_data=archive_data,
                                  tol=0.05,
                                  res='mon',
                                   non_tas_variables=['pr'],
                                  N_matches=4,
                                  reproducible=True)
print(my_recipes.head())
print('-----------------------------------')
# you can take a look at one of the actual file addresses to get a sense of
# what the Pangeo file addresses look like.:
print(my_recipes['pr_file'].iloc[0])
```

```
You have requested more recipes than possible for at least one target
trajectories, returning what can
  target_start_yr target_end_yr archive_experiment archive_variable  \
0            1850          1857         historical              tas
1            1858          1866         historical              tas
2            1867          1875         historical              tas
3            1876          1884         historical              tas
4            1885          1893         historical              tas

  archive_model archive_ensemble       stitching_id archive_start_yr  \
0       CanESM5         r5i1p1f1  ssp245~r1i1p1f1~1             1912
1       CanESM5        r22i1p1f1  ssp245~r1i1p1f1~1             1921
2       CanESM5        r12i1p1f1  ssp245~r1i1p1f1~1             1921
3       CanESM5         r7i1p1f1  ssp245~r1i1p1f1~1             1858
4       CanESM5         r2i1p1f1  ssp245~r1i1p1f1~1             1912

  archive_end_yr                                           tas_file  \
0           1919  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
1           1929  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
2           1929  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
3           1866  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
4           1920  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...

                                             pr_file
0  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
1  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
2  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
3  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
4  gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical...
```

```
-----------------------------------
gs://cmip6/CMIP6/CMIP/CCCma/CanESM5/historical/r5i1p1f1/Amon/pr/gn/v20190429/
```

If you wanted to include sea level pressure in addition to precipitation, you would use `non_tas_variables=['pr', 'psl']`.

stitching and plotting

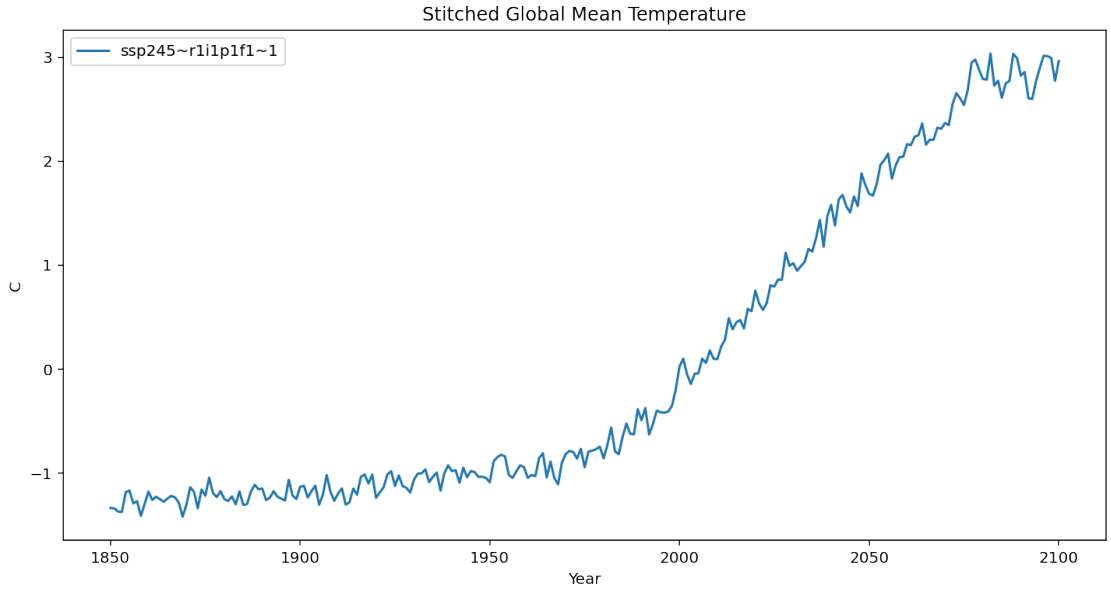
Nearest neighbor result

Stitch the global average temperature for the nearest neighbor result, and see it in the context of the actual ESM data that was not used in the archive at all.

```
stitched_global_temp = stitches.gmat_stitching(nn_recipes)
```

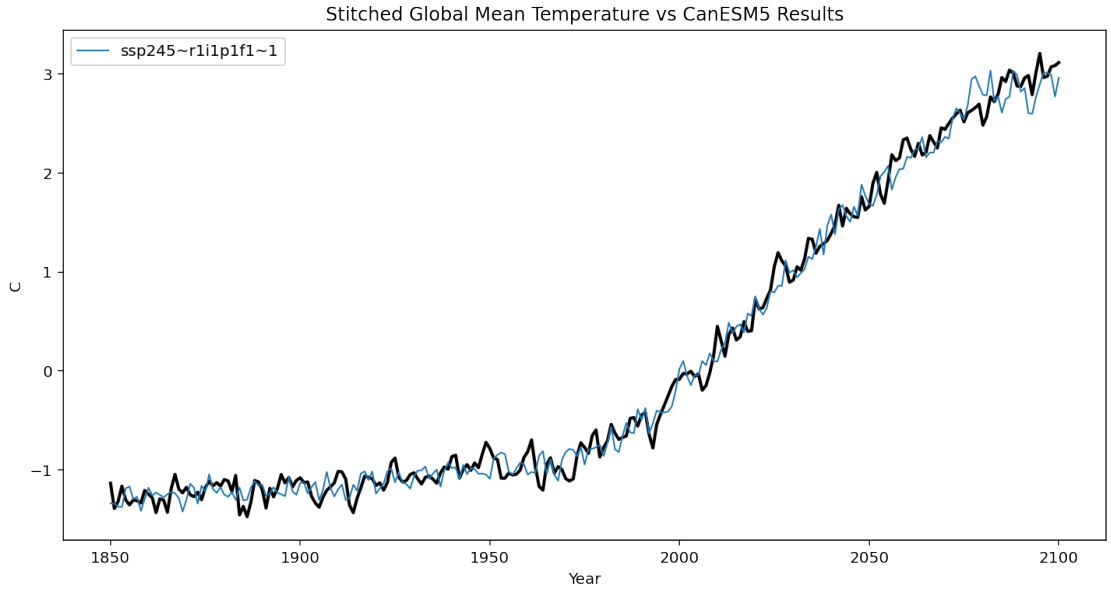
nearest neighbor stitched realization

```
groups = stitched_global_temp.groupby('stitching_id')

for name, group in groups:
    plt.plot(group.year, group.value, label = name)

plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature")
plt.legend()
plt.show()
plt.close()



# Load the comparison GSAT data
data_directory = pkg_resources.resource_filename("stitches", "data")
data_path = os.path.join(data_directory, "tas-data", "CanESM5_tas.csv")

comp_data = pd.read_csv(data_path)
comp_data = comp_data.loc[comp_data["experiment"] == "ssp245"]
```



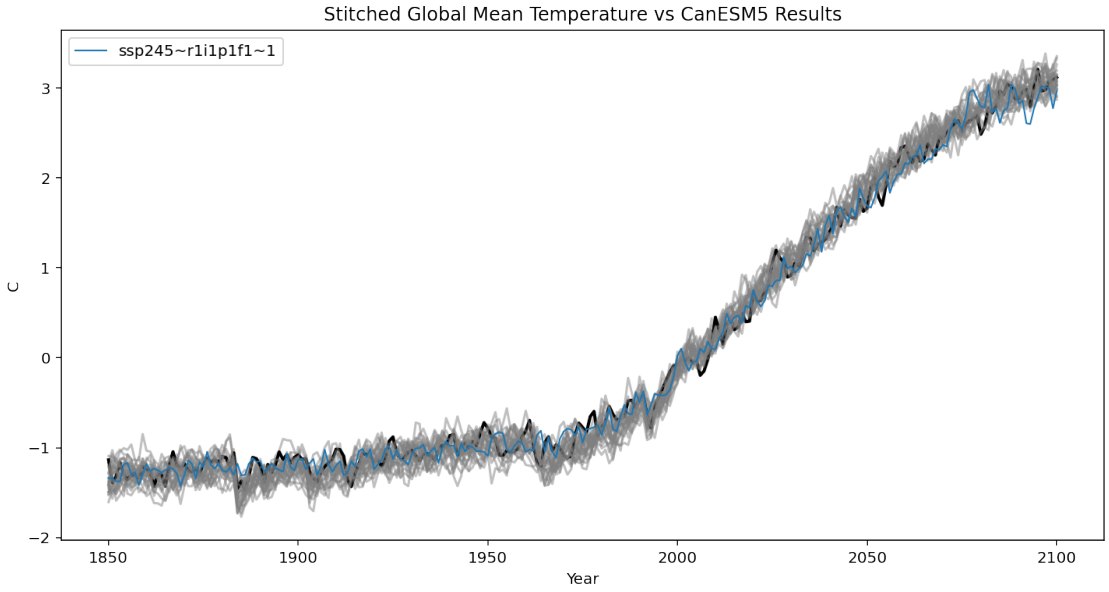
stitched realization and the target ensemble member

```
groups = comp_data.groupby('ensemble')
for name, group in groups:
    if(group.ensemble.unique() == 'r1i1p1f1'):
        plt.plot(group.year, group.value, color = "black", linewidth = 2.0)
# The stitched realizations:
groups = stitched_global_temp.groupby('stitching_id')
for name, group in groups:
    plt.plot(group.year, group.value, linewidth= 1.0, label = name)

plt.legend()
plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature vs CanESM5 Results")
plt.show()
plt.close()
```



stitched realization and the entire scenario ensemble

```
# full ensemble of actual ESM runs:
groups = comp_data.groupby('ensemble')
for name, group in groups:
    if(group.ensemble.unique() == 'r1i1p1f1'):
        plt.plot(group.year, group.value, color = "black", linewidth = 2.0)
    else:
        plt.plot(group.year, group.value, color = "0.5", alpha=0.5)

# The stitched realizations:
groups = stitched_global_temp.groupby('stitching_id')
for name, group in groups:
    plt.plot(group.year, group.value, linewidth= 1.0, label = name)

plt.legend()
plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature vs CanESM5 Results")
plt.show()
plt.close()
```



gridded stitching of the non-NN recipes

This is a little slow, but it will create the netcdfs according to our stitched recipes that we can load in and work with.

```
stitches.gridded_stitching(out_dir='.',  rp=my_recipes)
```

```
['Stitching gridded netcdf for: CanESM5 tas ssp245~r1i1p1f1~1']
['Stitching gridded netcdf for: CanESM5 tas ssp245~r1i1p1f1~2']
['Stitching gridded netcdf for: CanESM5 tas ssp245~r1i1p1f1~3']
```

```
['./stitched_CanESM5_tas_ssp245~r1i1p1f1~3.nc',
 './stitched_CanESM5_pr_ssp245~r1i1p1f1~3.nc']
```

now you have created multiple gridded, monthly tas and pr files that are statistically consistent with the target: SSP245 realization 1.

```
import xarray as xr

gen_tas = xr.open_dataset('stitched_CanESM5_tas_ssp245~r1i1p1f1~1.nc')
gen_tas
```

```
<xarray.Dataset>
Dimensions:  (time: 3012, lat: 64, lon: 128)
Coordinates:
  * time     (time) datetime64[ns] 1850-01-31 1850-02-28 ... 2100-12-31
  * lat      (lat) float64 -87.86 -85.1 -82.31 -79.53 ... 79.53 82.31 85.1
87.86
  * lon      (lon) float64 0.0 2.812 5.625 8.438 ... 348.8 351.6 354.4 357.2
Data variables:
    tas      (time, lat, lon) float32 ...
```

```
gen_pr = xr.open_dataset('stitched_CanESM5_pr_ssp245~r1i1p1f1~1.nc')
gen_pr
```

```
<xarray.Dataset>
Dimensions:  (time: 3012, lat: 64, lon: 128)
Coordinates:
  * time     (time) datetime64[ns] 1850-01-31 1850-02-28 ... 2100-12-31
  * lat      (lat) float64 -87.86 -85.1 -82.31 -79.53 ... 79.53 82.31 85.1
87.86
  * lon      (lon) float64 0.0 2.812 5.625 8.438 ... 348.8 351.6 354.4 357.2
Data variables:
    pr       (time, lat, lon) float32 ...
```

Pull comparison netcdfs

```
# Fetch the actual data directly from pangeo
data_directory = pkg_resources.resource_filename("stitches", "data")
pangeo_path = os.path.join(data_directory, "pangeo_table.csv")

pangeo_data = pd.read_csv(pangeo_path)

pangeo_data = pangeo_data.loc[(pangeo_data['variable'].isin(['tas', 'pr']))
                              & (pangeo_data['domain'].str.contains('mon'))
                              & (pangeo_data['experiment'].isin(['ssp245']))
                              & (pangeo_data['ensemble'].isin(['r1i1p1f1']))
                              &
(pangeo_data['model'].isin(['CanESM5']))].copy()

# load the target tas netcdf files
tas_address = pangeo_data.loc[pangeo_data['variable']== 'tas'].zstore.copy()
tar_tas = stitches.fetch_nc(tas_address.values[0])

# load the target pr netcdf files
pr_address = pangeo_data.loc[pangeo_data['variable']== 'pr'].zstore.copy()
tar_pr = stitches.fetch_nc(pr_address.values[0])
```

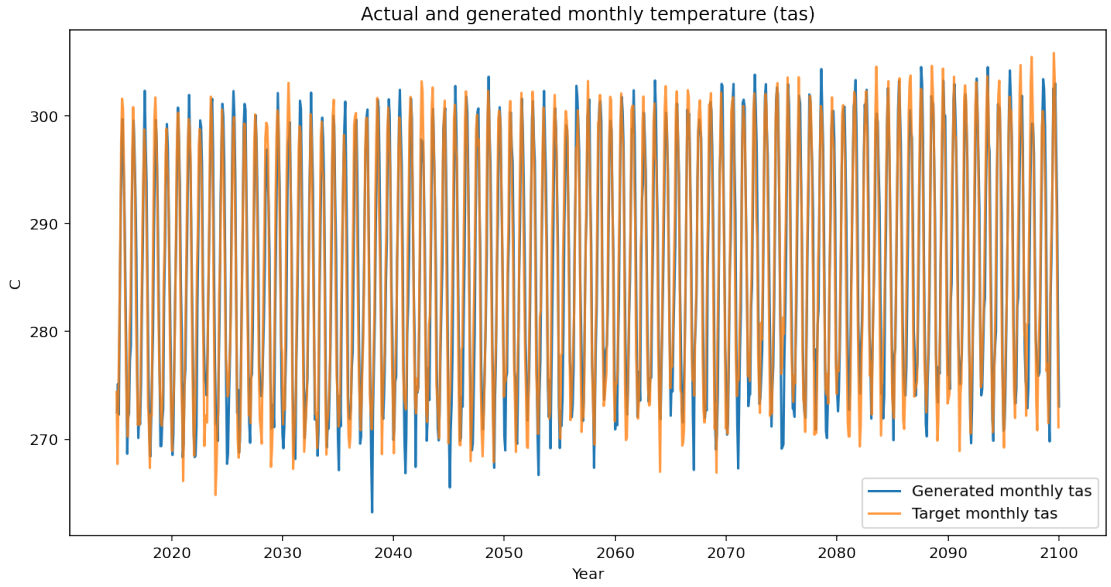
Visualize

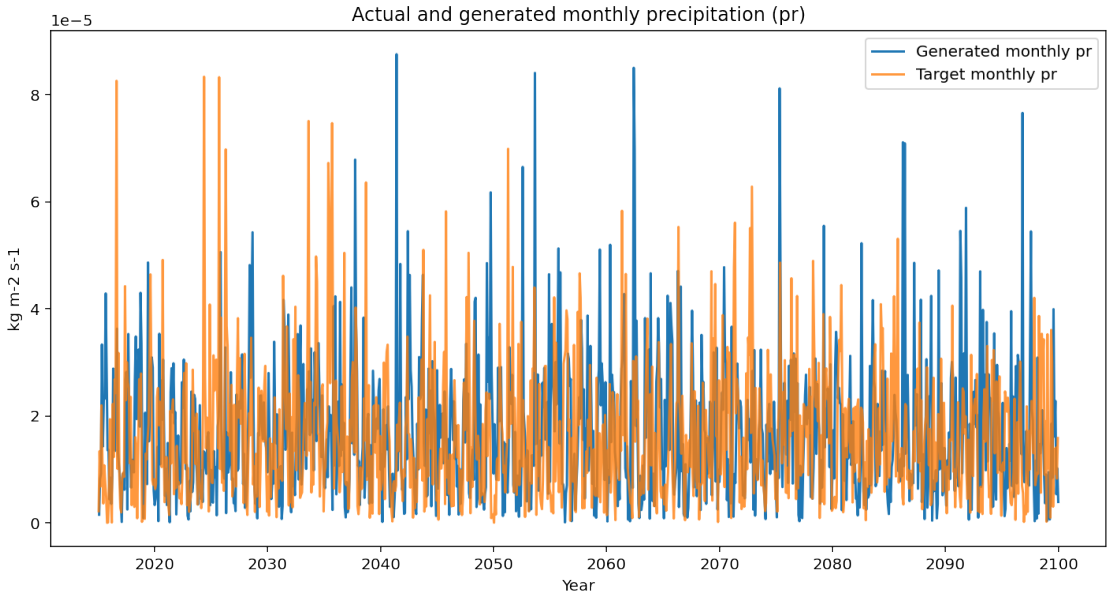
Select a grid cell and plot the generated and target tas, pr data for first-cut comparison

```
# define a helper function
def plot_comparison(generated_data,
                    target_data,
                    variable,
                    alpha=0.8):
    """Plot comparision between target variable time series and generated
data"""
```

```
    if variable.casefold() == "pr":
        variable_name = "precipitation"
        units = "kg m-2 s-1"
    else:
        variable_name = "temperature"
        units = "C"

    # temperature (tas)
    plt.plot(generated_data.time,
             generated_data[variable],
             label=f"Generated monthly {variable}")

    with warnings.catch_warnings():
        warnings.filterwarnings("ignore")

        plt.plot(target_data.indexes['time'].to_datetimeindex(),
                 target_data[variable],
                 alpha=alpha,
                 label = f"Target monthly {variable}")

    plt.legend()
    plt.xlabel("Year")
    plt.ylabel(units)
    plt.title(f"Actual and generated monthly {variable_name} ({variable})")
    plt.show()
    plt.close()


# lon and lat values for a grid cell near the Joint Global Change Research
Institute in College Park, MD, USA
cp_lat = 38.9897
cp_lon = 180 + 76.9378

# lat and lon coordinates closest
abslat = np.abs(gen_tas.lat - cp_lat)
abslon = np.abs(gen_tas.lon-cp_lon)
c = np.maximum(abslon, abslat)
([lon_loc], [lat_loc]) = np.where(c == np.min(c))
lon_grid = gen_tas.lon[lon_loc]
lat_grid = gen_tas.lat[lat_loc]

cp_tas_gen = gen_tas.sel(lon=lon_grid,
                         lat=lat_grid,
                         time=slice('2015-01-01', '2099-12-31')).copy()

cp_tas_tar = tar_tas.sel(lon=lon_grid,
                         lat=lat_grid,
                         time=slice('2015-01-01', '2099-12-31')).copy()
```

```
cp_pr_gen = gen_pr.sel(lon=lon_grid,
                       lat=lat_grid,
                       time=slice('2015-01-01', '2099-12-31')).copy()

cp_pr_tar = tar_pr.sel(lon=lon_grid,
                       lat=lat_grid,
                       time=slice('2015-01-01', '2099-12-31')).copy()

# temperature (tas)
plot_comparison(generated_data=cp_tas_gen,
                target_data=cp_tas_tar,
                variable="tas")

# precipitation (pr)
plot_comparison(generated_data=cp_pr_gen,
                target_data=cp_pr_tar,
                variable="pr")
```





Visual validation of the complex spatial, temporal, and cross-variable relationships present in ESM outputs is not possible. We extensively validate that the method reproduces ESM internal variability in the ESD paper, but this visual plotting at least suggests that nothing is obviously wrong. In particular, there are no obvious artifacts occurring every 9-years in the generated time series.

In other words, it's not inconceivable from these plots that the orange time series were sampled from the same underlying multivariate distribution that generated the blue time series.

Draws of collapse-free generated ensembles

As mentioned above, we restrict the generated ensembles of recipes so that they do not undergo envelope collapse.

Multiple stochastic draws of such ensembles can, however, be made by turning off the `reproducible` argument. If these draws of well-behaved ensembles were concatenated into a 'super' ensemble, there WOULD be envelope collapse.

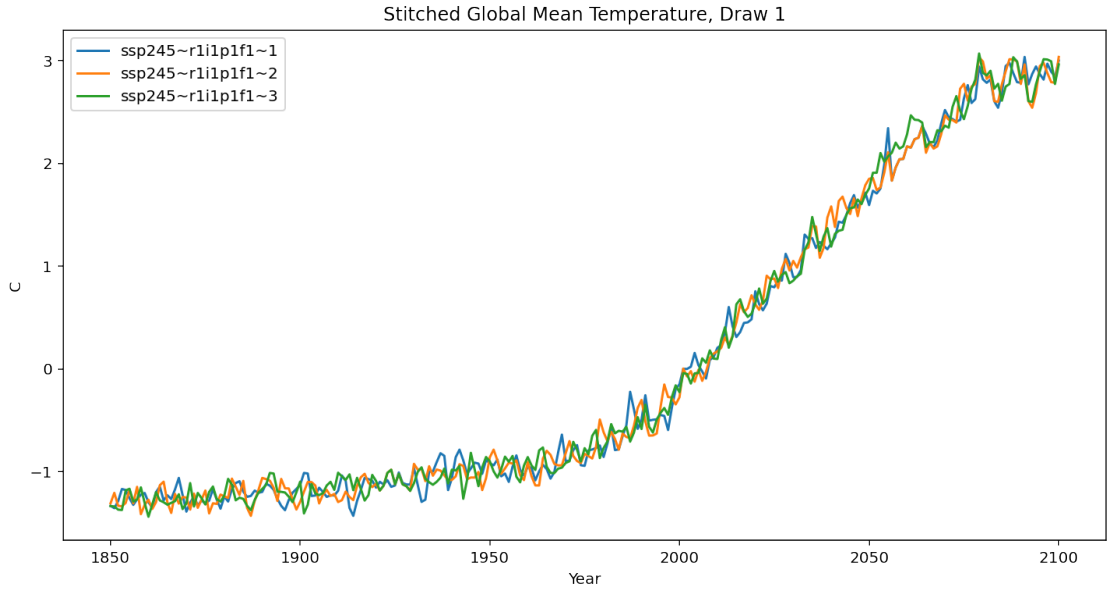
```
draw1_recipes = stitches.make_recipe(target_data = target_data3,
                                     archive_data=archive_data,
                                     tol=0.05,
                                     N_matches=4,
                                     reproducible=True)

draw2_recipes= stitches.make_recipe(target_data = target_data3,
                                     archive_data=archive_data,
                                     tol=0.05,
                                     N_matches=4,
                                     reproducible=False)
```

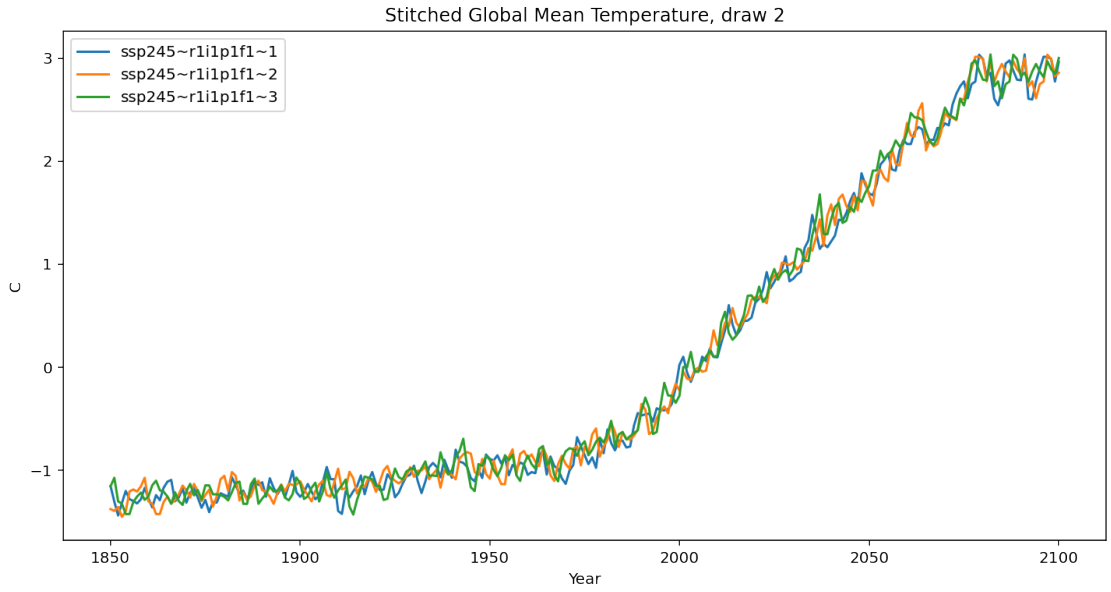
```
# stitch tgav
stitched_global_temp_draw1 = stitches.gmat_stitching(draw1_recipes)
stitched_global_temp_draw2 = stitches.gmat_stitching(draw2_recipes)
```

```
You have requested more recipes than possible for at least one target
trajectories, returning what can
You have requested more recipes than possible for at least one target
trajectories, returning what can
```

plot the two well behaved ensembles

```
groups = stitched_global_temp_draw1.groupby('stitching_id')

for name, group in groups:
    plt.plot(group.year, group.value, label = name)

plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature, Draw 1")
plt.legend()
plt.show()
plt.close()


groups = stitched_global_temp_draw2.groupby('stitching_id')

for name, group in groups:
    plt.plot(group.year, group.value, label = name)

plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature, draw 2")
plt.legend()
plt.show()
plt.close()
```

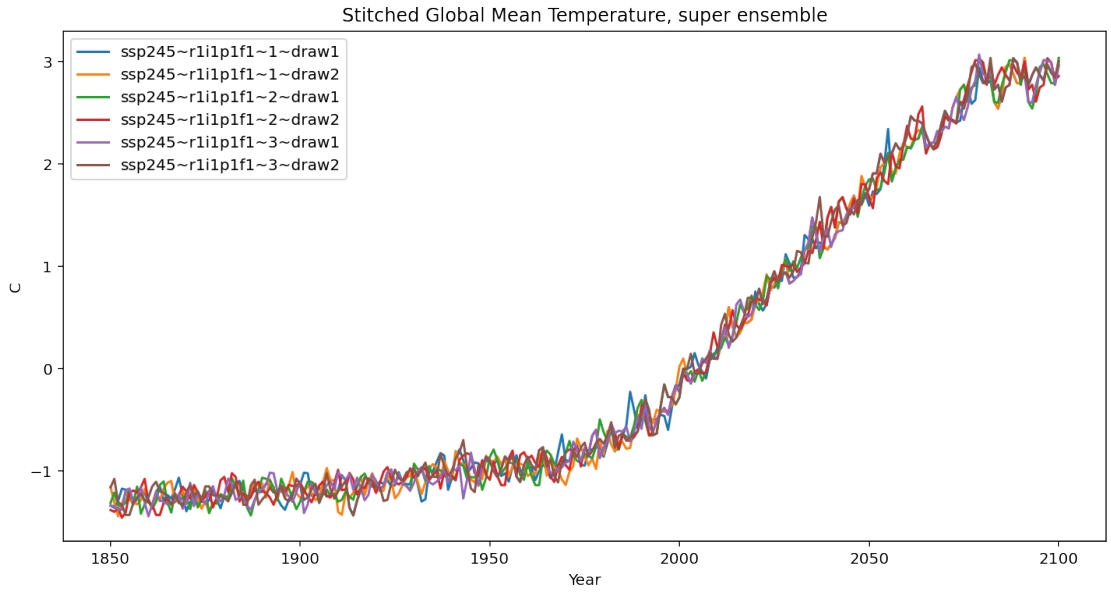




concatenate to a super-ensemble and plot

```
#update the stitching ids to reflect draws
stitched_global_temp_draw1['stitching_id'] =
stitched_global_temp_draw1['stitching_id'] + '~draw1'
stitched_global_temp_draw2['stitching_id'] =
stitched_global_temp_draw2['stitching_id'] + '~draw2'

# concatenate
super_ensemble = pd.concat([stitched_global_temp_draw1,
stitched_global_temp_draw2]).reset_index(drop=True)

# plot
```

```
groups = super_ensemble.groupby('stitching_id')

for name, group in groups:
    plt.plot(group.year, group.value, label = name)

plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature, super ensemble")
plt.legend()
plt.show()
plt.close()
```



Again, around 2075, you can really see that there are not 6 distinct curves, and the same trajectory is being followed for multiple ensemble members.

Bonus example

When discussing pre-processing the archive data above, we emphasized not wanting years of ESM data to be included in multiple archive windows.

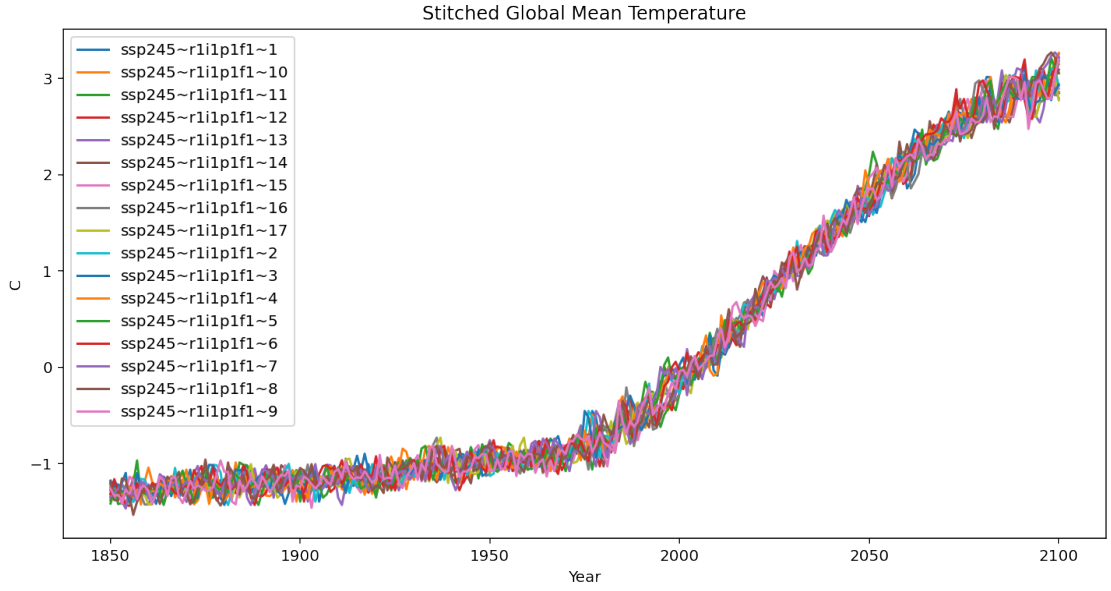
Here, we will use the entire staggered archive, so every year appears in 9 total archive windows. We will just look at the global average temperatures for expediency,

```
# All windows for the experiments we want
full_staggered_archive = staggered_archive[(staggered_archive['model']==
'CanESM5')&

(staggered_archive['experiment'].isin(['ssp126',

'ssp370', 'ssp585']))]
```

```
# make recipes
bad_recipes = stitches.make_recipe(target_data = target_data3,
                                   archive_data=full_staggered_archive,
                                   tol=0.06,
                                   N_matches=25,
                                   reproducible=True)
# stitch tgav
stitched_global_temp = stitches.gmat_stitching(bad_recipes)
```

```
You have requested more recipes than possible for at least one target
trajectories, returning what can
```

```
# plot

groups = stitched_global_temp.groupby('stitching_id')

for name, group in groups:
    plt.plot(group.year, group.value, label = name)

plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature")
plt.legend()
plt.show()
plt.close()
```

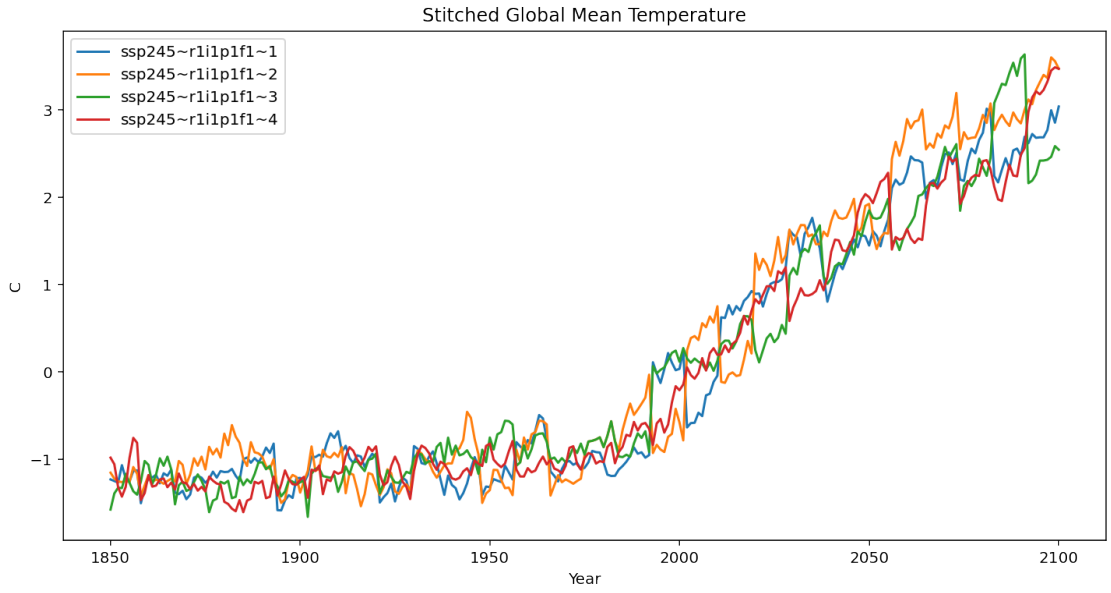


It's not necessarily easy to see, but if you look closely around 1975, you can see several blue and purple curves that are obviously the same archive window offset from each other by a year or two. While this 'wave' is NOT envelope collapse, it's also not especially realistic. Having years only occur in 1-2 archive windows helps prevent this from happening.

Bonus 2!

What does a fully 'bad' match look like? We can go far past the cutoff tolerance values provided in the paper to see

```
bad_recipes2 = stitches.make_recipe(target_data = target_data3,
                                    archive_data=archive_data,
                                    tol=0.5,
                                    N_matches=4,
                                    reproducible=True)
# stitch tgav
stitched_global_temp = stitches.gmat_stitching(bad_recipes2)

# plot
groups = stitched_global_temp.groupby('stitching_id')

for name, group in groups:
    plt.plot(group.year, group.value, label = name)

plt.xlabel("Year")
plt.ylabel("C")
plt.title("Stitched Global Mean Temperature")
plt.legend()
plt.show()
plt.close()
```



These curves (especially the red curve) are clearly rapidly switching between archive scenarios as they sort of follow the target scenario's mean, rather than matching the target scenario well.

The validation in the ESD paper and tolerance cutoff estimates intentionally controls to avoid this.