FAIR Documentation

Release 1.3

FAIR development team

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CHAPTER

ONE

Introduction

The Finite Amplitude Impulse Response (FAIR) model is a simple emissions-based climate model. It allows the user to input emissions of greenhouse gases and short lived climate forcers in order to estimate global mean atmospheric GHG concentrations, radiative forcing and temperature anomalies.

The original FAIR model (v1.0) was developed to simulate the earth system response to CO_2 emissions, with all non-CO_2 forcing implemented as an "external" source. It was developed by Richard Millar, Zebedee Nicholls, Pierre Friedlingstein and Myles Allen. The motivation for developing it and its formulation is documented in a paper published in Atmospheric Chemistry and Physics in 2017.

The emissions-based model (v1.3) extends FAIR by replacing all sources of non-CO_2 forcing with relationships that are based on the source emissions, with the exception of natural forcings (variations in solar irradiance and volcanic eruptions). It is useful for assessing future policy commitments to anthropogenic emissions (something which we can control) than to radiative forcing (something which is less certain and which we can only partially control).

CHAPTER

TWO

Installation

2.1 From the Python Package Index (PyPI)

Probably the easiest way: simply type `pip install fair` from a terminal.

2.2 From GitHub

The latest release (as a tar.gz or zip file) can be obtained from https://github.com/OMS-NetZero/FAIR/releases, or the most current unreleased version can be cloned from https://github.com/OMS-NetZero/FAIR.

CHAPTER

THREE

Examples

Here are some simple examples of how to run and use the Finite Amplitude Impulse Response (FAIR) model run in the jupyter notebook.

```
%matplotlib inline
```

```
import fair
fair.__version__

import numpy as np

from matplotlib import pyplot as plt
plt.style.use('seaborn-darkgrid')
plt.rcParams['figure.figsize'] = (16, 9)
```

The “engine” of FAIR is the `fair_scm` function in the `forward` module.

```
from fair.forward import fair_scm
```

3.1 CO2 driven run

3.1.1 Basic example

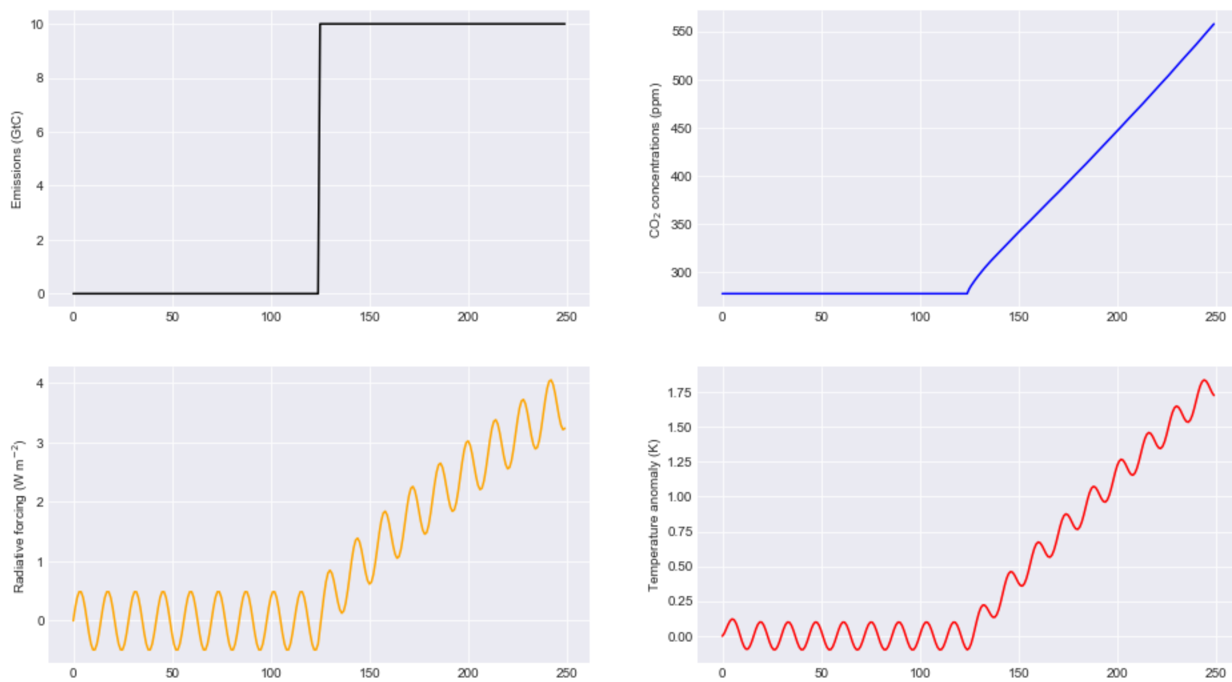
Here we show how FAIR can be run with step change CO2 emissions and sinusoidal non-CO2 forcing timeseries. This is a FAIR v1.0-style setup in which CO2 is the only emitted species.

In almost every application of FAIR you will probably want to vary the `emissions` time series going in to `fair_scm`. In CO2-only mode this is a 1D array of CO2 emissions. Setting `useMultigas=False` turns off the emissions from non-CO2 species.

The output from FAIR is a 3-tuple of `(C,F,T)` arrays. In CO2 mode, both `C` (representing CO2 concentrations in ppm) and `F` (total radiative forcing in W m-2) are 1D arrays. `T` (temperature change since the pre-industrial) is always output as a 1D array.

```
# set up emissions and forcing arrays
emissions = np.zeros(250)    # Unit: GtC
emissions[125:] = 10.0
other_rf = np.zeros(emissions.size)
for x in range(0, emissions.size):
    other_rf[x] = 0.5 * np.sin(2 * np.pi * (x) / 14.0)

# run the model
```

```
C,F,T = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False
)

# plot the output
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax1.plot(range(0, emissions.size), emissions, color='black')
ax1.set_ylabel('Emissions (GtC)')
ax2 = fig.add_subplot(222)
ax2.plot(range(0, emissions.size), C, color='blue')
ax2.set_ylabel('CO$_2$ concentrations (ppm)')
ax3 = fig.add_subplot(223)
ax3.plot(range(0, emissions.size), F, color='orange')
ax3.set_ylabel('Radiative forcing (W m$^{-2}$)')
ax4 = fig.add_subplot(224)
ax4.plot(range(0, emissions.size), T, color='red')
ax4.set_ylabel('Temperature anomaly (K)');
```

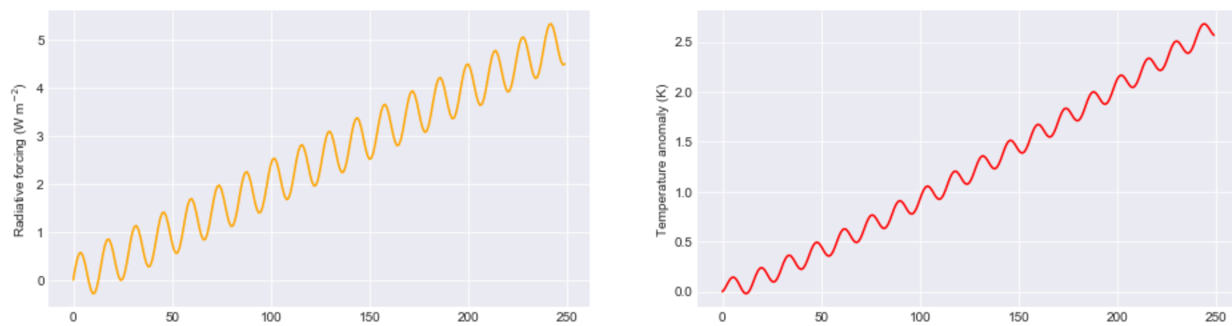


3.1.2 Forcing-only runs

If you want to specify a pure forcing and bypass the carbon cycle routine this is also possible by setting `emissions=False`. This time, we will add a linear forcing to the sinusodal forcing above. Note that the CO2 concentrations are not updated from their pre-industrial value.

```
# Define a forcing time series
for x in range(0, emissions.size):
    other_rf[x] = 0.02*x + 0.5 * np.sin(2 * np.pi * (x) / 14.0)

# run the model with emissions off
```

```
_,F,T = fair.forward.fair_scm(
    emissions=False,
    other_rf=other_rf,
    useMultigas=False
)

# plot the output
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax1.plot(range(0, other_rf.size), F, color='orange')
ax1.set_ylabel('Radiative forcing (W m$^{-2}$)')
ax1 = fig.add_subplot(222)
ax1.plot(range(0, other_rf.size), T, color='red')
ax1.set_ylabel('Temperature anomaly (K)');
```



3.1.3 Varying the carbon cycle parameters

FAIR is set up to simulate the responses to more complex earth system models. This is achieved by a scaling of a four-box decay model for atmospheric carbon dioxide emissions based on the airborne fraction of carbon dioxide. This in turn depends on the efficiency of carbon sinks, which is a function of temperature change and total accumulated carbon uptake. Much of the technical detail is described in Millar et al., (2017).

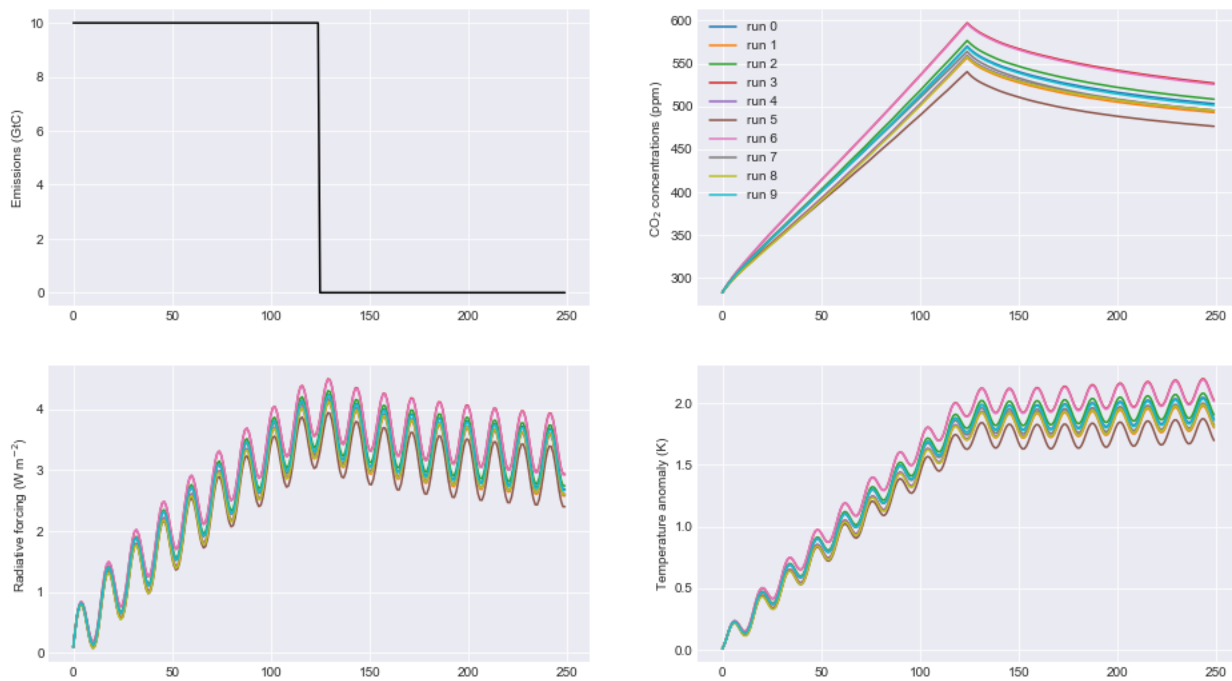
In the carbon cycle, the important variables are `r0`, `rc` and `rt` which are in turn the pre-industrial sensitivity of carbon sinks, the sensitivity to cumulative carbon dioxide emissions, and sensitivity to temperature change.

This time we will demonstrate with a 10 Gt constant pulse and use a 10-member ensemble.

```
# set up emissions and forcing arrays
emissions = np.ones(250) * 10.0   # Unit: GtC
emissions[125:] = 0.0
other_rf = np.zeros(emissions.size)
for x in range(0, emissions.size):
    other_rf[x] = 0.5 * np.sin(2 * np.pi * (x) / 14.0)

# create output arrays
nrun = 10
C = np.empty((emissions.size, nrun))
F = np.empty((emissions.size, nrun))
T = np.empty((emissions.size, nrun))

# Generate some random values of carbon cycle parameters
# use a seed for reproducible results
from scipy.stats import norm
r0 = norm.rvs(size=nrun, loc=35, scale=5.0, random_state=42)
rc = norm.rvs(size=nrun, loc=0.019, scale=0.003, random_state=77)
```

```
rt = norm.rvs(size=nrun, loc=4.165, scale=0.5, random_state=1729)

# initialise plot
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax1.plot(range(0, emissions.size), emissions, color='black')
ax1.set_ylabel('Emissions (GtC)')
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)
ax4 = fig.add_subplot(224)
# run the model and plot outputs
print ("run       r0      rc     rt")
for i in range(nrun):
    print ("  %d  %5.3f %5.4f %5.3f" % (i, r0[i], rc[i], rt[i]))
    C[:,i],F[:,i],T[:,i] = fair.forward.fair_scm(
        emissions=emissions,
        other_rf=other_rf,
        useMultigas=False,
        r0 = r0[i],
        rc = rc[i],
        rt = rt[i]
    )
    ax2.plot(range(0, emissions.size), C[:,i], label='run %d' % i)
    ax2.set_ylabel('CO$_2$ concentrations (ppm)')
    ax3.plot(range(0, emissions.size), F[:,i])
    ax3.set_ylabel('Radiative forcing (W m$^{-2}$)')
    ax4.plot(range(0, emissions.size), T[:,i])
    ax4.set_ylabel('Temperature anomaly (K)');
ax2.legend();
```

```
run       r0      rc     rt
  0  37.484 0.0197 3.821
  1  34.309 0.0210 3.755
  2  38.238 0.0173 4.991
  3  42.615 0.0202 3.877
  4  33.829 0.0204 4.714
  5  33.829 0.0131 4.628
  6  42.896 0.0198 3.668
  7  38.837 0.0143 3.736
  8  32.653 0.0237 4.202
  9  37.713 0.0168 4.430
```



3.1.4 Changing CO2 lifetime and partitioning coefficients

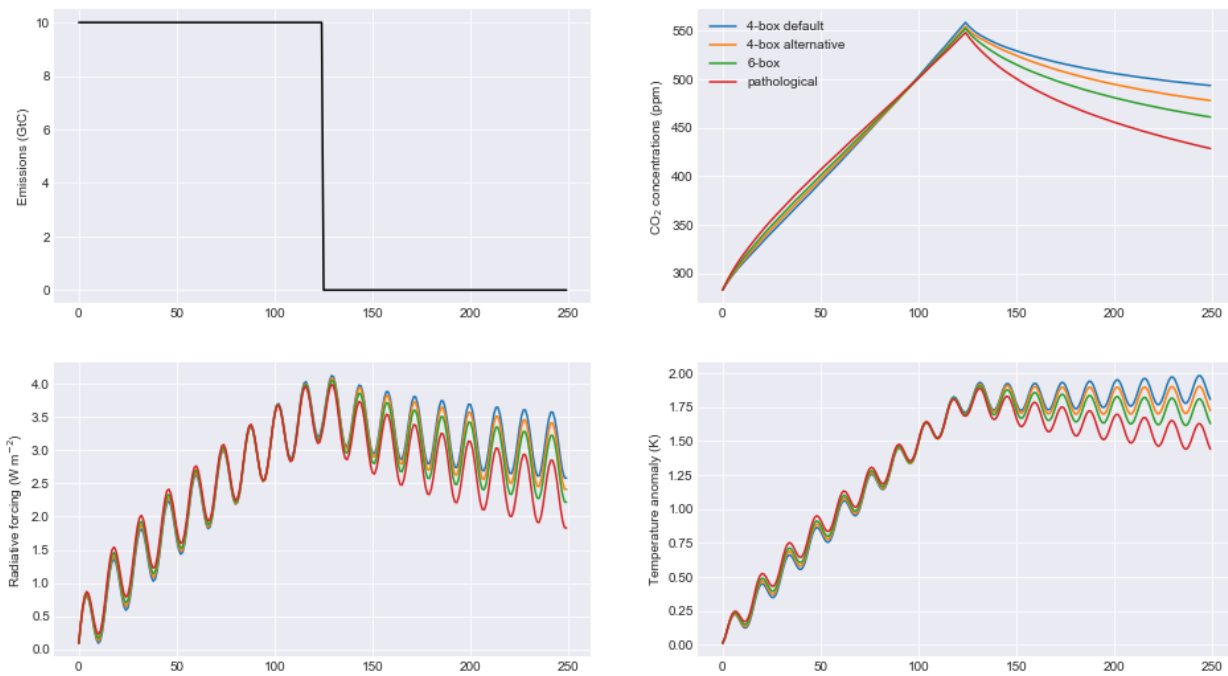
The CO2 initial lifetime and partitioning coefficients are quantified by the `tau` and `a` parameters respectively. The rationale follows the four-box model in Myhre et al. (2013), scaled by the impact of land and ocean carbon uptake as described in Millar et al., (2017).

`tau`, in years, is the time constant for each carbon pool and is ordered from slowest carbon pool to fastest, and `a` is the fraction of new CO2 emissions going in to each pool. The first element of `tau` is usually very large and represents the fraction of CO2 emissions that remain in the atmosphere "quasi-permanently", i.e. removed only on geological time scales, far past the range of times in which FAIR is expected to give useful results (although nobody will stop you using a smaller value as we demonstrate). An error should be thrown if the sum of `a` is not one.

In the second figure it can be seen that these parameter settings are important for the rate of decay of atmospheric CO2 in particular.

```
# set up emissions and forcing arrays
emissions = np.ones(250) * 10.0   # Unit: GtC
emissions[125:] = 0.0
other_rf = np.zeros(emissions.size)
for x in range(0, emissions.size):
    other_rf[x] = 0.5 * np.sin(2 * np.pi * (x) / 14.0)

# create output arrays
nrun=4
C = np.empty((emissions.size, nrun))
F = np.empty((emissions.size, nrun))
T = np.empty((emissions.size, nrun))

# Play with the carbon boxes
tau2 = np.array([1e6, 400.0, 100.0, 5.0])
a2   = np.ones(4) * 0.25

# Nobody said we had to stick to a four-box model...
```

```
tau3 = np.array([1e6, 1000.0, 150.0, 70.0, 15.0, 3.0])
a3   = np.array([0.1, 0.2, 0.2, 0.2, 0.2, 0.1])

# A pathological case where tau0 is much smaller than 1e6
# in this example CO2 behaves more like other GHGs
tau4 = np.array([10., 4., 1., 0.3])
a4   = np.ones(4) * 0.25

# run the model for default values
C[:,0],F[:,0],T[:,0] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False)

# ... and for our alternatives
C[:,1],F[:,1],T[:,1] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False,
    tau=tau2,
    a=a2)
C[:,2],F[:,2],T[:,2] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False,
    tau=tau3,
    a=a3)
C[:,3],F[:,3],T[:,3] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False,
    tau=tau4,
    a=a4)

# plot the output
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax1.plot(range(0, emissions.size), emissions, color='black')
ax1.set_ylabel('Emissions (GtC)')
ax2 = fig.add_subplot(222)
handles = ax2.plot(range(0, emissions.size), C)
labels = ['4-box default','4-box alternative','6-box','pathological']
ax2.legend(handles, labels)
ax2.set_ylabel('CO$_2$ concentrations (ppm)')
ax3 = fig.add_subplot(223)
ax3.plot(range(0, emissions.size), F)
ax3.set_ylabel('Radiative forcing (W m$^{-2}$)')
ax4 = fig.add_subplot(224)
ax4.plot(range(0, emissions.size), T)
ax4.set_ylabel('Temperature anomaly (K)');
```



3.1.5 ECS and TCR

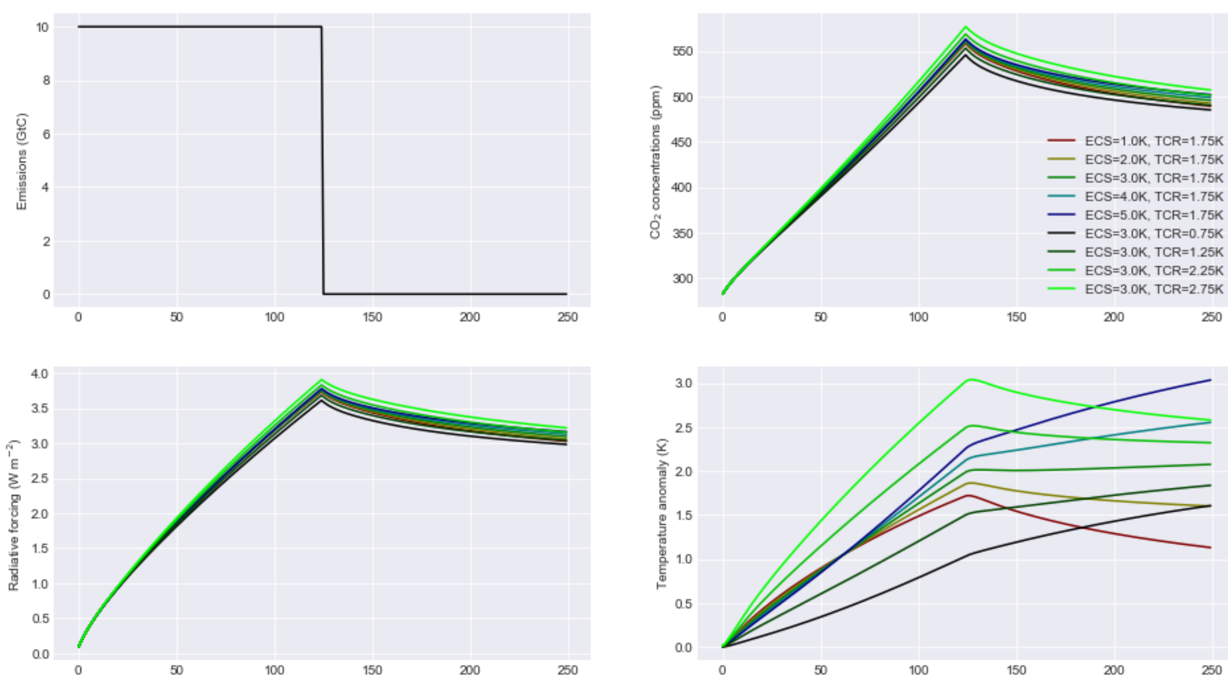
The equilibrium climate sensitivity (defined as the equilibrium warming for an abrupt doubling of CO2 concentrations) and transient climate response (defined as the temperature change after a CO2 doubling to a 1% per year compound increase in CO2 concentrations - approximately 70 years) are both key uncertainties in climate science. The temperature response in FAIR depends on both. The `tcrecs` parameter, a 2-element array, controls this.

This next example shows the effect of varying the ECS and TCR. (Note that by definition the case ECS=1.0, TCR=1.75 is not possible, but FAIR can handle such cases anyway).

The biggest effect is on the temperature response, but as the temperature feeds back into the carbon cycle, this also affects the CO2 concentrations and the radiative forcing.

```
# set up emissions and forcing arrays
emissions = np.zeros(250)
emissions[:125] = 10.0

# create output arrays
nrun=9
C = np.empty((emissions.size, nrun))
F = np.empty((emissions.size, nrun))
T = np.empty((emissions.size, nrun))

# initialise plot
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax1.plot(range(0, emissions.size), emissions, color='black')
ax1.set_ylabel('Emissions (GtC)')
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)
ax4 = fig.add_subplot(224)

ecs = np.array([1.0, 2.0, 3.0, 4.0, 5.0, 3.0, 3.0, 3.0, 3.0])
```

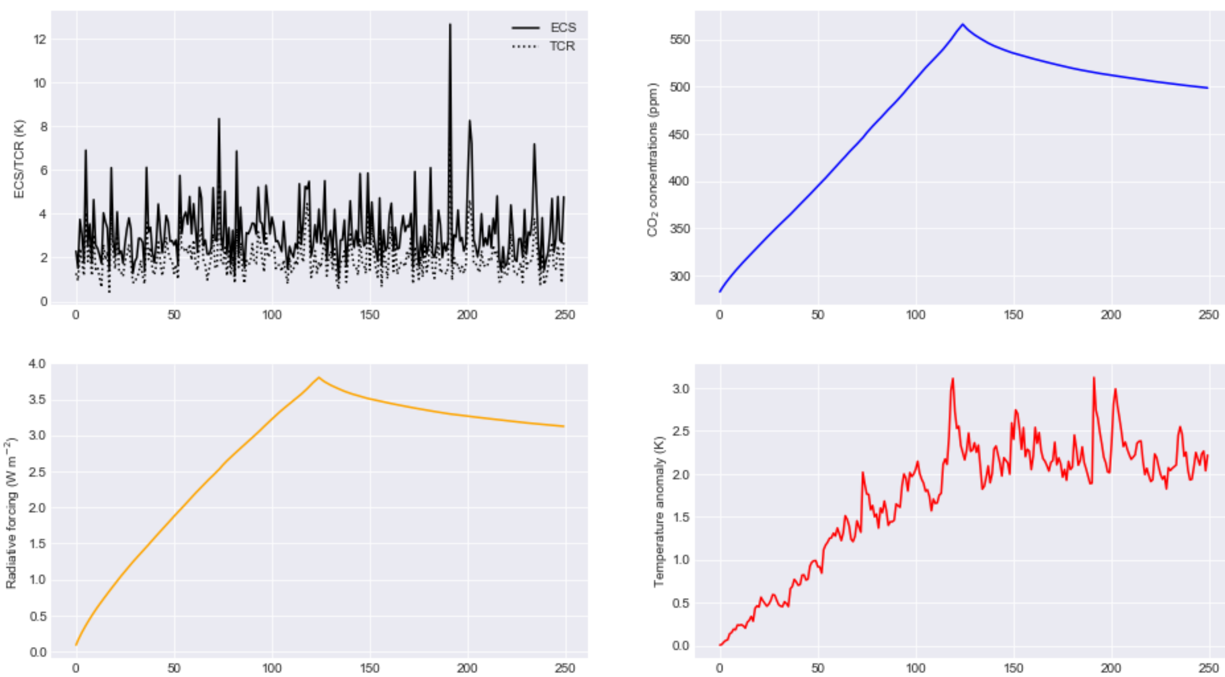
```
tcr = np.array([1.75, 1.75, 1.75, 1.75, 1.75, 0.75, 1.25, 2.25, 2.75])
colors = ['#800000','#808000','#008000','#008080','#000080', '#000000', '#004000', '
↪#00c000', '#00ff00']

# run the model and plot outputs
for i in range(nrun):
    C[:,i],F[:,i],T[:,i] = fair.forward.fair_scm(
        emissions=emissions,
        useMultigas=False,
        tcrecs=[tcr[i], ecs[i]],
    )

    ax2.plot(range(0, emissions.size), C[:,i], color=colors[i], label='ECS=%3.1fK,␣
↪TCR=%4.2fK' % (ecs[i], tcr[i]))
    ax2.set_ylabel('CO$_2$ concentrations (ppm)')
    ax3.plot(range(0, emissions.size), F[:,i], color=colors[i])
    ax3.set_ylabel('Radiative forcing (W m$^{-2}$)')
    ax4.plot(range(0, emissions.size), T[:,i], color=colors[i])
    ax4.set_ylabel('Temperature anomaly (K)');
ax2.legend();
```



Some recent studies (Armour 2017; Gregory and Andrews 2016) suggest that ECS and TCR may not be constant. Fortunately we can investigate this in FAIR by specifying `tcrecs` as a two dimensional `(nt, 2)` array. Notice the effect that a varying ECS/TCR has on the temperature.

```
from scipy.stats import lognorm, truncnorm

# generate an ECS time series that roughly follows the AR5 likely range
ecs = lognorm.rvs(0.4, size=250, scale=3, random_state=299)

# define TCR in terms of a realised warming fraction
rwf = truncnorm.rvs(-3, 3, loc=0.6, scale=0.1, size=250, random_state=301)
tcr = rwf*ecs
```

```
emissions = np.zeros(250)
emissions[:125] = 10.0

C,F,T = fair.forward.fair_scm(
    emissions=emissions,
    useMultigas=False,
    tcrecs=np.vstack([tcr, ecs]).T,
)

# plot the output
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax1.plot(range(0, emissions.size), ecs, color='black', label='ECS')
ax1.plot(range(0, emissions.size), tcr, color='black', ls=':', label='TCR')
ax1.legend()
ax1.set_ylabel('ECS/TCR (K)')
ax2 = fig.add_subplot(222)
ax2.plot(range(0, emissions.size), C, color='blue')
ax2.set_ylabel('CO$_2$ concentrations (ppm)')
ax3 = fig.add_subplot(223)
ax3.plot(range(0, emissions.size), F, color='orange')
ax3.set_ylabel('Radiative forcing (W m$^{-2}$)')
ax4 = fig.add_subplot(224)
ax4.plot(range(0, emissions.size), T, color='red')
ax4.set_ylabel('Temperature anomaly (K)');
```



The alternative is to specify the values of `q` directly (a 2D array) that go into the temperature calculation, bypassing `tcrecs` completely (setting `tcrecs=None`). It is not known under what circumstances the user may want to do this, but be assured it's possible!

```
# set up emissions and forcing arrays
emissions = np.ones(250) * 10.0
emissions[125:] = 0.0
```

```
q = np.ones((250,2))
q[:,0] = 0.2
q[:,1] = 0.6
C,F,T = fair.forward.fair_scm(
    emissions=emissions,
    useMultigas=False,
    tcrecs=None,
    q=q,
)
print (C[-1], F[-1], T[-1])
```

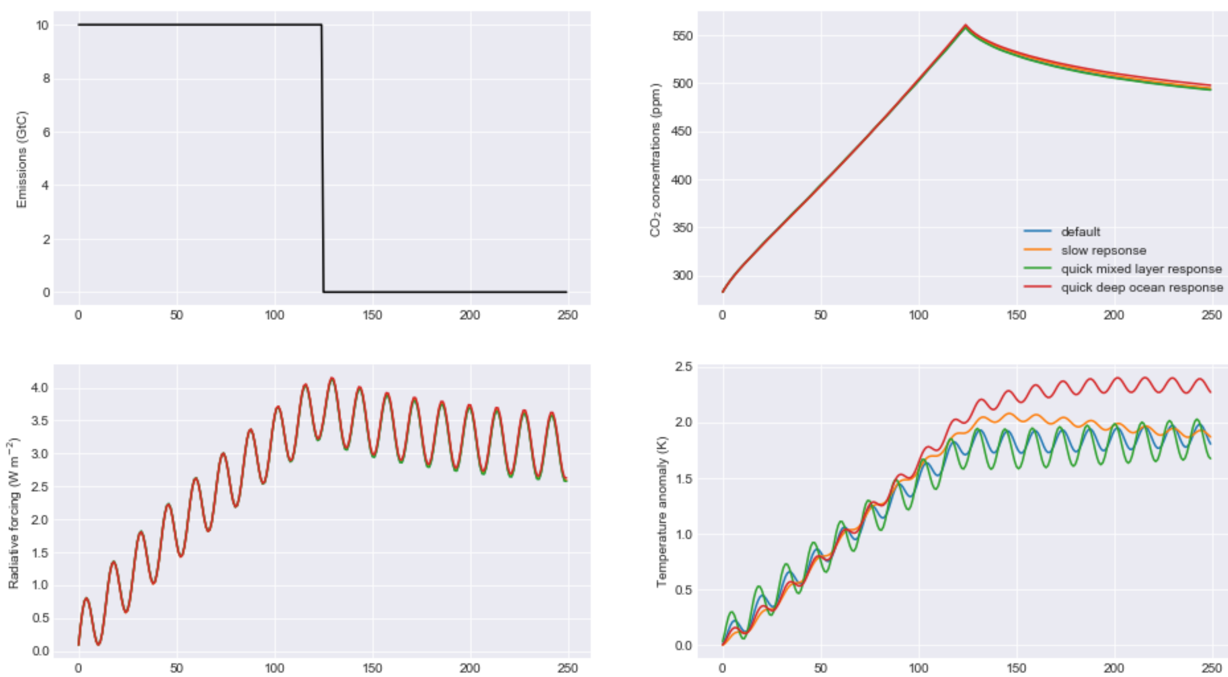
```
(500.5524349046043, 3.1476987553820677, 2.279051054881353)
```

3.1.6 Temperature time constants

The slow and fast response of global mean surface temperature is governed by the two-element array `d`: this parameter determines the rate at which radiative forcing is “realised” as a change in surface temperature.

```
# set up emissions and forcing arrays
emissions = np.ones(250) * 10.0   # Unit: GtC
emissions[125:] = 0.0
other_rf = np.zeros(emissions.size)
for x in range(0, emissions.size):
    other_rf[x] = 0.5 * np.sin(2 * np.pi * (x) / 14.0)

# create output arrays
nrun=4
C = np.empty((emissions.size, nrun))
F = np.empty((emissions.size, nrun))
T = np.empty((emissions.size, nrun))

# run the model for default values
C[:,0],F[:,0],T[:,0] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False)

# ... and for our alternatives
C[:,1],F[:,1],T[:,1] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False,
    d=[1000.0, 18.0])
C[:,2],F[:,2],T[:,2] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False,
    d=[239.0, 1.0])
C[:,3],F[:,3],T[:,3] = fair.forward.fair_scm(
    emissions=emissions,
    other_rf=other_rf,
    useMultigas=False,
    d=[60., 4.1])

# plot the output
fig = plt.figure()
```

```
ax1 = fig.add_subplot(221)
ax1.plot(range(0, emissions.size), emissions, color='black')
ax1.set_ylabel('Emissions (GtC)')
ax2 = fig.add_subplot(222)
handles = ax2.plot(range(0, emissions.size), C)
labels = ['default','slow repsonse','quick mixed layer response','quick deep ocean response']
ax2.legend(handles, labels)
ax2.set_ylabel('CO$_2$ concentrations (ppm)')
ax3 = fig.add_subplot(223)
ax3.plot(range(0, emissions.size), F)
ax3.set_ylabel('Radiative forcing (W m$^{-2}$)')
ax4 = fig.add_subplot(224)
ax4.plot(range(0, emissions.size), T)
ax4.set_ylabel('Temperature anomaly (K)');
```



3.2 Multi-species mode

More interesting scenarios can be created with the full suite of forcing agents. The key changes from CO2-only mode that should be remembered are:

- This time the emissions dataset is a (nt, 40) array of inputs
- `useMultigas` should be set to `True`, or omitted (this is the default option)
- The concentration and forcing outputs are themselves 2-dimensional arrays of size (nt, 31) and (nt, 13) respectively
- More input options to `fair_scm` become available.

The basic call to fair_scm remains the same:

```
(C,F,T) = fair_scm(emissions=emissions, **kwargs)
```

3.2.1 Emissions

In multi-species model, emissions are input as an `(nt, 40)` emissions array. The index order and units of the columns are as follows:

Index	Species	Units
0	Year	year
1	CO2-fossil	GtC/yr
2	CO2-landuse	GtC/yr
3	CH4	Mt/yr
4	N2O	MtN2/yr
5	SOx	MtS/yr
6	CO	Mt/yr
7	NMVOC	Mt/yr
8	NOx	MtN/yr
9	BC	Mt/yr
10	OC	Mt/yr
11	NH3	Mt/yr
12	CF4	kt/yr
13	C2F6	kt/yr
14	C6F14	kt/yr
15	HFC23	kt/yr
16	HFC32	kt/yr
17	HFC43-10	kt/yr
18	HFC125	kt/yr
19	HFC134a	kt/yr
20	HFC143a	kt/yr
21	HFC227ea	kt/yr
22	HFC245fa	kt/yr
23	SF6	kt/yr
24	CFC11	kt/yr
25	CFC12	kt/yr
26	CFC113	kt/yr
27	CFC114	kt/yr
28	CFC115	kt/yr
29	CCl4	kt/yr
30	Methyl chloroform	kt/yr
31	HCFC22	kt/yr
32	HCFC141b	kt/yr
33	HCFC142b	kt/yr
34	Halon 1211	kt/yr
35	Halon 1202	kt/yr
36	Halon 1301	kt/yr
37	Halon 2401	kt/yr
38	CH3Br	kt/yr
39	CH3Cl	kt/yr

The index order of the columns follows that of the RCP datasets at http://www.pik-potsdam.de/~mmalte/rcps/.

3.2.2 GHG Concentrations

Multi-species FAIR tracks the atmospheric concentrations of 31 GHG species; `C` is returned as a `(nt, 31)` array. The colums are indexed as follows:

Index	Species	Units
0	CO2	ppm
1	CH4	ppb
2	N2O	ppb
3	CF4	ppt
4	C2F6	ppt
5	C6F14	ppt
6	HFC23	ppt
7	HFC32	ppt
8	HFC43-10	ppt
9	HFC125	ppt
10	HFC134a	ppt
11	HFC143a	ppt
12	HFC227ea	ppt
13	HFC245fa	ppt
14	SF6	ppt
15	CFC11	ppt
16	CFC12	ppt
17	CFC113	ppt
18	CFC114	ppt
19	CFC115	ppt
20	CCl4	ppt
21	Methyl chloroform	ppt
22	HCFC22	ppt
23	HCFC141b	ppt
24	HCFC142b	ppt
25	Halon 1211	ppt
26	Halon 1202	ppt
27	Halon 1301	ppt
28	Halon 2401	ppt
29	CH3Br	ppt
30	CH3Cl	ppt

3.2.3 Effective radiative forcing

Finally, a `(nt, 13)` array `F` of effective radiative forcing is returned (all units W m-2):

Index	Species
0	CO2
1	CH4
2	N2O
3	All other well-mixed GHGs
4	Tropospheric O3
5	Stratospheric O3
6	Stratospheric water vapour from CH4 oxidation
7	Contrails
8	Aerosols
9	Black carbon on snow
10	Land use change
11	Volcanic
12	Solar

With the exception of volcanic and solar, all forcing outputs are calculated from the input emissions.

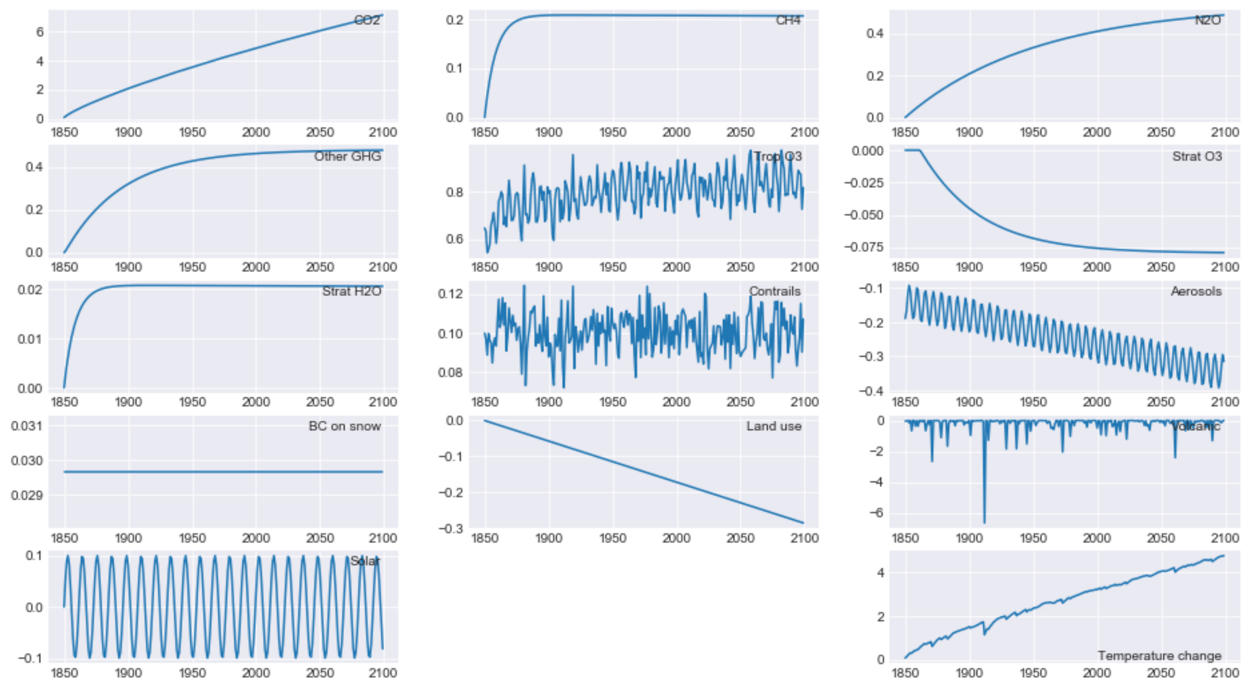
3.3 A multi-gas example

This sets up a multi-gas emissions array and serves to demonstrate some of the options that can be specified in `fair_scm` for multi-gas runs (most are changed from the default and some are non-sensical but shown for illustration). Note this is a completely hypothetical scenario!

```
from scipy.stats import gamma
emissions = np.zeros((250,40))

# remember column zero is the years
emissions[:,0] = np.arange(1850,2100)

# add some CO2 fossil and land use, GtC/yr
emissions[:,1] = 10.
emissions[:,2] = 1.

# some methane and nitrous oxide in this example, Mt/yr
emissions[:,3] = 300.
emissions[:,4] = 19.

# aerosol and ozone precursors, Mt/yr
emissions[:,5] = 0.1*np.arange(250)    # SOx
emissions[:,6] = 500.*np.log(1+np.arange(250))  # CO
emissions[:,7] = 100.+100.*np.cos(np.arange(250))  # NMVOC
emissions[:,8] = 40.*norm.rvs(loc=1, scale=0.1, size=250, random_state=9)    # NOx
emissions[:,9] = 6.    # BC
emissions[:,10] = 30.  # OC
emissions[:,11] = 35.  # NH3

# throw in some CFCs
emissions[:,24] = 1000. # CFC11
# and leave all other emissions as zero.

# Volcanic and solar forcing are provided externally. Let's invent some
solar = 0.1 * np.sin(2 * np.pi * np.arange(250) / 11.5)
volcanic = -gamma.rvs(0.2, size=250, random_state=100)

# efficacies are the temperature change for each forcing agent compared to CO2
```

```
# in our runs we usually set the efficacy of BC on snow to 3, following Bond et
# al (2013)
eff = np.ones(13)
eff[9] = 3.0

# b_aero: ERFari for each SLCF species (indices 5 to 11)
# b_tro3: tropospheric ozone coeffs for CH4, CO, NMVOC, NOx
C,F,T = fair_scm(emissions=emissions,
                 natural=np.zeros((250,2)), # natural emissions of CH4 and N2O
                 aviNOx_frac=0.05, # proportion of NOx emissions from aviation
                 fossilCH4_frac=0.25, # proportion of anthro CH4 emis from fossil␣
↪fuels
                 oxCH4_frac=0.61, # proportion of fossil CH4 eventually oxidised to␣
↪CO2
                 stwv_from_ch4=0.1, # proportion of CH4 ERF contributing to strat H2O
                 ghg_forcing='Etminan',  # etminan or myhre
                 useStevenson=False, # Stevenson or regression based trop. O3 forcing?
                 b_aero = np.array([-35,0,-5,-6,450,-40,-10])*1e-4,
                 b_tro3 = np.array([3., 1., 8., 99.])*1e-4,
                 aerosol_forcing = 'aerocom+ghan',  # aerocom, aerocom+ghan or stevens
                 F_solar = solar,
                 F_volcanic = volcanic,
                 efficacy = eff
                )

# Plot the forcing from each component
fig = plt.figure()
label = ['CO2','CH4','N2O','Other GHG','Trop O3','Strat O3','Strat H2O','Contrails',
↪'Aerosols',
         'BC on snow', 'Land use', 'Volcanic', 'Solar']
for i in range(13):
    ax = fig.add_subplot(5,3,i+1)
    ax.plot(np.arange(1850,2100), F[:,i])
    ax.text(0.95,0.95,label[i],transform=ax.transAxes,va='top', ha='right')
# plot temperature change
ax = fig.add_subplot(5,3,15)
ax.plot(np.arange(1850,2100),T)
ax.text(0.95, 0, 'Temperature change', transform=ax.transAxes, va='bottom', ha='right
↪')
```

```
Text(0.95,0,u'Temperature change')
```



3.4 RCP scenarios

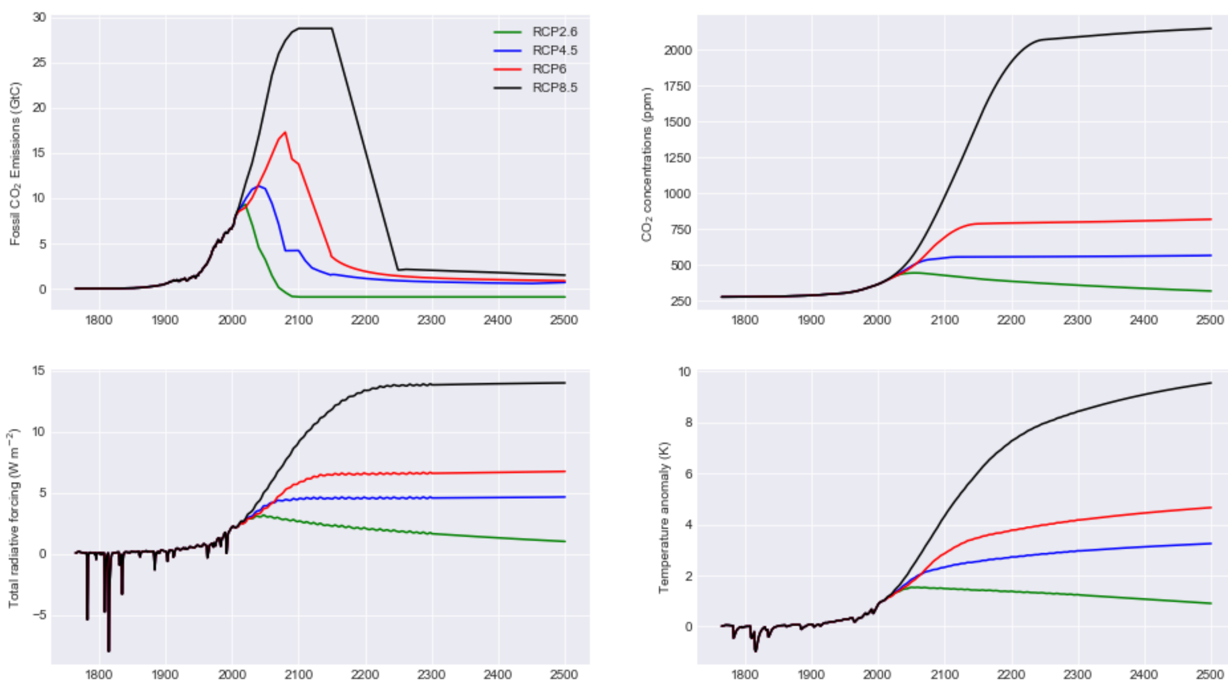
Creating a 40-column emissions input table may seem a lot of work. FAIR comes with tools to make your life easier!

We can run FAIR with the CO2 emissions and non-CO2 forcing from the four representative concentration pathway scenarios. These can be imported from the `RCPs` module and have inbuilt `Forcing` and `Emissions` classes. There is also a tool for converting MAGICC6 *.SCEN files into FAIR input (in `fair/tools/magicc`).

Here we show the FAIR implementation of the RCP scenarios. Following Meinshausen's convention RCP3PD is an alias for RCP2.6.

```
# Get RCP modules
from fair.RCPs import rcp3pd, rcp45, rcp6, rcp85

# Basic RCP runs
C26, F26, T26 = fair.forward.fair_scm(emissions=rcp3pd.Emissions.emissions)
C45, F45, T45 = fair.forward.fair_scm(emissions=rcp45.Emissions.emissions)
C60, F60, T60 = fair.forward.fair_scm(emissions=rcp6.Emissions.emissions)
C85, F85, T85 = fair.forward.fair_scm(emissions=rcp85.Emissions.emissions)

fig = plt.figure()
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)
ax4 = fig.add_subplot(224)

ax1.plot(rcp3pd.Emissions.year, rcp3pd.Emissions.co2_fossil, color='green', label=
↪'RCP2.6')
# just show CO2 conc.
ax2.plot(rcp3pd.Emissions.year, C26[:, 0], color='green')
# sum over axis 1 to get total ERF
ax3.plot(rcp3pd.Emissions.year, np.sum(F26, axis=1), color='green')
```

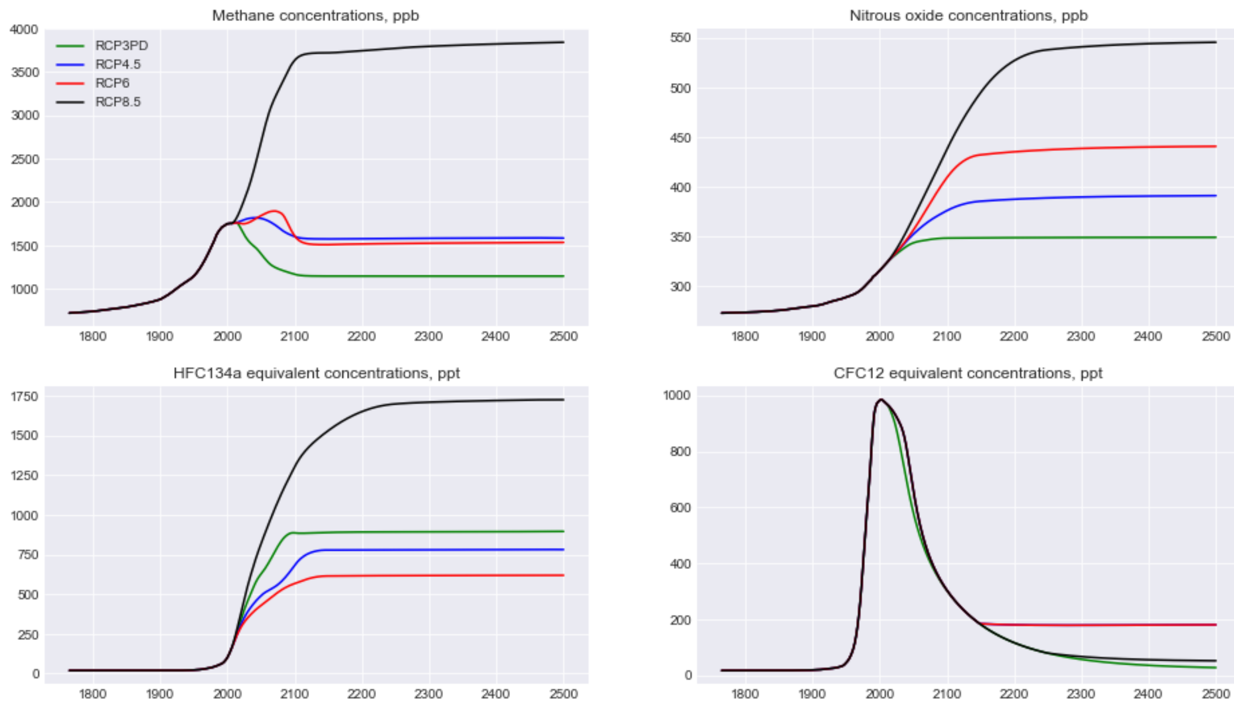
```
ax4.plot(rcp3pd.Emissions.year, T26, color='green')

ax1.plot(rcp45.Emissions.year, rcp45.Emissions.co2_fossil, color='blue', label='RCP4.5
↪')
ax2.plot(rcp45.Emissions.year, C45[:, 0], color='blue')
ax3.plot(rcp45.Emissions.year, np.sum(F45, axis=1), color='blue')
ax4.plot(rcp45.Emissions.year, T45, color='blue')

ax1.plot(rcp6.Emissions.year, rcp6.Emissions.co2_fossil, color='red', label='RCP6')
ax2.plot(rcp6.Emissions.year, C60[:, 0], color='red')
ax3.plot(rcp6.Emissions.year, np.sum(F60, axis=1), color='red')
ax4.plot(rcp6.Emissions.year, T60, color='red')

ax1.plot(rcp85.Emissions.year, rcp85.Emissions.co2_fossil, color='black', label='RCP8.
↪5')
ax2.plot(rcp85.Emissions.year, C85[:, 0], color='black')
ax3.plot(rcp85.Emissions.year, np.sum(F85, axis=1), color='black')
ax4.plot(rcp85.Emissions.year, T85, color='black')

ax1.set_ylabel('Fossil CO$_2$ Emissions (GtC)')
ax1.legend()
ax2.set_ylabel('CO$_2$ concentrations (ppm)')
ax3.set_ylabel('Total radiative forcing (W m$^{-2}$)')
ax4.set_ylabel('Temperature anomaly (K)');
```



3.5 Concentrations of well-mixed greenhouse gases

In this example we also show how to group minor gases into CFC12 and HFC134a equivalent concentrations. Refer to table above for gas indices.

```
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)
ax4 = fig.add_subplot(224)

ax1.plot(rcp3pd.Emissions.year, C26[:,1], color='green', label='RCP3PD')
ax1.plot(rcp45.Emissions.year, C45[:,1], color='blue', label='RCP4.5')
ax1.plot(rcp6.Emissions.year, C60[:,1], color='red', label='RCP6')
ax1.plot(rcp85.Emissions.year, C85[:,1], color='black', label='RCP8.5')
ax1.set_title("Methane concentrations, ppb")

ax2.plot(rcp3pd.Emissions.year, C26[:,2], color='green', label='RCP3PD')
ax2.plot(rcp45.Emissions.year, C45[:,2], color='blue', label='RCP4.5')
ax2.plot(rcp6.Emissions.year, C60[:,2], color='red', label='RCP6')
ax2.plot(rcp85.Emissions.year, C85[:,2], color='black', label='RCP8.5')
ax2.set_title("Nitrous oxide concentrations, ppb")

# Weight H and F gases by radiative efficiency
from fair.constants import radeff

# indices 3:15 are HFCs and PFCs
C26_hfc134a_eq = np.sum(C26[:,3:15]*radeff.aslist[3:15],axis=1)/radeff.HFC134A
C45_hfc134a_eq = np.sum(C45[:,3:15]*radeff.aslist[3:15],axis=1)/radeff.HFC134A
C60_hfc134a_eq = np.sum(C60[:,3:15]*radeff.aslist[3:15],axis=1)/radeff.HFC134A
C85_hfc134a_eq = np.sum(C85[:,3:15]*radeff.aslist[3:15],axis=1)/radeff.HFC134A

# indices 15:31 are ozone depleters
C26_cfc12_eq = np.sum(C26[:,15:31]*radeff.aslist[15:31],axis=1)/radeff.CFC12
C45_cfc12_eq = np.sum(C45[:,15:31]*radeff.aslist[15:31],axis=1)/radeff.CFC12
C60_cfc12_eq = np.sum(C60[:,15:31]*radeff.aslist[15:31],axis=1)/radeff.CFC12
C85_cfc12_eq = np.sum(C85[:,15:31]*radeff.aslist[15:31],axis=1)/radeff.CFC12

ax3.plot(rcp3pd.Emissions.year, C26_hfc134a_eq, color='green', label='RCP2.6')
ax3.plot(rcp45.Emissions.year, C45_hfc134a_eq, color='blue', label='RCP4.5')
ax3.plot(rcp6.Emissions.year, C60_hfc134a_eq, color='red', label='RCP6')
ax3.plot(rcp85.Emissions.year, C85_hfc134a_eq, color='black', label='RCP8.5')
ax3.set_title("HFC134a equivalent concentrations, ppt")

ax4.plot(rcp3pd.Emissions.year, C26_cfc12_eq, color='green', label='RCP2.6')
ax4.plot(rcp45.Emissions.year, C45_cfc12_eq, color='blue', label='RCP4.5')
ax4.plot(rcp6.Emissions.year, C60_cfc12_eq, color='red', label='RCP6')
ax4.plot(rcp85.Emissions.year, C85_cfc12_eq, color='black', label='RCP8.5')
ax4.set_title("CFC12 equivalent concentrations, ppt")
ax1.legend();
```

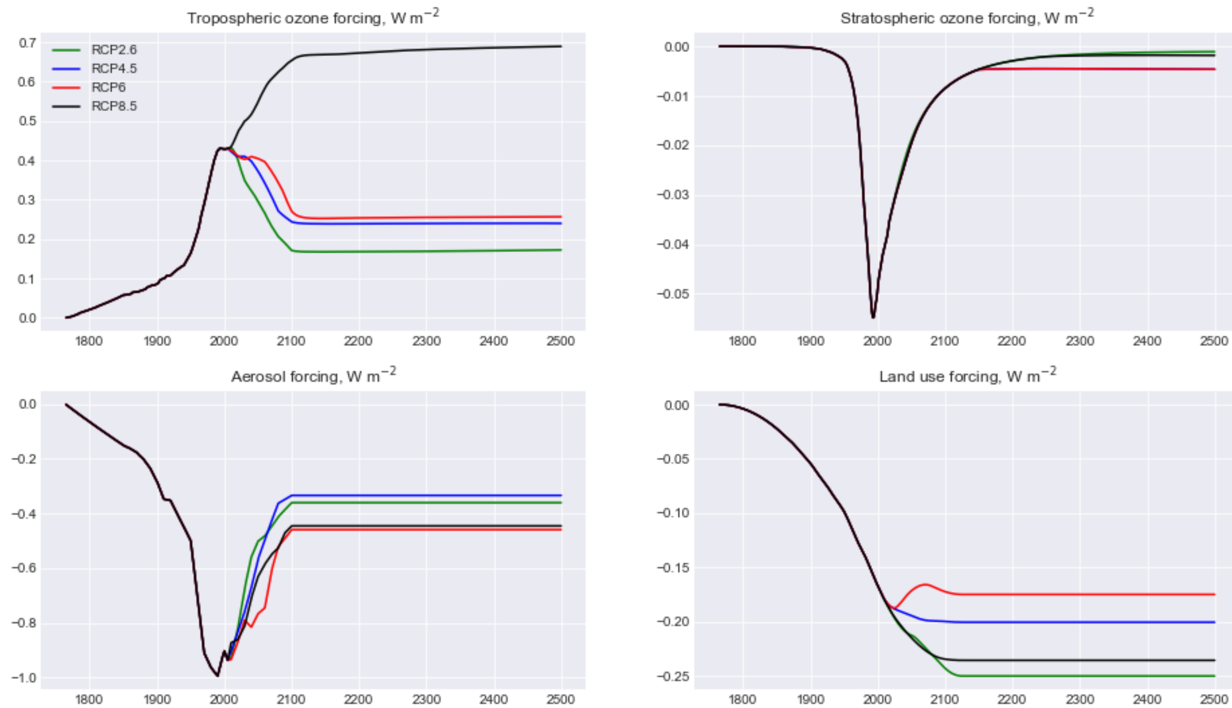


3.6 Radiative forcing

Here we show some of the more interesting examples for the effective radiative forcing time series coming out of FAIR.

```
fig = plt.figure()
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)
ax4 = fig.add_subplot(224)

ax1.plot(rcp3pd.Emissions.year, F26[:,4], color='green', label='RCP2.6')
ax1.plot(rcp45.Emissions.year, F45[:,4], color='blue', label='RCP4.5')
ax1.plot(rcp6.Emissions.year, F60[:,4], color='red', label='RCP6')
ax1.plot(rcp85.Emissions.year, F85[:,4], color='black', label='RCP8.5')
ax1.set_title("Tropospheric ozone forcing, W m$^{-2}$")

ax2.plot(rcp3pd.Emissions.year, F26[:,5], color='green', label='RCP2.6')
ax2.plot(rcp45.Emissions.year, F45[:,5], color='blue', label='RCP4.5')
ax2.plot(rcp6.Emissions.year, F60[:,5], color='red', label='RCP6')
ax2.plot(rcp85.Emissions.year, F85[:,5], color='black', label='RCP8.5')
ax2.set_title("Stratospheric ozone forcing, W m$^{-2}$")

ax3.plot(rcp3pd.Emissions.year, F26[:,8], color='green', label='RCP2.6')
ax3.plot(rcp45.Emissions.year, F45[:,8], color='blue', label='RCP4.5')
ax3.plot(rcp6.Emissions.year, F60[:,8], color='red', label='RCP6')
ax3.plot(rcp85.Emissions.year, F85[:,8], color='black', label='RCP8.5')
ax3.set_title("Aerosol forcing, W m$^{-2}$")

ax4.plot(rcp3pd.Emissions.year, F26[:,10], color='green', label='RCP2.6')
ax4.plot(rcp45.Emissions.year, F45[:,10], color='blue', label='RCP4.5')
```

```
ax4.plot(rcp6.Emissions.year, F60[:,10], color='red', label='RCP6')
ax4.plot(rcp85.Emissions.year, F85[:,10], color='black', label='RCP8.5')
ax4.set_title("Land use forcing, W m$^{-2}$")
ax1.legend();
```



3.7 Natural emissions and GHG lifetimes

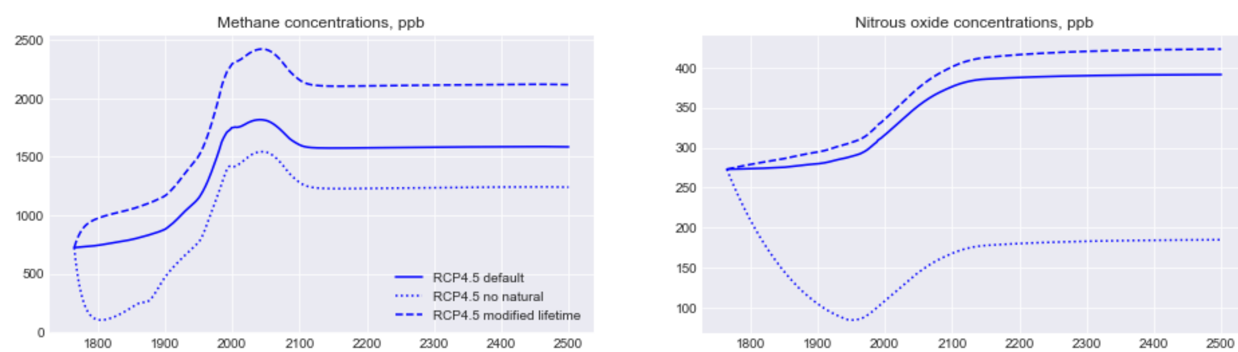
In order to balance historical concentrations of methane and nitrous oxide, we assume a time-varying profile of natural emissions. This can be varied with the `natural` keyword (a `(nt, 2)` array of methane and nitrous oxide emissions). Additionally, the default greenhouse gas decay constants can be modified with the `lifetimes` keyword (shape `(31,)`).

It can clearly be seen that natural emissions are important in maintaining historical concentrations.

```
# Change default lifetimes of CH4 and N2O
from fair.constants import lifetime
lt = lifetime.aslist
lt[1] = 12.6
lt[2] = 131.

# what are the defaults?
print (lifetime.CH4, lifetime.N2O)

# How long are the RCPs?
nt = len(rcp45.Emissions.year)

# Run FAIR under RCP4.5 with no natural emissions
C1,F1,T1 = fair_scm(emissions=rcp45.Emissions.emissions,
                    natural=np.zeros((nt,2))
                    )
```

```python
# Run FAIR under RCP4.5 with modified lifetimes
C2,F2,T2 = fair_scm(emissions=rcp45.Emissions.emissions,
                    lifetimes=lt
                    )

fig = plt.figure()
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)

ax1.plot(rcp45.Emissions.year, C45[:,1], color='blue', label='RCP4.5 default')
ax1.plot(rcp45.Emissions.year, C1[:,1], color='blue', ls=':', label='RCP4.5 no natural')
ax1.plot(rcp45.Emissions.year, C2[:,1], color='blue', ls='--', label='RCP4.5 modified lifetime')
ax1.set_title("Methane concentrations, ppb")
ax2.plot(rcp45.Emissions.year, C45[:,2], color='blue', label='RCP4.5')
ax2.plot(rcp45.Emissions.year, C1[:,2], color='blue', ls=':', label='RCP4.5 no natural')
ax2.plot(rcp45.Emissions.year, C2[:,2], color='blue', ls='--', label='RCP4.5 modified lifetime')
ax2.set_title("Nitrous oxide concentrations, ppb")
ax1.legend();
```

```
(9.3, 121.0)
```



3.8 Ensemble generation

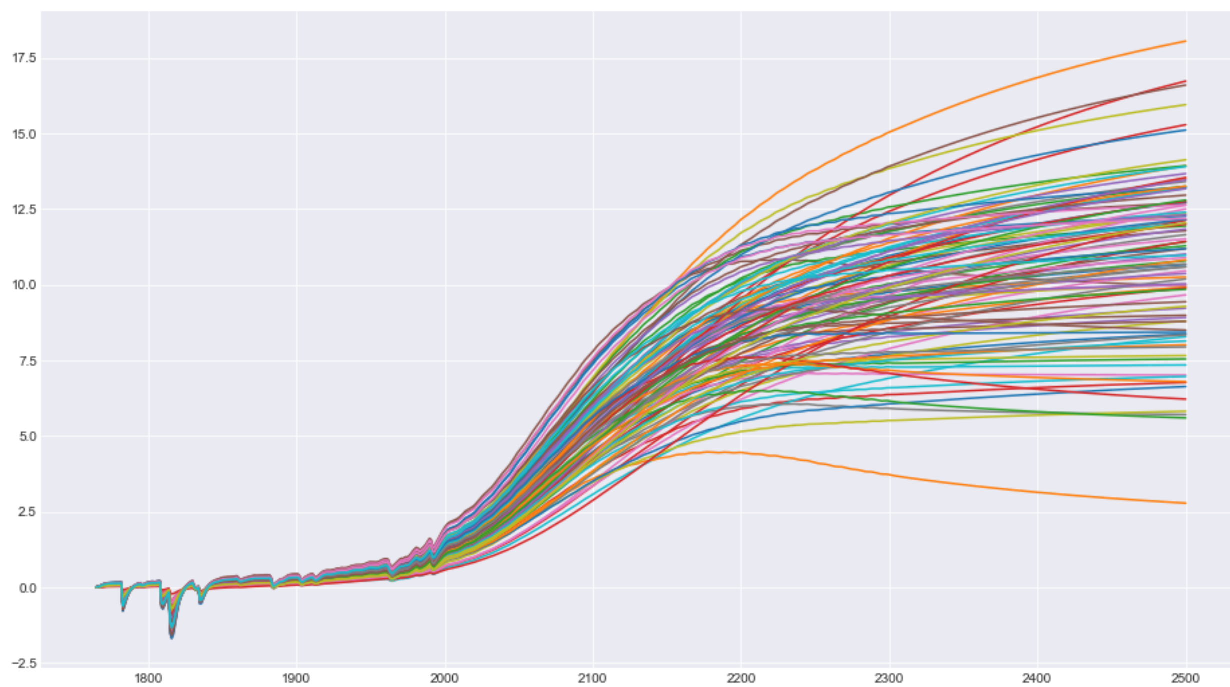
An advantage of FAIR is that it is very quick to run (much less than a second on an average machine). Therefore it can be used to generate probabilistic future ensembles. We'll show a 100-member ensemble.

This example also introduces the `scale` and `F2x` keywords. `scale` (a 13 element array) governs the forcing scaling factor of each of the 13 categories of forcing, whereas `F2x` determines the ERF from a doubling of CO2.

```python
from scipy import stats

# generate some (bad) TCR and ECS pairs
tcrecs = stats.norm.rvs(size=(100,2), loc=[1.75,3], scale=[0.4,0.8], random_state=38571)

# generate some forcing scale factors with SD of 10% of the best estimate
F_scale = stats.norm.rvs(size=(100,13), loc=1, scale=0.1, random_state=40000)
F2x = 3.71 * F_scale[:,0]
```

```
F_scale[:,0] = 1.0  # set CO2 forcing scaling with F2x above

# generate ensemble for carbon cycle parameters
r0 = stats.norm.rvs(size=100, loc=35, scale=3.5, random_state=41000)
rc = stats.norm.rvs(size=100, loc=0.019, scale=0.0019, random_state=42000)
rt = stats.norm.rvs(size=100, loc=4.165, scale=0.4165, random_state=45000)

T = np.zeros((nt,100))

# notice that we
for i in range(100):
    _, _, T[:,i] = fair_scm(emissions=rcp85.Emissions.emissions,
                            r0 = r0[i],
                            rc = rc[i],
                            rt = rt[i],
                            tcrecs = tcrecs[i,:],
                            scale = F_scale[i,:],
                            F2x = F2x[i]
                           )
```

```
fig = plt.figure()
ax1 = fig.add_subplot(111)
ax1.plot(rcp85.Emissions.year, T);
```



3.8.1 Adding a temperature constraint

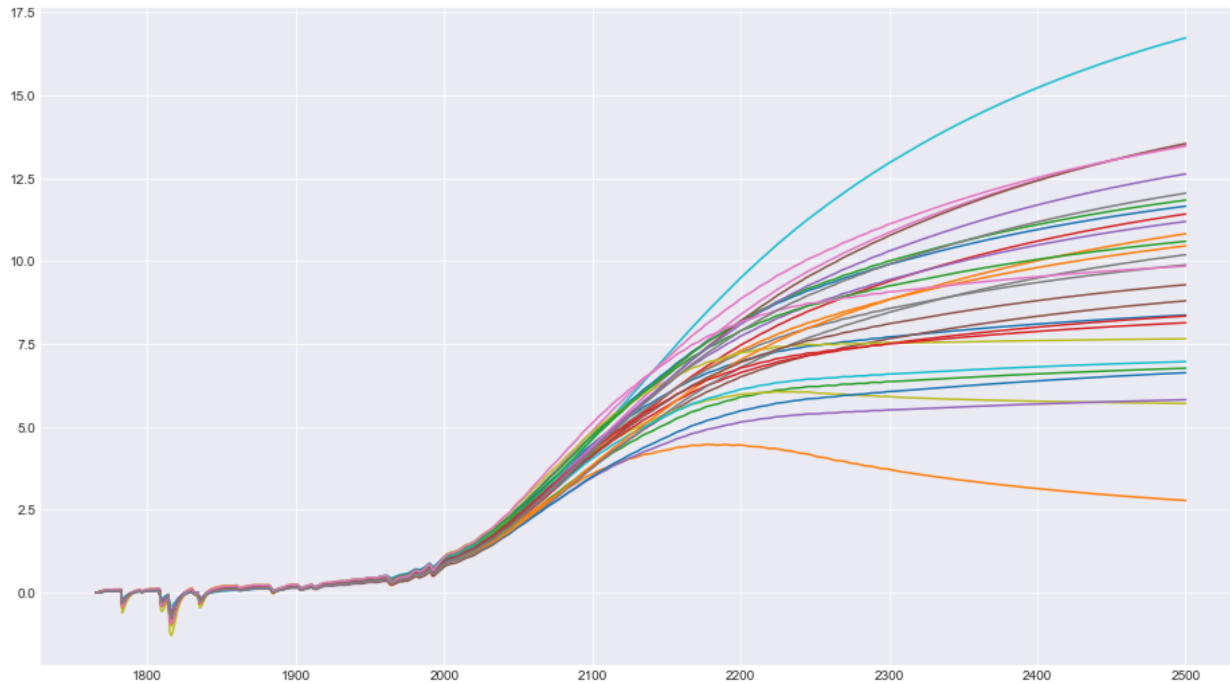
The resulting projections show a large spread. Some of these ensemble members are unrealistic, ranging from around 0.4 to 2.0 K temperature change in the present day, whereas we know in reality it is more like 0.95 (plus or minus 0.2). Therefore we can constrain this ensemble to observations.

```
from fair.tools.constrain import hist_temp

# Cowtan & Way in-filled dataset of global temperatures
CW = np.loadtxt('../fair/tools/tempobs/had4_krig_annual_v2_0_0.csv')
constrained = np.zeros(100, dtype=bool)
for i in range(100):
    # we use observed trend from 1880 to 2016
    constrained[i],_,_,_,_ = hist_temp(
        CW[30:,1], T[1880-1765:2017-1765,i], CW[30:,0])
```

```
# How many ensemble members passed the constraint?
print np.sum(constrained)
```

```
28
```

```
# What does this do to the ensemble?
fig = plt.figure()
ax1 = fig.add_subplot(111)
ax1.plot(rcp85.Emissions.year, T[:,constrained]);
```



Some, but not all, of the higher end scenarios have been constrained out, but there is still quite a large range of total temperature change projected for 2500 even under this constraint.

From these constraints it is possible to obtain posterior distributions on effective radiative forcing, ECS, TCR, TCRE and other metrics.