

Master 2 SOAC
Université Paul Sabatier

Travaux Pratiques "Simulation Climatique"
Modelling Climate with simple climate models
Promotion 2022-2023

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Modelling Earth climate and response to external forcing

1 Download and Install SimClimat

1. Search "SimClimat MétéoFrance" on google, consider the first link.
2. Download Simclimat (zip-files so-called sim18.zip) on your desktop
3. unzip sim18.zip
4. run setup.exe

2 Sensitivity to terms in the global radiative budget

Control simulation : 5 ky, starting from pre-industrial state

Important to start from a "stable" state, before present-day climate change. Click on "new simulation"

Chose initial state (1750) and length.

Add sensitivity tests to radiative budget terms : click on "add"

2.1 Sensitivity to solar constant S_0

This is an external forcing to the Earth system.

Astronomic parameters > Earth-Sun distance (e.g. 95 and 105%)

Astronomic parameters > solar power (e.g. 95 and 105%, or like at the beginning of Earth History)

Questions :

1. Is the effect on temperature, sea-ice extent and sea level expected ?

2.2 Sensitivity to albedo

By default, albedo is interactively calculated as a function of ice-sheet extension.

climate feedbacks > unplug the feedback.

Tune the albedo e.g. : 20%-40%.

Questions :

1. Is the albedo effect on temperature expected ?

2.3 Sensitivity to greenhouse gases

CO₂ concentration

By default, CO₂ concentration is interactively calculated as a function of CO₂ sources and sinks.

Concentration or CO₂ emissions > set the concentration, then chose the concentration

value e.g. pre-industrial, as today, twice as much as today, zero
water vapor concentration

By default, water vapor concentration is interactively calculated as a function of temperature.

Climate feedbacks > water vapor > unplug the feedback,
then chose the concentration value e.g. pre-industrial, as today, twice as much as today,
zero.

Questions :

1. Are the effects of CO₂ and water vapor expected?
2. What is the relative importance of CO₂ and water vapor in natural greenhouse effect? And on anthropogenic greenhouse effect?

3 Climate changes at geological time scales

3.1 Climate equilibria and reversibility of climate changes

In previous tests, have you noticed extreme behaviors in term of temperature and sea-ice extent? How can we interpret them?

Control simulations, 50 ky, starting from pre-industrial.

Click on new simulation.

Interpret the results :

1. Reduce the solar power in different proportions : 98%, 96%, 94%, 90%. What happens?
What are the different possible climate states?
2. Come back to the present-day solar power by extending the previous simulation :
New simulation > final state of the previous simulation > solar power = 100%.
Does the climate come back to its initial state before solar power reduction?
Why?
3. Add other simulations with present-day solar power, but at the same time increase the CO₂ concentration.
Is there a CO₂ threshold beyond which the climate comes back to the initial state?
Don't forget to set back the solar power to its present-day value (100%) for each simulation.
4. In the real world, how can we get out of a snow ball earth?

3.2 CO₂ sources and sinks

Control simulation, 500 ky, starting from pre-industrial state Test the sensitivity to carbon sources and sinks

Questions :

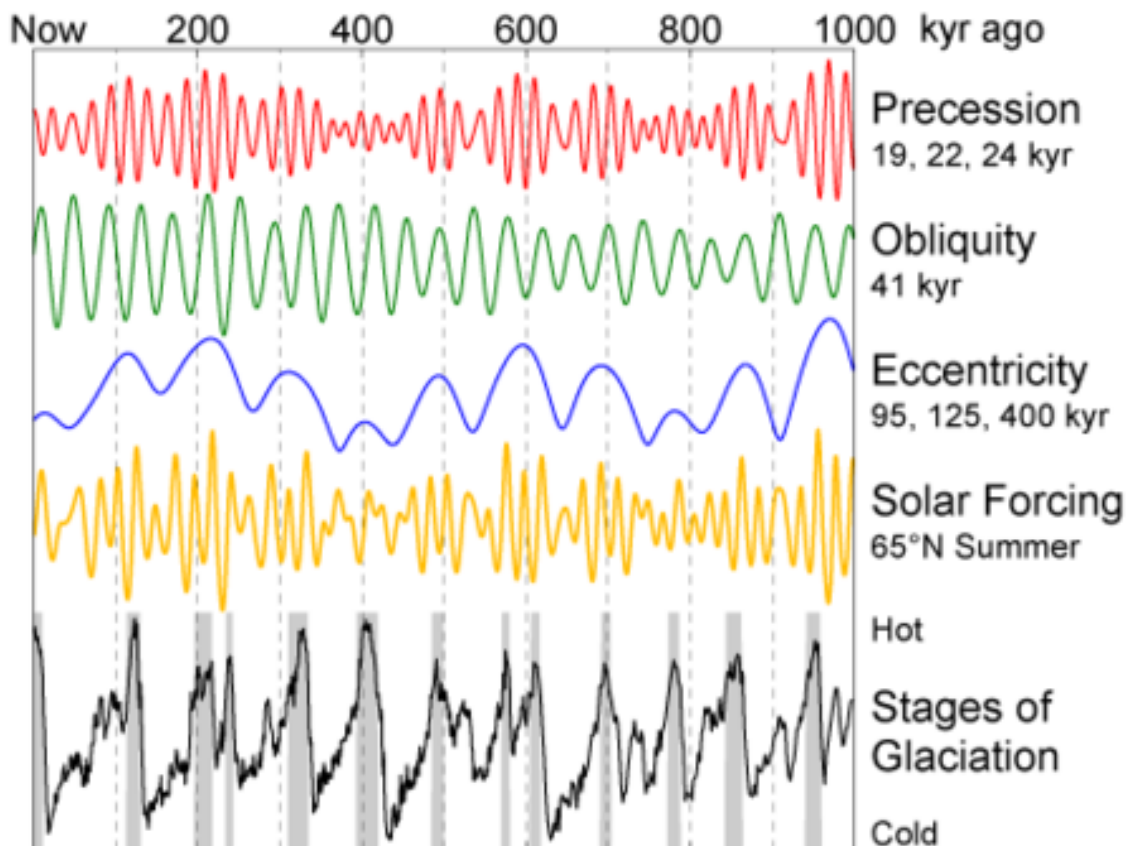
1. Compare the time scales at which geological (volcanism, land alteration) and anthropogenic sources and sinks play a role

4 Sensitivity to orbital parameters

Control simulation, 50 kyr, starting from pre-industrial state

Test the sensitivity to orbital parameters within their range of minimum and maximum values :

add > astronomic parameters



1. obliquity
2. excentricity
3. precession

Interpret the results :

1. Why does it impact temperature ?
2. How do ice-sheet extent, planetary albedo, sea-level and CO₂ change?
What are the cause-consequence links bewteen these variables ?
3. Chose one case of orbital parameter variation (e.g. obliquity to maximal value).
Test the role of ice-albedo feedback : climate feedbacks > albedo > unplug the feedback.
Conclude on the role of this feedback.
4. On this same case, test the role of oceanic carbon fluxes.
climate feedbacks > ocean > authorize oceanic carbon fluxes but without depending on temperature.
Conclude on the role of this feedback.

5. What is the consequence on sea-level?
Why?

5 Sensitivity to anthropogenic emissions and role of various feedbacks

5.1 Response to anthropogenic emissions

500-years simulation starting from the present-day state.
By default, it includes the anthropogenic emissions.

Questions :

1. Consequences on temperature and sea level?

5.2 Carbon cycle feedbacks

Show the evolution of CO₂ concentration and emission
Test the impact of carbon fluxes associated with the ocean and with vegetation.
add >climate feedbacks > ocean > don't consider oceanic fluxes
add > climate feedbacks > vegetation > don't consider vegetation fluxes

Questions :

1. Does CO₂ concentration increase as much as expected from CO₂ emissions?
2. What is the sign of these feedbacks?
3. What factors could modulate their effects?

5.3 Relative role of climate feedbacks

1. Albedo feedback :
add >climate feedbacks > albedo > unplug the albedo feedback
2. Water vapor feedbacks :
add >climate feedbacks > water vapor > unplug the water vapor feedback

Questions :

1. What is the relative importance of these 2 feedbacks?
2. At what time scales do they play?

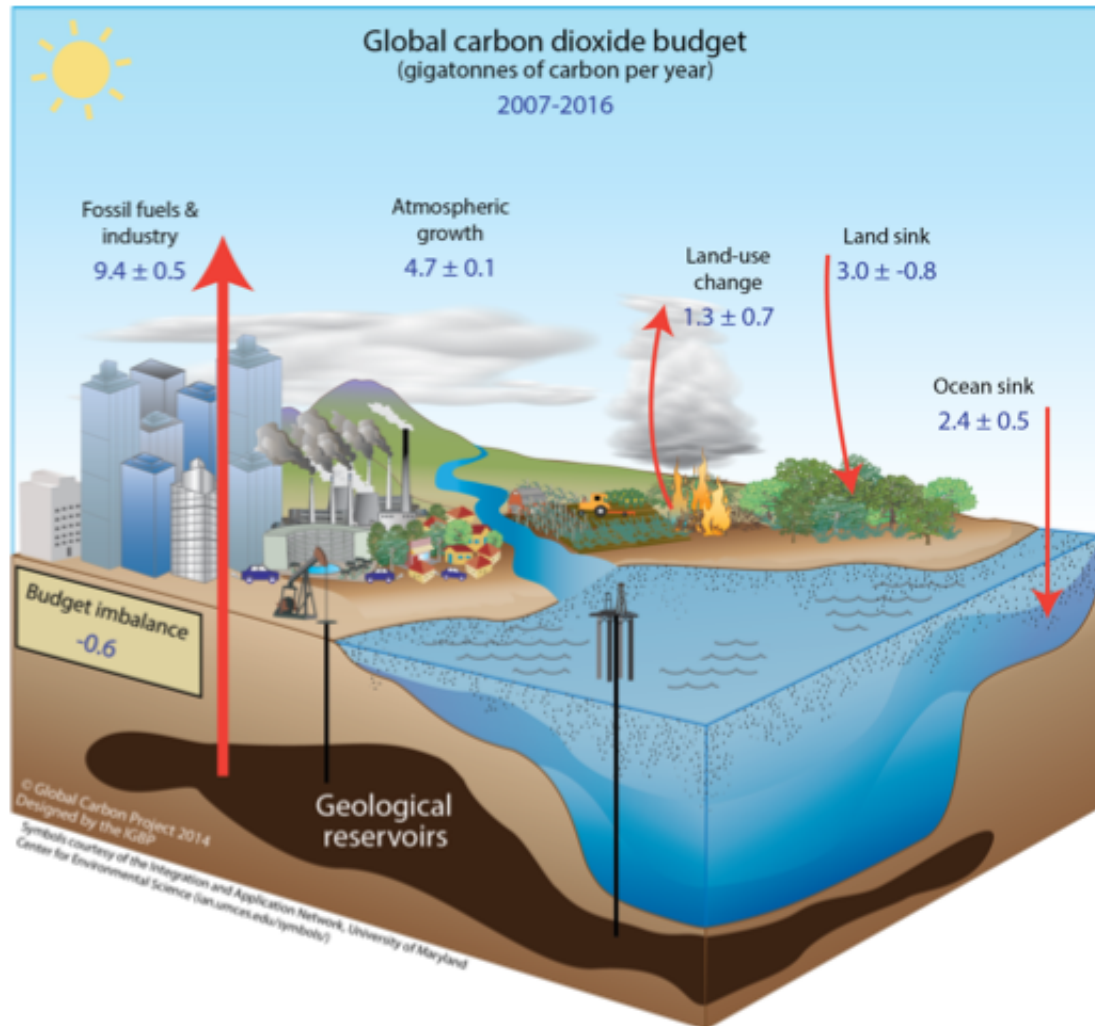
5.4 Reversibility of changes

Extend the simulation for another 500 years, but without anthropogenic emissions.

Questions :

1. Are these changes reversible?
2. At which time scales?

Modelling the global carbon cycle



1 Introduction

Over time scales of several hundred of years, atmospheric CO_2 is ruled by a suite of processes involving human activities (fossil fuel combustion, cement production, agriculture, deforestation), land biosphere and ocean. The temporal evolution of atmospheric CO_2 can be written as follows :

$$\frac{d\text{CO}_2(t)}{dt} = E_{\text{fossil}} + E_{\text{land-use}} + S_{\text{land-biosphere}} + S_{\text{ocean}} \quad (1)$$

Emissions, E , correspond to a positive flux of CO_2 to the atmosphere while source minus sink, S , can be either a net positive or a net negative flux of CO_2 to the atmosphere.

Using a first-order decay hypothesis, this formulation can be simply written as :

$$\frac{dCO_2(t)}{dt} = E(t) - \frac{CO_2}{\tau_{CO_2}} \quad (2)$$

The analytical solution of this equation is called an impulsional response or *irf*. It mimics the temporal evolution of the atmospheric CO₂ to a emission pulse of CO₂.

In this work, we will represent a simple box model to track the evolution of the atmospheric CO₂ in course of time.

2 Impulse response function for atmospheric CO₂ : an introduction to Python

In the last IPCC repor Myrhe et al. (2013a) propose an impulsional response function derived from Joos et al. (2013), written as follows :

$$irf_{CO_2}(t) = a_{C,0} + a_{C,1} \exp \frac{-t}{\tau_{C,1}} + a_{C,2} \exp \frac{-t}{\tau_{C,2}} + a_{C,3} \exp \frac{-t}{\tau_{C,3}} \quad (3)$$

This *irf* is defined by :

1. $a_{C,0} + a_{C,1} + a_{C,2} + a_{C,3} = 1$
2. when $t=+\infty$, $\lim irf = a_{C,0}$

Now, let's play with Python.

We start by defining the impulse response function for CO₂ at a given year, t :

First, use this header to run useful function in Python :

```
# header: importing useful modules and functions
import csv
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import fmin
```

Then, implement this code :

```
# definition of the impulse response function for atmospheric CO2
def irf_CO2(t):
    irf = a_C0 + a_C1 * np.exp(-t/tau_C1) + \
          a_C2 * np.exp(-t/tau_C2) + a_C3 * np.exp(-t/tau_C3)
    return irf
```

with the following set of parameters :

```
# with the following values of the parameters
a_C0 = 0.2173
a_C1 = 0.2240
a_C2 = 0.2824
a_C3 = 0.2763
tau_C1 = 394.4 #{yr}
tau_C2 = 36.54 #{yr}
tau_C3 = 4.304 #{yr}
```

In Python, parameters can be defined after implemented any function. However, they should be defined in either case before running the function to avoid error message.

Now, we can produce a figure of the CO₂'s *irf* using this code :

```
# plot the IRF for atmospheric CO2
plt.figure()
# over the first 100 years
time1 = np.arange(0,100)
plt.subplot(1,2,1)
plt.plot(time1,irf_CO2(time1))
plt.plot(time1,a_CO*np.ones(np.shape(time1)),ls="--")
# up to 1000 years
time2 = np.arange(100,1000)
plt.subplot(1,2,2)
plt.plot(time2,irf_CO2(time2),label="irf_CO2")
plt.plot(time2,a_CO*np.ones(np.shape(time2)),ls="--",label="a_CO")
```

We can improve a bit the readability of the figure using these commands :

```
# polishing the figure
plt.subplot(1,2,1)
plt.axis([0,100,0,1])
plt.xlabel("time (yr)")
plt.ylabel("airborne fraction (.)")
plt.subplot(1,2,2)
plt.axis([100,1000,0,1])
plt.xticks([200,400,600,800,1000])
plt.yticks([0,0.2,0.4,0.6,0.8,1],["", "", "", "", "", ""])
plt.legend(loc=0)
plt.subplots_adjust(left=0.10,bottom=0.10,right=0.95,top=0.95,wspace=0.01)
```

Questions :

1. From an emission pulse, how much CO₂ stays in the atmosphere after 10 years, 100 years, 1000 years ?
2. Does this model behave linearly in function of time ? in terms of amplitude ?
3. what should be the long-term response of an emission pulse according this model ?
4. According your knowledge, which processes are simulated by the various terms of this equation ?
5. What is the mathematical relationship between the sink of CO₂ and the *irf* for atmospheric CO₂ ? Determine the formulation of this flux of CO₂ and produce a figure.

3 Simulated the historical evolution of the atmospheric CO₂

In this section, we will use some of the mathematical properties of the *irf* to determine the evolution of the atmospheric CO₂ since 1751. Direct measurement of atmospheric CO₂ started in 1959 (with Keeling in Revelle at Mona Loa). Data before this year are derived from paleo-climatic data like ice-core and other indirect evidences. Compare to atmospheric CO₂, anthropogenic CO₂ emissions are pretty well known since they are estimated

from human/commercial/energetical activity. They are collected by various institute and countries since decades. This emissions data are available on the **Carbon Dioxide Information Analysis Center (CDIAC)**. We will use this emission data and our simple model to reconstruct temporal evolution of atmopsheric CO₂.

First, we load the data as follows :

```
# load the historical data on fossil CO2 emissions
EFF_type = np.array([line for line in \
csv.reader(open("data/CDIAC_EFF_global.1751_2011.csv","r"))] \
[2:],dtype=float)[: ,2:-1] / 1000 * 44/12. #{GtCO2/yr}
EFF_lgd = [line for line in \
csv.reader(open("data/CDIAC_EFF_global.1751_2011.csv","r"))][0][2:-1]
EFF = np.sum(EFF_type,1)
```

Since these data are given in GtCO₂/yr and atmopsheric CO₂ is usually measured in ppm, we need a conversion factor. In the followings, we will use that given in Prather et al. (2012) :

```
# use the IRF to simulate past changes in atmospheric CO$_2$
# conversion factor
k_CO2 = 0.1765 * 44 #{GtCO2/ppm}
```

Three approaches are now available to determine the temporal evolution of the atmospheric CO₂. First, we can rely on Python to determine the convolution of emission data and our model response :

```
# using the built-in convolution function
time = np.arange(len(EFF))
D_CO2_mod1 = 1/k_CO2 * np.convolve(EFF,irf_CO2(time))[:len(time)]
```

Or, we can expliciteley resolve this convolution as follows :

```
# explicitly calculating the convolution
D_CO2_mod2 = np.zeros(np.shape(EFF))
for t in range(len(EFF)):
    D_CO2_mod2[t] = 1/k_CO2 * np.sum(EFF[:t+1] * irf_CO2(np.arange(t+1))[::-1])
```

Finally, we can solve each equation of the box model (Equation ??) using 4 states variables. These for states variables correspond to the coefficients of the *irf* (Equation ??)¹. This solution is implemented in Python as follows :

```
# using the corresponding box-model
D_CO2_mod3 = np.zeros(np.shape(EFF))
D_CO = 0
D_C1 = 0
D_C2 = 0
D_C3 = 0
for t in range(len(EFF)):
    D_CO += a_CO * EFF[t]
    D_C1 += a_C1 * EFF[t] - D_C1/tau_C1
```

1. This implies that a model with a set of two coefficients would have require solely two states variables to be solved.

```

D_C2 += a_C2 * EFF[t] - D_C2/tau_C2
D_C3 += a_C3 * EFF[t] - D_C3/tau_C3
D_CO2_mod3[t] = 1/k_CO2 * (D_CO+D_C1+D_C2+D_C3)

```

Questions :

1. Produce figures corresponding to the three approaches and compare results.
2. Compare results of each reconstruction of atmospheric CO₂ to that used in the last IPCC report (Ciais et al., 2013) :

```

# load atmospheric CO2 reconstruction by IPCC
CO2_ipcc = np.array([line for line in \
csv.reader(open("data/HistAtmo_IPCC.1750-2011.CO2.csv", "r"))] \
, dtype=float)[: , 0] # {ppm}

```

3. Identify missing processes : A better fit would imply greater sources of CO₂ or greater sink of CO₂ ?

4 Improved the representation of atmospheric CO₂

Previous results should have pointed out the fact that important process of the global carbon cycle is missing. Here, we will try to improve the model by adding this process so-called the land-use change. This latter is related to human activities over land, i.e., agriculture and deforestation. The following pieces of Python code will help to determine the amplitude of this process, running our model in "inversion mode" :

```

# inversion of ELUC needed to fit reconstructed CO2
ELUC_inv = np.zeros(np.shape(EFF))
# define error function
def err(e,t):
    # create ELUC vector used in error function
    ELUC_tmp = ELUC_inv.copy()
    ELUC_tmp[t:] = 0
    ELUC_tmp[t] = e
    # calculate simulated CO2
    D_CO2_tmp = 1/k_CO2 * np.sum((EFF+ELUC_tmp)[:t+1] \
* irf_CO2(np.arange(t+1))[::-1])
    return ( D_CO2_tmp - (CO2_ipcc[t+1]-CO2_ipcc[0]) )**2
# fit at every time-step
for t in range(len(EFF)):
    ELUC_inv[t] = fmin(err, [0], args=(t,), disp=False)

```

Questions :

1. Explain the approach employed in this code
2. Compare the result to the estimated from Le Quéré et al. (2013), available using the following code :

```

# load historical emissions from land-use change
ELUC_data = np.array([line for line in \
csv.reader(open("data/GCP+_ELUC.global.1850_2010.csv", "r"))] \
, dtype=float)[: , 0] / 1000 * 44/12. # {GtCO2/yr}

```

3. Discuss the results of our estimate of $E_{land-use}$ in regards of the accepted uncertainties of 1GtC/yr in land-use-induced CO₂ emission.

Analysis of IPCC/CMIP5 Earth system model results

1 An introduction to the climate sensitivity at the equilibrium (ECS)

In this part, we analyse the impulsional response of several climate variables as simulated by various state-of-the-art Earth system models. For your information, these models have contributed to the **fifth Intercomparison project (CMIP5)**, which has provided simulation results for the fifth IPCC report (IPCC, 2013).

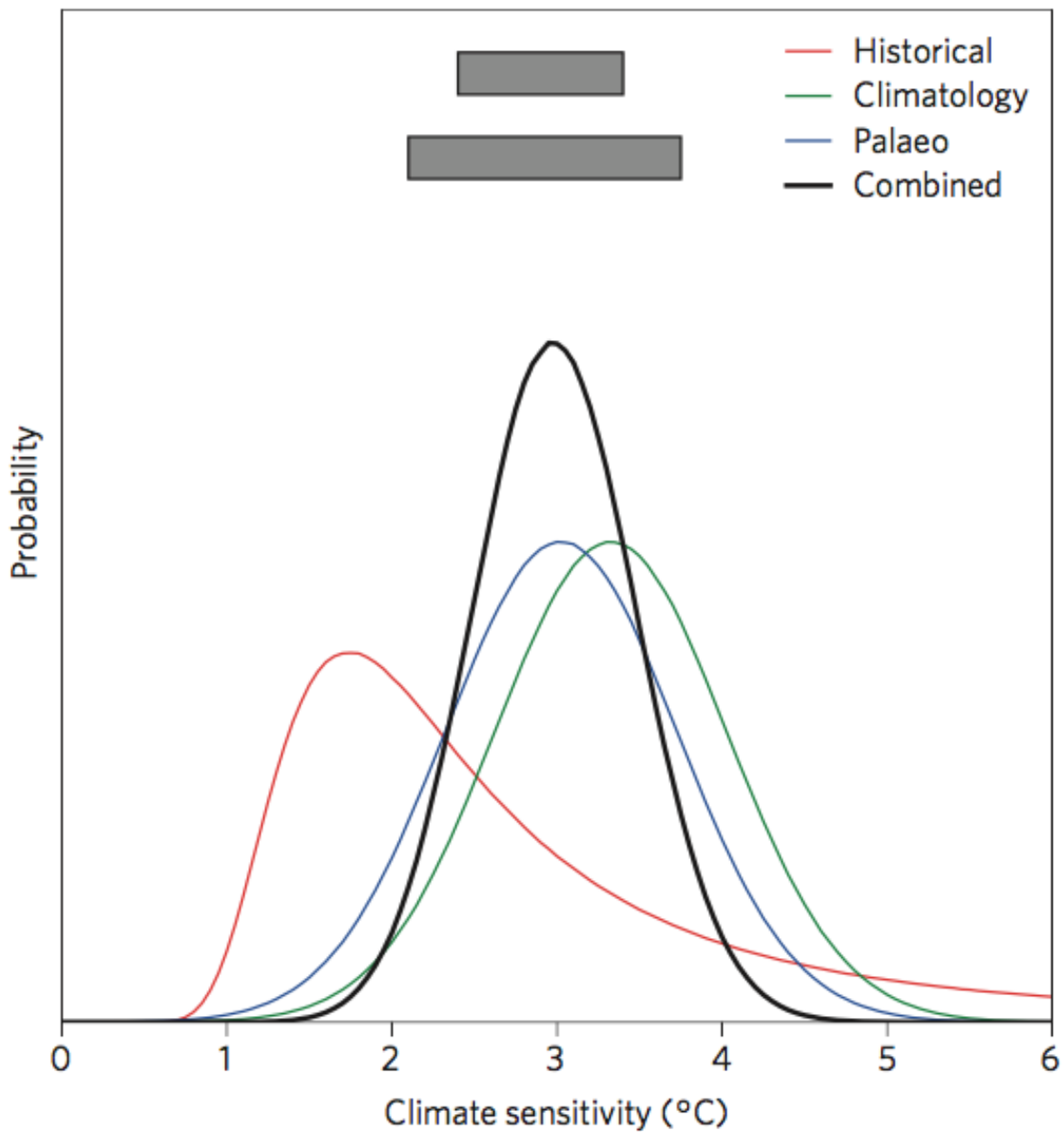
1.1 First analysis

The code below loads results from a preindustrial control simulation (1850 cycling over years), so-called *ctrl*, and a $4\times$ CO₂ control simulation, so-called *quad*, for the following set of climate variables :

1. tas : temperature air surface
2. rsdt : radiation shotwave downward top-of-the-atmosphere
3. rlut : radiation longwave upward top-of-the-atmosphere
4. rsut : radiation shortwave upward top-of-the-atmosphere

These climate variables have been globally averaged. The original data can be found on international data node like http://cmip-pcmdi.llnl.gov/cmip5/data_portal.html.

```
# ancillary lists for loading data
model_list = ["ACCESS-10", "ACCESS-13", "BCC-CSM-11", \
"BCC-CSM-11m", "CanESM2", "CCSM4", "CNRM-CM5", \
"CNRM-CM5-2", "CSIRO-Mk360", "GFDL-CM3", "GFDL-ESM2G", \
"GFDL-ESM2M", "GISS-E2-H", "GISS-E2-R", \
"HadGEM2-ES", "IPSL-CM5A-LR", "IPSL-CM5A-MR", \
"IPSL-CM5B-LR", "MIROC5", "MIROC-ESM", "MPI-ESM-LR", \
"MPI-ESM-MR", "MPI-ESM-P", "MRI-CGCM3", "NorESM1-M"]
model_length = {"ACCESS-10":150, "ACCESS-13":151, "BCC-CSM-11":150, \
"BCC-CSM-11m":150, "CanESM2":150, \
"CCSM4":151, "CNRM-CM5":150, "CNRM-CM5-2":140, \
"CSIRO-Mk360":150, "GFDL-CM3":150, "GFDL-ESM2G":300, \
"GFDL-ESM2M":300, "GISS-E2-H":151, "GISS-E2-R":151, \
"HadGEM2-ES":151, "IPSL-CM5A-LR":260, \
"IPSL-CM5A-MR":140, "IPSL-CM5B-LR":160, "MIROC5":151, \
"MIROC-ESM":150, "MPI-ESM-LR":150, "MPI-ESM-MR":150, \
"MPI-ESM-P":150, "MRI-CGCM3":150, "NorESM1-M":150}
# create array of final variables
# tas in {degC}; rsdt,rlut,rsut in {W/m2}
```



```

for var in ["tas","rsdt","rsut","rlut"]:
    exec(var+"_ctrl = np.zeros((np.max(model_length.values()),\
    len(model_list))) * np.nan")
    exec(var+"_quad = np.zeros((np.max(model_length.values()),\
    len(model_list))) * np.nan")
# load pre-processed CMIP5 results
for mod in model_list:
    for sim in ["ctrl","quad"]:
        TMP = np.array([line for line in csv.reader(open("data/Climate_CMIP5/"+\
        "Climate_"+mod+"."+sim+"_global.csv", "r"))][1:],dtype=float)
        lgd = [line for line in csv.reader(open("data/Climate_CMIP5/"+\
        "Climate_"+mod+"."+sim+"_global.csv", "r"))][0]
        for var in ["tas","rsdt","rsut","rlut"]:
            exec(var+"_"+sim+"[:len(TMP),model_list.index(mod)] \

```

```
= TMP[:,lgd.index(var)]")
```

Questions :

1. For all models, present on two separate figures the time series of tas and rsut. The code can start with the following commands :


```
# plot temperature and radiative budget
plt.figure()
for mod in model_list:
    m = model_list.index(mod)
```
2. What do you see? Did you expect this result? Why?
3. Propose a new figure to better represent this relationship. Note that *ctrl* simulation can be used to define the unperturbed state of the climate.

1.2 Gregory’s analysis

Now, we will employ the approach proposed by Gregory et al. (2004) to determine the climate sensitivity at the equilibrium (ECS). This approach relies on the same conclusion you have done.

Questions :

1. On the previous figure, is there a way to determine the ECS?
2. Below is a set of lines to compute ECS :


```
# fit equilibrium temperature change
coeff = np.zeros(len(model_list))
T4x = np.zeros(len(model_list))
for mod in model_list:
    m = model_list.index(mod)
    length = model_length[mod] #!!!
def err(var):
    D_T = var[0] * ((netrad_quad-netrad_ctrl)[:length,m]) + var[1]
    return sum(( D_T - (tas_quad-tas_ctrl)[:length,m] )**2)
[coeff[m],T4x[m]] = fmin(err, [-1.,3.],disp=False)
```

Compare the two approaches.
3. Based on this analysis, do you think that another method (quadratic, cubic...) could out-perform a linear fit proposed by Gregory et al. (2004)?

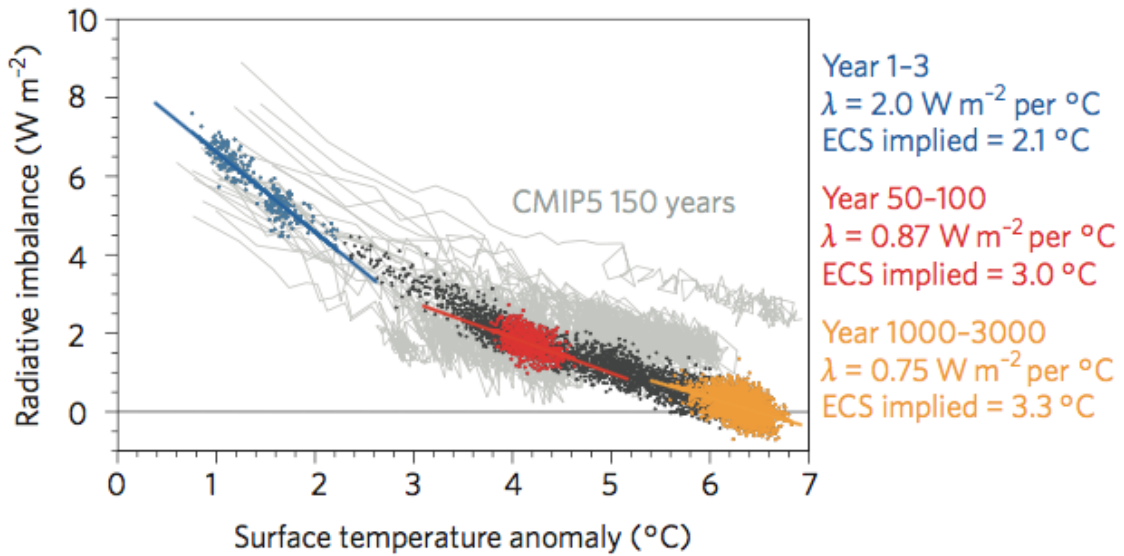
Since the third IPCC report (Ramaswamy et al., 2001), the radiative forcing for CO₂ is deduced from the relationship :

$$RF_{CO_2} = 5.35 \times \ln \frac{CO_2(t)}{CO_2(t=0)} \tag{4}$$

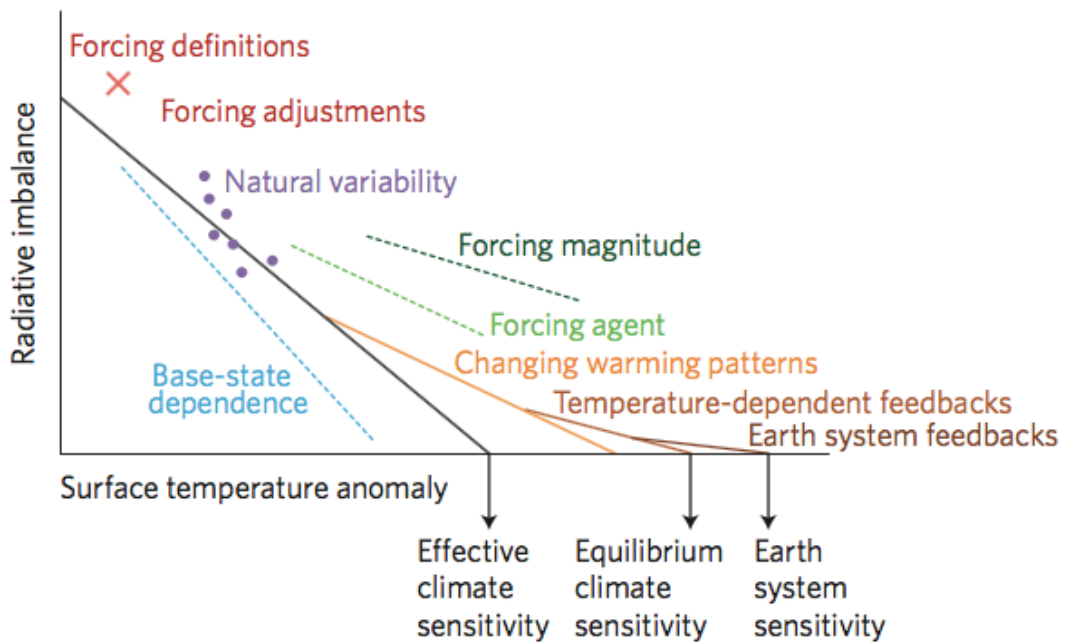
Questions :

1. What is the ECS in $K[Wm^2]^{-1}$ of each model, considering that canonical ECS is given for a doubling of CO₂.

a Equilibration of CESM and CMIP5 models



b Processes influencing the evolution of climate feedbacks



1.3 Investigate time variation of climate sensitivity

Knutti et al., 2017 (see Figure below) show that ECS varies across time scales. Here, we will perform this analysis across available CMIP5 models and try to characterize this phenomenon.

Questions :

1. Using a conceptual model (e.g., exponential), fit the evolution of the ECS estimates across a range of time-scales.

2. Create a figure showing change in ECS estimate as a function of time-scales = interannual O(1-5yrs), decadal O(10-30yrs) and centennial (50-100yrs).
3. Discuss potential explanations for those fluctuations, i.e., is there are link between variations in ECS and amplitude of internal variability (standard deviation of *tas*).
4. Using your model, estimate ECS at millennial time-scale which is close to the Earth system sensitivity.

2 Detection & Attribution of climate change

2.1 Elaborate the *tas* irf

Now that the ECS for a quadrupling of CO₂ is known, we can try to model changes in surface temperature with this simple formulation :

$$tas(t) = ECS_{4 \times CO_2} (1 - a_{T,1} \exp \frac{-t}{\tau_{T,1}} - a_{T,2} \exp \frac{-t}{\tau_{T,2}}) \quad (5)$$

Questions :

1. Using the code for the Gregory's approach (section ??), determine the 4 parameters $a_{T,1}$, $a_{T,2}$, $\tau_{T,1}$ and $\tau_{T,2}$. Check if the computation match graphical analysis.
2. Determine the derivative of Equation ?? to get the irf for surface temperature. Develop a code to compute the irf for each CMIP5 models.

2.2 Attributed changes in *tas*

With the irf for surface temperature established, we can try to detect and attribute impact of climate change on observed global mean temperature. Estimate of radiative forcings at top of the atmosphere from observations employed in the IPCC report can be loaded using the following set of commands :

```
# load the historical data on radiative forcing by IPCC
RF_comp = np.array([line for line in \
csv.reader(open("data/Historic_IPCC.1750-2011.RF.csv","r"))] \
[1:],dtype=float)[:,:] # {W/m2}
RF_comp[:, -1] *= 0.7 # arbitrary climate efficiency for volcanoes
RF_lgd = [line for line in \
csv.reader(open("data/Historic_IPCC.1750-2011.RF.csv","r"))] [0]
RF_all = np.sum(RF_comp,1)
```

Questions :

1. Using one of the convolution methods as well as the previous dataset, determine change in surface temperature as simulated by each CMIP5 model.
2. Compare these simulations to that observed since 1880. In order to compare changes in surface temperature, one uses 1900-1920 as a reference period. That is, we will analyse temperature anomaly with the respect to the 1900-1920 average. Observed data of global mean surface temperature can be loaded using :

```
# load temperature reconstructions by NASA/GISS
GMT_giss = np.array([line for line in \
csv.reader(open("data/HistClim_GISS.1880-2014.gmt.csv","r"))] \
,dtype=float)[:,:] # {degC}
```

3. Repeat the previous computation keeping solely (1) natural forcings [last column of RF_comp] or (2) anthropogenic forcings. Present figures from each analyses.
4. Discuss the cause of climate change based on this analysis in the light of the proposed decomposition of observed forcings and previous section.

3 Analysis of future climate change projections

In this section, we will use the above-defined function to estimate change in surface temperature under climate change projections. We will use the last IPCC projections, so-called RCP for Representative concentration pathways.

We start this section by loading variation in radiative forcing for each RCP using the following set of commands :

```
# load RCP radiative forcing scenarios
for rcp in ["26","45","60","85","60to45","45to26"]: \
TMP = np.array([line for line in \
csv.reader(open("data/Scen_RCP"+rcp+".2000-2500.RF.csv","r"))]\
[1:],dtype=float)[:,:] #{W/m2}
TMP[:, -2] *= 0.7 # arbitrary climate efficiency for volcanoes
exec("RF_rcp"+rcp+" = np.sum(TMP,1)")
```

Questions :

1. Display time series of radiative forcing from 1750 to 2500 using historical data and future projections.
2. Future projections start in 2000 and radiative forcing between projection of historical data slightly differ. Write a code in order to ensure continuity in radiative forcing between historical and projections (hint : use RF_{all}).
3. For each projection, estimate change in surface temperature. Display the results on a figure.
4. Discuss the results, focus on the difference between models as well as the difference between projections.

Investigating the contribution of various greenhouse gases

1 An introduction to the Global Warming Potential (GWP) and the Global Temperature Potential (GTP)

In our previous work, we have investigated the role of the rising CO₂ to the change in surface temperature. Now, let's have a look to the role of the methane, another powerful greenhouse gas.

In the last IPCC report, Myrhe et al. (2013a) employed the *irf* for surface temperature in response to a pulse of methane emission which has been established by Boucher et Reddy (2008). It is written as :

$$irf_{tas}(t) = \frac{0.631}{8.4} \exp \frac{-t}{8.4} + \frac{0.429}{409.5} \exp \frac{-t}{409.5} \quad (6)$$

In the following, we will use this formulation to study the Global Warming Potential (GWP) and the Global Temperature Potential (GTP).

The *Absolute Global Warming Potential* (AGWP) of a chemical species X is defined by the cumulative sum of the radiatif forcing over a temporal horizon (TH) induced by a pulse of emission, with an amplitude δE_{pulse}^X . That is :

$$AGWP^X(TH) = \frac{1}{\delta E_{pulse}^X} \int_0^{TH} RF_{pulse}^X(t) dt \quad (7)$$

We use $AGWP$ of a reference species ($X=CO_2$) to determine the *Global Warming Potential* (GWP) of a chemical species X :

$$GWP^X(TH) = \frac{AGWP^X(TH)}{AGWPCO_2(TH)} \frac{\delta E_{pulse}^{CO_2}}{\delta E_{pulse}^X} \quad (8)$$

Similarly, the *Absolute Global Temperature Potential* (AGTP) and the *Global Temperature Potential* (GTP) of a chemical species X is defined by the change in global mean temperature over a temporal horizon (TH) resulting from a emission pulse. Both metrics as written as follows :

$$AGTP^X(TH) = \frac{1}{\delta E_{pulse}^X} [tas^X(TH) - tas(t=0)] \quad (9)$$

$$GTP^X(TH) = \frac{AGTP^X(TH)}{AGTPCO_2(TH)} \frac{\delta E_{pulse}^{CO_2}}{\delta E_{pulse}^X} \quad (10)$$

Questions :

- Using Equation ??, determine the climate sensitivity of that response.
- Compare this latter to the previous results derived from CMIP5 models.
- Implement the function in Python in order to compute $AGWP$ and $AGTP$ for CH_4 and CO_2 for a time horizon ranging from 0 to 500 years.
Hint : We can assume that for methane change in radiative forcing responds linearly to rising CH_4 concentration (called rad_{eff}). In the last IPCC report, Myrhe et al. (2013a) use the following set of parameters :


```
# parameters
# CH4
tau_CH4 = 12.4 #{yr}
radeff_CH4 = 3.63E-4 #{W/m2 / ppb}
k_CH4 = k_CO2 * 16/44. #{TgCH4 / ppb}
# CO2
radeff_CO2 = 1.37E-5 #{W/m2 / ppb}
```
- Display $GWP(t)$ and $GTP(t)$ for methane.
- Compute their values for $TH=20$ years and 100 years and compare these latter to those given in the last IPCC report (Table ?? below).
- Discuss the results and proposed a solution to account for missing processes.

Metrics/ TH	20 years	100 years
GWP^{CH_4}	84	28
GTP^{CH_4}	67	4

2 Assessing the GWP and GTP for other chemical species

In this section, we will investigate the role of other chemical species like the nitrous oxide (N_2O), the sulfur hexafluoride (SF_6), the black carbon (BC) and the sulfate (SO_2).

Questions :

- Please characterize these chemical species (gas or aerosols, natural or anthropogenic, long-lived or short-lived species).

In the following, we will rely on the set of parameters proposed in Fuglestvedt et al. (2010) and Myrhe et al., (2013a,b) :

```
# parameters
# N2O
tau_N2O = 121. #{yr}
radeff_N2O = 3.00E-3 #{W/m2 / ppb}
k_N2O = k_CO2 * 44/44. #{TgN2O / ppb}
# SF6
tau_SF6 = 3200. #{yr}
radeff_SF6 = 0.57 #{W/m2 / ppb}
k_SF6 = k_CO2 * 146/44. #{TgSF6 / ppb}
# SO2
tau_SO2 = 0.011 #{yr}
radeff_SO2 = -0.55 #{W/m2 / TgSO2}
```

```
# BC
tau_BC = 0.020 #{yr}
radeff_BC = 2.82 #{W/m2 / TgC}
```

Questions :

1. Display the *GWP* and *GTP* for the various species.
2. Using a log-scale representation, compare *GWP* and *GTP*.
3. Discuss the potential limitation of this metrics.

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