THE IMPACT OF CLIMATE CHANGE AROUND THE WORLD

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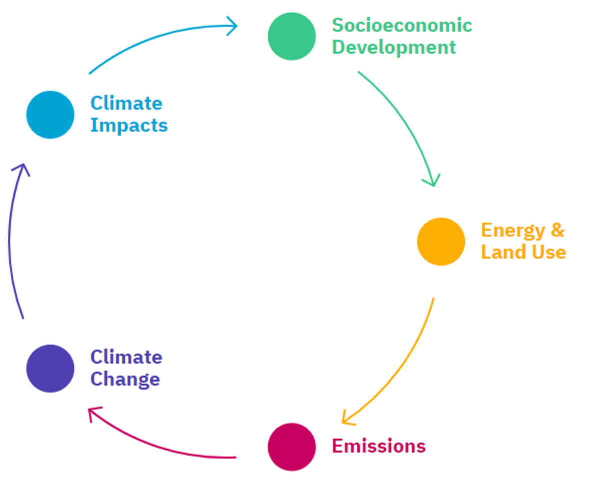


Figure 1 Integrated Assessment Models

INTRODUCTION

«Climate crisis is the risk number one to the global economy» (World Economic Forum). The goal of our analysis is to understand the impact of climate in different regions of the world. Which regions will suffer the most? Which ones will have an economic benefit? The main tools for this kind of analysis are called **IAMs** *(Integrated Assessment Models)*. They build scenarios about future temperature and emissions, linking economy, emissions, climate, and climate damages. They can be used to evaluate climate policies (*e.g.* a carbon tax). In particular, **SuperDICE** is an IAM with 57 regions. It directly outputs only a single variable related to the temperature, namely the global increase of temperature over time (baseline 1900), for each time step until 2100. This temperature is found as an optimal solution to an optimization problem: it is the one that maximises the **global utility**, a function strictly related to the economic damages caused by climate change. Since damages are region specific, this model needs a tool, called **downscaler**, to link the global temperature to the local one.

WHAT IS A DOWNSCALER?

Downscaling is the general name for a procedure that links an information known at large scales to a local one. In this case, it is a tool to find the 57 local temperatures (of the 57 regions of SuperDICE) starting from the global temperature, which is the only direct output variable of the model.

Figure 2 A downscaler

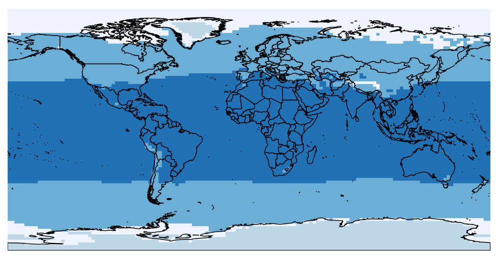
PRELIMINARY ANALYSIS

First of all, is the temperature growing the same way in every region of the world? If this was the case, given the global increase of temperature, the use of statistics would not be necessary to know the temperature of every region. By using a **clustering analysis** (*euclidean method* with *average linkage*) on the mean temperature between 1980 to 2010, it is possible to distinguish four areas of the world: the Equatorial region, the temperate belt and, at the poles, the dry lands (South Pole and Greenland) and the seas around their coasts (fig. 3a).

An **ANOVA permutation test** has been performed to understand if these clusters have been affected in the same way by temperature increase. The null hypothesis H_0 assumes that the difference of the mean temperature between two timeframes (1950-1980 and 1980-2010) was equal in the different clusters considered. The outcome of the test shows that there is statistical evidence ($p < 2 \cdot 10^{-16}$) that not all the areas had the same increase of temperature between the two timeframes. Moreover, univariate permutation tests among all possible pairs of regions have been performed: there is no statistical evidence to state that there are pairs of regions with the same increase of temperature.

Then a **functional data analysis** has been performed on the temperature of the 57 regions of SuperDICE. Given the results of the previous analysis, significant differences between historical growths of temperature were expected. Indeed, the derivatives of smoothed data have different patterns (fig 4).

It is possible to conclude that the temperature is not rising in the same way all over the world, and therefore a non-trivial downscaler is necessary.

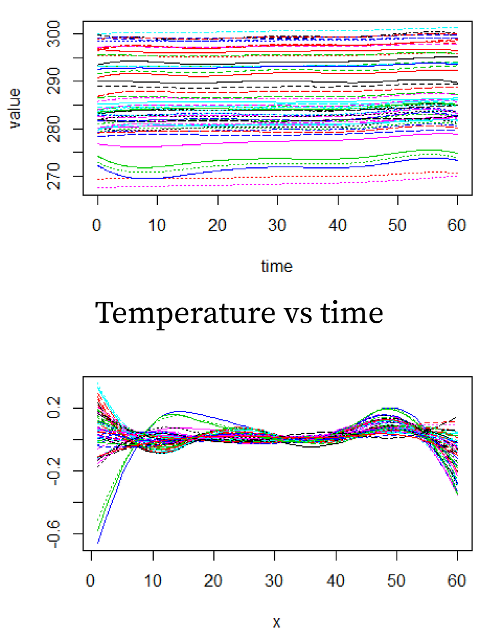


Clustering results

	μ	σ
	1.42	0.44
	0.88	0.46
	0.63	0.59
	0.36	0.15

Temperature increment (K)

Figure 3 Clustering and ANOVA



Temperature vs time

Temperature increase vs time

Figure 4 Functional data analysis

DATASET

The dataset contains the mean surface temperature for each month, from 1951 to 2010, in 90x144 cells all over the world. Data was originally collected by NASA, and was aggregated for this analysis by year and region.

LNG	LAT	MONTH	TEMP
-178.75	89	01/1951	-32.76
-101.25	45	01/1951	-4.75
78.75	21	01/1951	21.17
58.75	7	01/1951	26.53
18.75	-21	01/1951	25.36
61.25	-77	01/1951	-2.46

Figure 5 The dataset

OUR DOWNSCALERS

Three downscalers were built using linear methods. In order to reduce the variability of data caused by meteorologic fluctuations, data have been smoothed using splines. The number of basis was chosen through **cross-validation**. Using this procedure, a single downscaler is actually composed of 57 functions, one for each region, that link the global temperature to the local one. The first downscaler is a linear regression model between the local temperature and the global one: $T_{local} = \beta_0 + \beta_1 T_{global} + \varepsilon$. In this case the regression line minimizes the vertical distance between the line and the points (fig. 6a). The second downscaler is an **inverse regression** model: first of all, the regression model $T_{glob} = \beta_0 + \beta_1 T_{local} + \varepsilon$ was built and then inverted. Therefore, the regression line minimizes the horizontal distance (fig. 6b). In the third downscaler, the coefficients of the regression were extracted through **principal component analysis**, and so the regression line minimizes the orthogonal distance (fig. 6c). Quadratic and logarithmic terms were analyzed, but they were not significant in order to predict local temperatures.

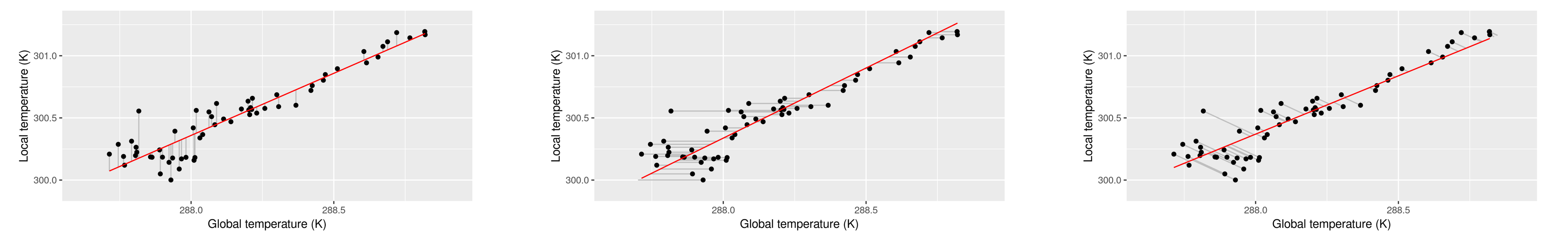


Figure 6 Downscaler plots for the indian region (nde)

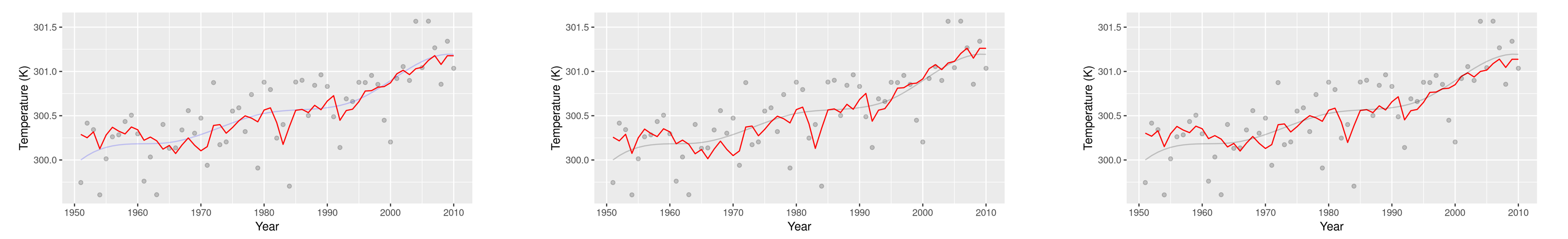


Figure 7 Original data, smoothed data and predictions

CROSS-VALIDATION

A *leave-one-out* cross-validation with 50 iterations has been performed in order to select the number of basis to use in the smoothing process and the downscaler to insert in SuperDICE. Computing the error for the three downscalers and for different numbers of basis, results show that the best number of basis is 7 and the best downscaler is the first one. For this reason the downscaler inserted in SuperDICE is the first one and it is built using splines with 7 basis.

#basis	1	2	3
4	0.1466110	0.1555622	0.1520207
5	0.2014903	0.2005151	0.2179932
6	0.1907813	0.1835271	0.2212083
7	0.1279014	0.1443377	0.1556490
8	0.1798634	0.2191123	0.1924924
9	0.1325293	0.1417672	0.1797156
10	0.1630696	0.1812961	0.1918607
11	0.1382239	0.1721964	0.1773422
12	0.1404163	0.1852602	0.2149784
13	0.1764221	0.2292914	0.2344777
14	0.1810929	0.2124818	0.2418471
15	0.1464988	0.2183089	0.2080660

Table 1 Cross-validation results

RESULTS

To look at the results two different scenarios were analysed. In the first one, non-cooperative case, each country maximizes its own utility, and the solution is found via **Nash equilibrium**. In the second scenario, cooperative case, all regions cooperate in order to reach the best global solution, the one that maximizes a weighted average of regional utilities. **Negishi weights** were considered, so for each region the weight is the inverse of the marginal consumption rate: this means that bigger weights are associated with poorer regions.

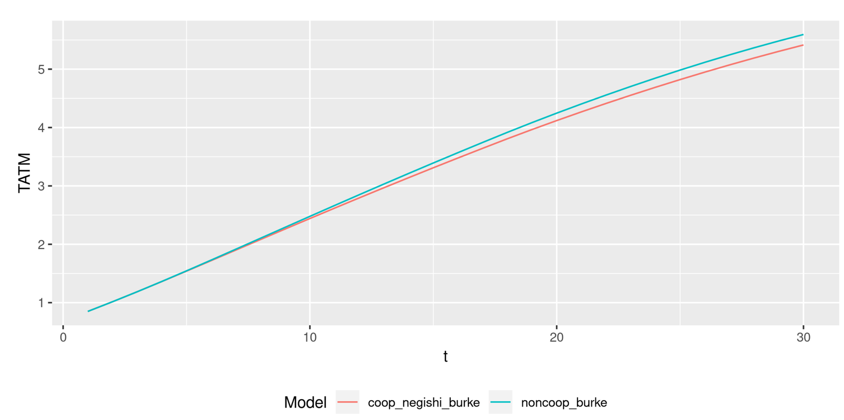


Figure 8 Predicted temperature increase from 1900

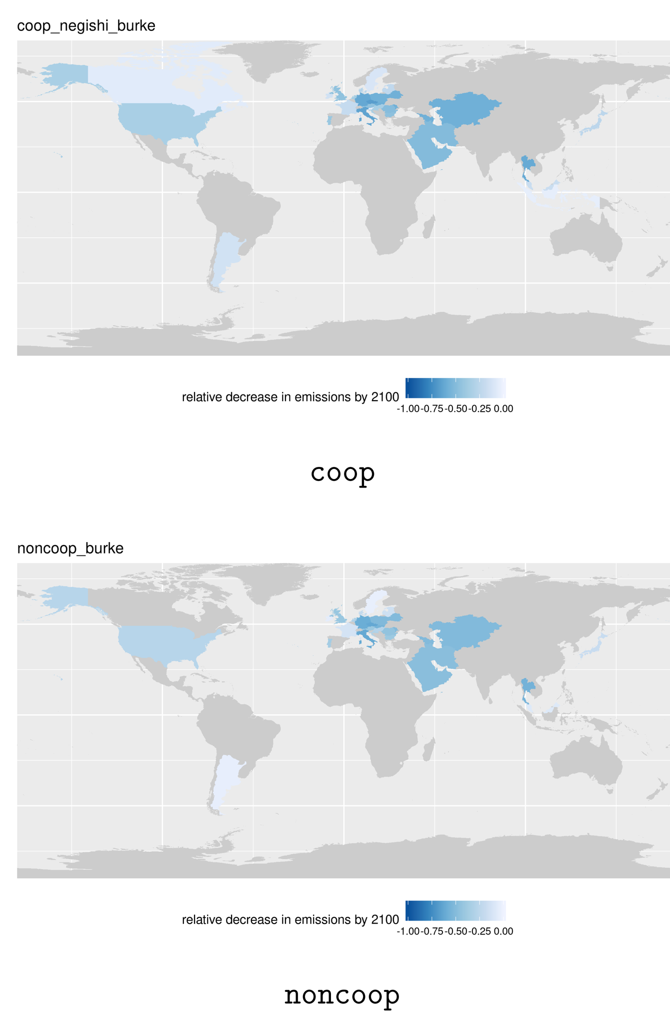


Figure 9 Countries that will reduce their emissions

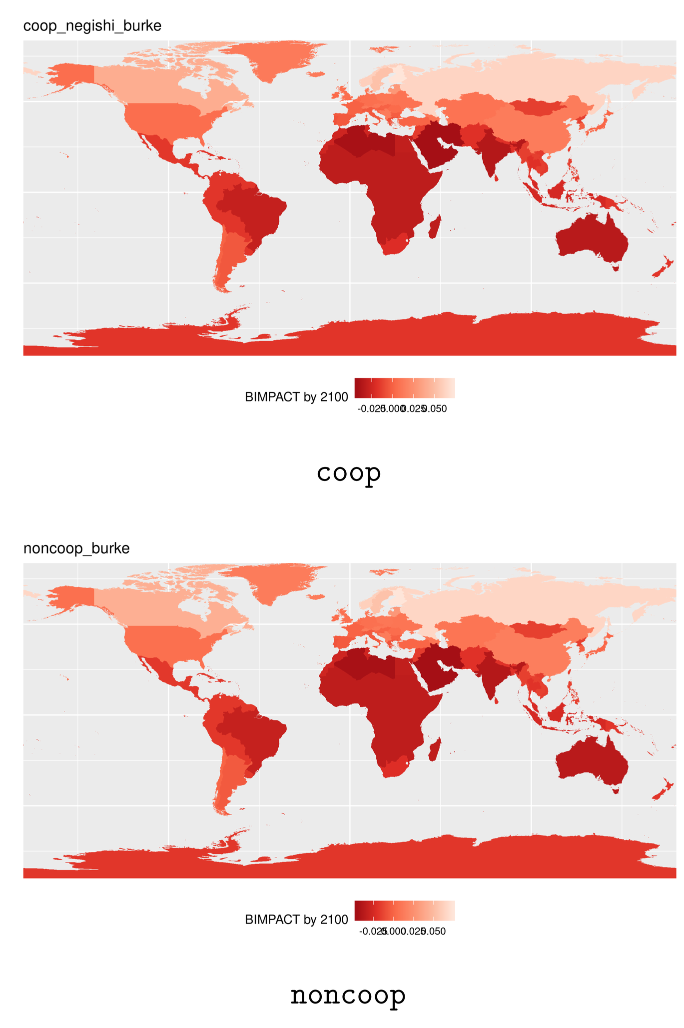


Figure 10 Impact of climate change

CONCLUSION

In order to build a proper downscaler, trends of historical temperature among different regions of the world were analysed. An ANOVA test suggests that the temperature does not grow in the same way all over the world. In addition, the analysis of temperature growth via functional data analysis confirm this hypothesis. Therefore, using smoothed data, three different downscalers have been built and the best one was chosen performing a cross-validation.

Looking at economic damages around the world, it is possible to see that not all regions will be penalized equally by climate change; in particular, the damage will be bigger for regions that are already hot, while some cold regions will have benefits. Comparing cooperative and non-cooperative cases, it is possible to see that Nash equilibrium is not the optimal global solution, and this means that climate agreements are necessary to limit impacts of global warming.

SuperDICE, as every IAM, does not make predictions, but it builds scenarios. The one shown does not consider any incentive to abate emissions, and this would cause a huge increase of temperature (fig. 8). Moreover, damages due to big increases of temperature are underestimated: indeed, the model does not take into account that many people would be forced to emigrate because of climate change. We can see that damages are bigger in countries which are expected to grow a lot in terms of population (Africa will double its population by 2050), and so the problem of immigration would be exacerbated. A scenario like the one shown is useful in order to understand the problem of climate change and of the inequality that it will cause among countries that even without climate crisis are already poorer.

BIBLIOGRAPHY

Caldeira K., Drouet L., Ricke K., & Tavoni M. Country-level social cost of carbon, *Nature Climate Change* 8 (2018)
Shayegh S., *et.al.* Recalculating the social cost of carbon, *SSRN Electronic Journal* (2018)
Burke M., Solomon M., Hsiang S.M, & Miguel E. Global non-linear effect of temperature on economic production, *Nature* 527 (2015)
R.A. Johnson, D.W. Wichern. Applied Multivariate Statistical Analysis, Pearson (2007)
Nordhaus W., Sztorc P. DICE 2013R: Introduction and User's Manual (2nd edition)
CMIP5 monthly data on single levels
Trading economics, https://tradingeconomics.com/

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