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# Uncertainty in future climate change impacts: the case of European agriculture

ECIP – Economic analysis of Climate Impacts and Policy Division

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**SUMMARY** This paper uses an econometric Ricardian model and more than 150 climate change scenarios generated by General and Regional Circulation Models to estimate the impact of climate change on the agricultural sector of the EU15. We find that impact estimates vary greatly depending on the climate models used. Unfortunately, it is not possible to attach probabilities to the climate scenarios. This leaves decision makers with a high degree of uncertainty. There are no obvious ways to deal with this uncertainty. Decision makers ultimately have to choose probabilities that they want to attach to each climate scenario based on their beliefs. This paper explores the implications of using alternative subjective probability distributions on impact estimates.

Keywords Climate change, agriculture, uncertainty.

JEL codes: D81, Q10, Q54

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## **1. INTRODUCTION**

Studies that estimate the economic impact of climate change typically rely on an economic model to determine the sensitivity of the economy to climate and on scenarios generated by Global Circulation models (GCMs) to predict how climate will change in the future. The typical study uses one economic model and one or very few GCMs among the many available (Burke et al. 2014). The impact studies thus use a small and potentially biased set of scenarios of future climate change. This choice is in part driven by practical reasons, as processing climate scenarios is a data intensive and time consuming task that requires specific skills. In many other cases the authors' main goal is to make a methodological contribution to the literature. The application of the method is of second-order importance and should not be used to provide a complete assessment of climate change impacts.

Whenever the goal of the paper is to provide a complete range of possible future climate change impacts all the available information on future climate should be used. Using a partial, possibly biased, set of models is problematic because the GCMs may project very different future climate patterns. For a given trajectory of Greenhouse Gases (GHGs) all models indicate that growing GHGs concentrations in the atmosphere lead to high temperature levels. But, the models disagree on how much temperature will increase. Differences among models are particularly stark at regional and sub-regional level. There are also sharp differences in the distribution of warming across seasons, between day and night, in the variance and higher moments of the distribution of temperature. The climate models also uniformly show that global rainfall will increase as the planet will warm, because the water cycle will accelerate. But different models predict very different regional and sub-regional precipitation patterns. The same area may get wetter according to some models and drier according to other models. All these differences in climate scenarios translate into different impact estimates.

Unfortunately, it is not possible to restrict the analysis only to a small subset of models that provide the most realistic future climate change scenarios. The forecasting accuracy of the models cannot be tested because a commensurable change of GHGs concentrations over a relatively short time frame has not been observed before. Climatologists are also wary of ranking models based on their ability to reproduce observed weather because past predictive accuracy is not necessarily a good indicator of future predictive accuracy. Models that are fine tuned to perfectly reproduce observed conditions may miss something important and not describe well future climate. It is also generally not possible to assess if a new generation of models provide scenarios of future climate change that are more accurate than those obtained using the older generation of models.

The ideal impact study should therefore use all the available climate change scenarios. These leaves researchers and policy makers with a remarkable degree of uncertainty. With uncertainty we refer to "deep" uncertainty – or "Knightian" uncertainty – which is the fundamental inability to attach probabilities to future uncertain events. Risky outcomes have known probabilities. In case of deep uncertainty future outcomes have unknown probabilities.

A common thread running through much of applied economics is a reliance on expected utility as a means of performing cost-benefit analysis and, more broadly, as a normative criterion. There are many compelling reasons behind its primacy: expected utility theory has solid theoretical underpinnings, going back to the work of Von Neumann and Morgenstern (2007) and Savage (1972), is conceptually intuitive, and leads to tractable optimization problems. At its cornerstone is the belief that a model's probabilistic structure can be fully captured by a single Bayesian prior, which is then used in the decision-making process to adjudicate between uncertain tradeoffs.

In the case of climate change impacts research the attractive qualities of the expected utility paradigm come at a steep price. Researchers must choose arbitrary

probabilities for future events. For example, it is standard practice in the literature to use the sample average of all available climate scenarios as the most representative climate outcome. The implicit assumption is that all models are equally likely to provide the correct description of future climate. This is known as the 'one model, one vote' rule, and is widely adopted by the IPCC. The rule would work well if the set of GCMs currently used were a random selection among the population of all possible GCMs. But, this is not true. Many GCMs share important components. Some GCMs are created and run by the same organization. Furthermore, the very structure of the scenario generation process makes it virtually impossible to have independent models and independent runs. Scenarios are generated as part of large modeling comparison exercises. Modelers meet numerous times to compare their scenarios and receive feedback from their peers. Convergence to the mean may occur as peer pressure may discourage large deviations from the most frequent outcomes. Thus, the sample average of climate scenarios should clearly not be interpreted as the most likely outcome. The sample average is only a convenient way to synthetically deal with a large amount of data. There is no reason to rule out the possibility that all the models are terribly wrong, but one. If the most accurate model is an outlier, the sample average provides severely biased estimates of future climate change.

A further layer of uncertainty is added when climate impact researchers match climate data from GCMs to the geographic units of their study. There has been considerable progress over the years but most GCMs have a resolution that is too low for impact studies. The methods used to downscale GCMs climate output range from simple interpolation methods to statistical and dynamical downscaling. Dynamical downscaling

There have been attempts at developing methods for dealing with deep uncertainty – also known as ambiguity – to deal with other economic problems. For example, Gilboa and Schmeidler (1989) developed the axiomatic foundations of maxmin expected utility (MEU), a substitute of classical expected utility for economic

environments featuring unknown risk. They argued that when the underlying uncertainty of an economic system is not well understood, it is sensible, and axiomatically sound, to optimize over the worst-case outcome (i.e. the worst-case prior) that may conceivably come to pass. Ghirardato, Maccheroni, and Marinacci (2004) took a step further and axiomatized a generalization of the Gilboa and Schmeidler model. A compelling special example of their model is their alpha-MEU framework in which a decision maker's preferences are captured by a convex combination of the worst- and best-case expected payoffs over a set of uncertain priors. The assigned weights vary parametrically, so that the more weight is placed on an agent's minimum payoff, the more ambiguity averse he is considered to be.

Methods like the one developed by Ghirardato, Maccheroni and Marinacci provide interesting attempts at solving a fundamentally complex problem. However, in order to be practically implemented these methods require knowing the preferences of the decision maker over ambiguity aversion. Ambiguity aversion is the adversity of individuals to making a decisions on outcomes with unknown probabilities rather than on outcomes with known probabilities. These preferences are often not known.

Finally, different impact models often generate different impact estimates. The accuracy with which impact models explain observed climate impacts is often used as a proxy for the accuracy of future impacts forecasts. However, also in this case it is hard to rank models based on their predictive ability.

Uncertainties on climate change amplify the uncertainty that surrounds estimates of the climate sensitivity of physical, ecological and economic systems. Researchers working on climate change impact estimates and policy makers are left with a large degree of uncertainty to deal with.

In this paper we provide an assessment of the possible range of climate change impacts on the European Agricultural Sector using a Ricardian model of agricultural impacts ant the largest possible set of scenario of future climate change developed by

the models that took part to the Climate Modeling Intercomparison Project 5 (CMIP5). The CMIP5 is the most recent set of climate scenarios and has been thoroughly reviewed by the IPCC Fifth Assessment Report. The climate scenarios have been run using four Representative Concentration Pathways (RCPs) (Van Vuuren et al. 2011). RCPs are hypothetical trajectories of GHGs emissions and of other forcing agents over the century. The RCPs span the technological, economic and political uncertainty about future emissions scenarios. We consider two time frames: 2046-2065 and 2081-2100.

In Ricardian models land values are assumed to reflect the long-term productivity of agricultural land. The cross-section variation of climate and land values is used to estimate how climate affects overall agricultural productivity. The Ricardian model assumes that farmers have adapted to the present climate and that they will adapt to the new climate over the century. The climate sensitivities are taken from the first continental Ricardian study for the EU (Van Passel, Massetti, and Mendelsohn 2012).

Finally, we illustrate how uncertainty increases when we introduce an additional layer of complexity: the regional climate models. The regional climate models provide a very accurate description of climate at very high resolution. These models are created to cover smaller portions of the world. The regional model is usually driven by a global model. As for the global models, the regional models generate scenarios that are fundamentally uncertain. The regional scenarios sum up two different layers of uncertainties: uncertainty about the future global climate and uncertainty about the regional manifestation of climate.

In total, we develop impact estimates at provincial level (NUTS3), country level (NUTS0) and Europe-15 level for 159 different climate change scenarios. To our knowledge, this is the largest consistent set of climate change impact estimates for the European Agricultural sector.

The rest of the paper is structured as follows. Section 2 presents the methods used in the paper. Section 3 presents and discusses results. Conclusions follow.

## 2. METHODS

## 2.1. The impact model

We use agricultural land sensitivity to climate estimated by Van Passel, Massetti, and Mendelsohn (2012). The Ricardian model is estimated using farm-level data and NUTS3 level geographic and climate data for the EU15. The model separately estimate the effect of temperature and rainfall, during the four seasons. The model uses a quadratic specification of seasonal temperature and precipitation to reflect the nonlinear response of agricultural productivity to climate. As the distribution of land values is highly skewed, the model is estimated using quantile regression for the median. Land values enter with a log transformation because they are log-normally distributed. The model is as follows:

$$Q_{\ln V_i}(\tau | T, R, E, D) = \alpha(\tau) + \beta_T(\tau)T_i + \gamma_T(\tau)T_i^2 + \beta_R(\tau)R_i + \gamma_R(\tau)R_i^2 + \eta(\tau)E_i + \xi(\tau)D(1)$$

where *T* and *R* are vectors of seasonal temperature and precipitation measurements, *E* is a set of exogenous control variables; *D* is a set of country fixed effects and  $u_i$  is a random error term which is assumed not to be correlated with climate. The authors control for country specific factors that affect farms by using country fixed effects.

In the Ricardian literature the effect of a different climate is estimated by imposing a shift of temperature and precipitation, ceteris paribus. For example, one can compare the predicted land value of a hypothetical climate  $(T_1, R_1)$  to the estimated value of land with the original climate  $(T_0, R_0)$  as follows:

$$\Delta W_{\rm r} = \sum_{i=1}^{n} \left[ Q_{\rm V_i}(\tau)({\rm T}_1, {\rm R}_1) - Q_{\rm V_i}(\tau)({\rm T}_0, {\rm R}_0) \right] \omega_{\rm i}$$
<sup>(2)</sup>

where  $Q_{V_i} = \exp(\alpha + \beta_T T_i + \gamma_T T_i^2 + \beta_R R_i + \gamma_R R_i^2 + \eta E_i + \xi D)$ .

## 2.2. Climate scenarios

Climate change scenarios are from the CMIP5 database. We use all the models available for which we have at least one Representative Concentration Pathway (RCPs) scenario with both temperature and precipitation data. The four RCPs are named using the corresponding level of radiative forcing in 2100: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. The RCP 2.6 describes a world in which emissions of GHGs quickly peak and decline to zero. The RCP 8.5 is instead a pessimistic scenario that assumes a very large growth of GHGs emissions over the entire century. The RCP 8.5 is not a baseline scenario, as the RCPs were developed to provide purely representative concentration trajectories. The full list of models and scenarios available is in Table 1. The RCP 4.5 and 8.5 are exogenous forcing scenarios for which the largest number of climate models runs is available.

The change of temperature and precipitation is calculated for each model by comparing the RCP run to the historical run. We calculate the average 2046-2065 and 2081-2100 monthly temperature at each grid cell and subtract from them the average 1986-2005 historical average. We calculate the temperature change at each centroid of the NUTS3 regions by interpolating with weights inverse to distance the four closest grid cells to the centroid of each county. We then add the temperature change to our historical thirty-year temperature climatologies. We proceed analogously for precipitation. We calculate the percentage precipitation change predicted by each GCM, we interpolate GCM grid cell data at NUTS3 level and we calculate the new level of rainfall using the historical climatology.



Notes: Two models for which data is available are not included in the analysis because they did not pass a first quality check. The last column indicates the number of scenarios available for each model. The bottom row indicates the total number of scenarios available for each RCP and for the historical climate run.

#### Table 1. List of GCMs and climate change scenarios.



We illustrate the implications for impact estimates and for policy makers' decisions of using regional models by using two coarse-resolution climate scenarios from the GCMs BCM2 and ECHAM5 under the SRES A1B emission scenario (CMIP3). We use the RCA3 and HIRHAM5 RCMs, nested in the two GCMs, to obtain finer resolution climate projections. We consider two time frames: 2031-2060 and 2071-2100. We calculate temperature and precipitation change as for the GCMs. However, as the regional climate models have higher resolution, we calculate temperature and precipitation change at NUTS3 level using an unweighted average of all the grid cells that fall within each NUTS3 region.

## 3. RESULTS AND DISCUSSION

## 3.1. Global circulation models

Figure 1 and Figure 2 display the percentage impact of climate change on EU-15 land values. The results reveal that a large fraction of climate change scenarios predicts declining land values in the EU-15 bloc. The severity of the losses increases as global GHG concentrations increase and global temperature raises. There is however a large difference among impact estimates obtained using different GCMs. Note that all impact estimates use the same set of climate coefficients estimated using the Ricardian model.

Each outcome has unknown probability to occur. One possibility is to assume that all climate change scenarios have equal probability of being true. The expected value of impacts is thus equal to the average of all the impact estimates. Another possibility is to assume that all the scenarios are independent random realizations of future climates. The analysis of the center and shape of the distribution of impacts may thus provide indications on the probable distribution of future impacts. At the extreme opposite of the equal probability scenario we have the assumption that only one of the models is correct (maximum level of ambiguity). However, one does not know which model among all those that are available. In this case it may be worth focusing on the worst possible outcome. An equally interesting possibility is that only the best possible outcome will certainly occur.



Notes: The vertical axis measure the EU-15 land value aggregate percentage loss due to climate change. On the horizontal axis the name of the GCM used to generate the scenario.

Figure 1. The percentage impact of climate change on the EU-15 agricultural sector: RCP 2.6 and RCP 4.5.





Notes: The vertical axis measure the EU-15 land value aggregate percentage loss due to climate change. On the horizontal axis the name of the GCM used to generate the scenario.

Figure 2. The percentage impact of climate change on the EU-15 agricultural sector: RCP6.0 and RCP 8.5.



Notes: The underlying vertical bars measure (right vertical axis) the difference between the best and the worst outcome.

## Figure 3. An overview of the distribution of climate change impacts at EU15-level.

Figure 3 displays the expected value (equal probability assumption), the first, second and third quantile (equal probability assumption) and the worst and best possible outcomes evolve over different scenarios and in two different time frames. The figure also displays vertical bars that measure the range between the best and the worst outcome. The figure reveals that the distribution of climate change impacts is fairly symmetric. The mean and the median are almost identical. The first and the third quartile are almost equally spread across the median. The range of the distribution is fairly large: from 60 to 80 percentage points. This indicates that some climate models generate radically opposite outcomes. The tails of the impacts distribution are not thick. A policy maker that is extremely risk adverse and is willing to assume that the only correct model is the most pessimistic model may make decisions that are too extreme. The same would apply to an optimistic policy maker. The policy maker that assumes that all models have equal chances of being true and relies on either the mean or the median of all outcomes to take climate policy decisions may have the illusion of comfort to have chosen the most robust course of action. However, the "expected" scenario is just as likely as the worst or best outcome scenario. The large spread in all impact estimates indicates that the implications of uncertainty for policy makers are large. Decision making is difficult.

		20	55		2090				
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	
BCC-CSM1-1-M	1	1	0	0	0	0	0	0	
BNU-ESM	2	2		0	0	1		0	
CANESM2	0	0		1	1	0		1	
CMCC-CESM				1				0	
CMCC-CM		1		0		0		0	
CSIRO-MK3-6-0	0	1	5	5	6	6	7	3	
FIO-ESM	1	0	0	0	4	1	4	0	
GFDL-CM3	8	9		4	2	4		6	
GFDL-ESM2M	0	1	0	2	0	0	1	0	
GISS-E2-R	0	0	5	0	0	0	0	0	
HADGEM2-AO	1	0	2	0	0	1	0	2	
INMCM4	0	0		1	0	1		1	
IPSL-CM5B-LR	0	0	0	1	1	1	0	1	
MIROC-ESM	2	0	3	0	1	0	2	1	
MIROC-ESM-CHEM	0	0	0	0	0	0	1	0	

Notes: The table reports the number of countries for which each GCM generates a worst-case scenario, for different RCPs and in different years. Blank space indicate that the scenario was not available for that GCM.

Table 2. The worst case scenario at national level.

		20	55		2090				
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	
BCC-CSM1-1-M	-15%	-27%	-20%	-35%	-13%	-30%	-35%	-51%	
BNU-ESM	-16%	-28%			-6%	-35%			
CANESM2	-25%	-26%		-48%	-32%	-40%		-67%	
CMCC-CESM				-38%				-47%	
CMCC-CM		-18%		-29%		-22%		-43%	
CSIRO-MK3-6-0	-28%	-23%	-29%	-47%	-34%	-46%	-50%	-65%	
FIO-ESM	9%	3%	-1%	-20%	7%	7%	-16%	-32%	
GFDL-CM3	-38%	-46%	-22%	-52%	-33%	-48%	-39%	-74%	
GFDL-ESM2M	-22%	-23%		-36%	-10%	-7%		-45%	
GISS-E2-R	15%	7%	-1%	8%	6%	2%	10%	4%	
HADGEM2-AO	-16%	-25%	-30%	-41%	-15%	-36%	-37%	-68%	
INMCM4		-24%		-30%		-24%		-36%	
IPSL-CM5B-LR		34%		-20%		-22%		-44%	
MIROC-ESM	-22%	-21%	-10%	-18%	-20%	-28%	-30%	-53%	
MIROC-ESM-CHEM	-17%	-21%	-13%	-32%	-11%	-20%	-37%	-51%	

Notes: The table reports the EU-15 loss estimated using the scenarios generated by the GCM, for different RCPs and in different years. Missing values indicate that the scenario was not available for that GCM.

#### Table 3. EU-15 percentage change of land value.

So far we have focused on EU15 aggregate impact estimates. The relative ranking of the scenarios at national level may be different. Not all countries will agree on the choice of the worst-case scenario, for example. Table 2 counts the number of countries in the EU-15 bloc for which each GCM scenario represents the worst case scenario. It is rare to find that more than 50% of the countries agree on the worst-case scenario.

There are regional peculiarities that make some scenarios particularly harmful for some regions, but not for others. Table 3 displays the EU15 impact estimate that correspond to each scenario. There are some interesting cases. The RCP 6.0 GISS-E2-R scenario may be voted as the worst case scenario by 5 out of 15 countries but it is also the least harmful at EU15 level. This implies that the adverse impacts of climate change are concentrated in few countries, while the others benefit from gains. In 2080-2100 the worst case scenarios for the majority of countries are generated by the GCM CSIRO-MK3-6-0. The same model also usually generates the worst economic impact at EU15 level, but not for the RCP 8.5.

Similar patterns may emerge when comparing choices at local and national level. Policy makers at different levels of government may choose different worst-case scenarios. The impossibility to have a uniform ranking of climate change scenarios across space raises interesting questions for future research.

## 3.2. Results – Regional Scenarios

Regional scenarios results indicate that the choice of the regional model is as relevant as the choice of the global circulation model. In the medium-run the two regional scenarios provide diverging impact estimates. In the long run the choice of the regional model is also relevant and in one case we cannot find conclusive evidence on the sign of the aggregate impact of climate change on European agricultural land values. Regional and general circulation models provide sharply diverging impact estimates in some regions, thus further increasing the level of uncertainty that policy makers face.

## 4. CONCLUSIONS

This paper uses a large set of climate change scenarios generated by Global and Regional Circulation Climate models to estimate the impact of future climate change on the EU15 agricultural sector. We find that the estimated impacts vary greatly depending on the climate models used to generate future climate scenarios. The

difference between impacts in the best and the worst case scenarios is usually equal to 60% of total present land values. Negative climate change impacts increase as the level of radiative forcing increases. But the range and the overall distribution of predicted impacts across GCMs does not change. This means that a stronger climate signal is unambiguously harmful for the EU15 agricultural sector, but large uncertainty remains about the magnitude of the damages.

Decision makers that will assume that all models have equal probability of being true and that available scenarios are random independent realizations of the unknown distribution of future climate may make very large errors if it turns out that the most extreme scenarios are indeed true.

Voting on which climate model to use for decision making at the central government level may be hard because the relative ranking of GCMs based on projected impacts varies greatly across countries. Fundamental disagreement may arise among countries.

There is no easy answer to the question of what climate model should be used to make impact forecasts and to guide policy analysis. The expected value approach currently used is not defensible from a theoretical standpoint. Focusing on the best/worst case scenarios and on the range between them reduces the number of assumptions that need to be made but it may be cause of tensions among EU15 member states, because what is worst and best changes across countries



Figure 4. The impact of climate change on land values at national level.



## REFERENCES

- Burke, Marshall, John Dykema, David B. Lobell, Edward Miguel, and Shanker Satyanath. 2014. "Incorporating Climate Uncertainty into Estimates of Climate Change Impacts." *Review of Economics and Statistics* 97 (2):461-471. doi: 10.1162/REST\_a\_00478.
- Ghirardato, Paolo, Fabio Maccheroni, and Massimo Marinacci. 2004. "Differentiating ambiguity and ambiguity attitude." *Journal of Economic Theory* 118 (2):133-173.
- Gilboa, Itzhak, and David Schmeidler. 1989. "Maxmin expected utility with non-unique prior." Journal of mathematical economics 18 (2):141-153.

Savage, Leonard J. 1972. The foundations of statistics: Courier Corporation.

- Van Passel, Steven, Emanuele Massetti, and Robert Mendelsohn. 2012. A Ricardian analysis of the impact of Climate Change on European Agriculture. Nota di Lavoro, Fondazione Eni Enrico Mattei.
- Van Vuuren, Detlef P, Jae Edmonds, Mikiko Kainuma, Keywan Riahi, Allison Thomson, Kathy Hibbard, George C Hurtt, Tom Kram, Volker Krey, and Jean-Francois Lamarque. 2011. "The representative concentration pathways: an overview." *Climatic change* 109:5-31.
- Von Neumann, John, and Oskar Morgenstern. 2007. *Theory of games and economic behavior*. Princeton university press.

## **APPENDIX**

The following table report summary statistics of impact estimates at country level.

Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
EU	2046-2065	RCP 2.6	-38%	-17%	-8%	-5%	0%	15%	52%
EU	2046-2065	RCP 4.5	-46%	-22%	-11%	-11%	-5%	34%	81%
EU	2046-2065	RCP 6.0	-30%	-13%	-8%	-6%	-1%	25%	55%
EU	2046-2065	RCP 8.5	-52%	-31%	-23%	-24%	-12%	8%	59%
EU	2081-2100	RCP 2.6	-34%	-15%	-6%	-4%	6%	23%	57%
EU	2081-2100	RCP 4.5	-48%	-27%	-16%	-16%	-5%	20%	68%
EU	2081-2100	RCP 6.0	-50%	-35%	-21%	-16%	-13%	10%	60%
EU	2081-2100	RCP 8.5	-74%	-51%	-40%	-43%	-30%	12%	86%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
AT	2046-2065	RCP 2.6	-21%	-3%	7%	8%	19%	39%	61%
AT	2046-2065	RCP 4.5	-37%	-9%	6%	2%	23%	53%	89%
AT	2046-2065	RCP 6.0	-26%	-3%	3%	3%	8%	29%	54%
AT	2046-2065	RCP 8.5	-55%	-22%	-1%	-3%	17%	78%	133%
AT	2081-2100	RCP 2.6	-30%	-7%	4%	4%	17%	43%	73%
AT	2081-2100	RCP 4.5	-58%	-12%	5%	2%	23%	79%	136%
AT	2081-2100	RCP 6.0	-42%	-24%	0%	-6%	21%	58%	99%
AT	2081-2100	RCP 8.5	-71%	-45%	-10%	-25%	-7%	310%	381%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
BE	2055	RCP 2.6	-41%	-13%	-6%	-3%	5%	19%	60%
BE	2055	RCP 4.5	-49%	-20%	-8%	-7%	1%	37%	86%
BE	2055	RCP 6.0	-47%	-20%	-6%	-1%	12%	24%	70%
BE	2055	RCP 8.5	-62%	-34%	-20%	-21%	-4%	13%	75%
BE	2090	RCP 2.6	-54%	-17%	-2%	-6%	15%	46%	100%
BE	2090	RCP 4.5	-58%	-29%	-15%	-9%	-1%	22%	80%
BE	2090	RCP 6.0	-59%	-26%	-16%	-12%	-4%	28%	87%
BE	2090	RCP 8.5	-81%	-49%	-37%	-42%	-21%	33%	114%

Notes: EU: EU15. AT: Austria. BE: Belgium.

Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
DE	2055	RCP 2.6	-29%	-16%	-4%	0%	8%	24%	53%
DE	2055	RCP 4.5	-37%	-18%	-7%	-6%	6%	39%	76%
DE	2055	RCP 6.0	-46%	-18%	-6%	-5%	5%	20%	67%
DE	2055	RCP 8.5	-56%	-36%	-20%	-21%	-2%	18%	74%
DE	2090	RCP 2.6	-47%	-11%	-3%	-3%	8%	44%	91%
DE	2090	RCP 4.5	-57%	-26%	-13%	-10%	1%	22%	79%
DE	2090	RCP 6.0	-53%	-28%	-13%	-10%	1%	23%	76%
DE	2090	RCP 8.5	-82%	-51%	-37%	-42%	-21%	27%	109%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
DK	2055	RCP 2.6	-29%	-10%	-3%	-5%	5%	30%	59%
DK	2055	RCP 4.5	-39%	-13%	-2%	-5%	7%	47%	86%
DK	2055	RCP 6.0	-38%	-11%	-1%	-3%	11%	28%	66%
DK	2055	RCP 8.5	-33%	-22%	-11%	-10%	-3%	28%	61%
DK	2090	RCP 2.6	-30%	-12%	0%	-2%	12%	32%	62%
DK	2090	RCP 4.5	-35%	-19%	-6%	-6%	3%	28%	63%
DK	2090	RCP 6.0	-29%	-19%	-6%	-9%	4%	22%	51%
DK	2090	RCP 8.5	-57%	-37%	-25%	-25%	-12%	18%	76%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
ES	2055	RCP 2.6	-53%	-34%	-17%	-19%	1%	35%	88%
ES	2055	RCP 4.5	-68%	-38%	-24%	-28%	-10%	36%	103%
ES	2055	RCP 6.0	-42%	-29%	-14%	-24%	-3%	49%	91%
ES	2055	RCP 8.5	-75%	-54%	-37%	-41%	-25%	24%	99%
ES	2090	RCP 2.6	-63%	-36%	-15%	-20%	-1%	49%	112%
ES	2090	RCP 4.5	-74%	-48%	-30%	-34%	-16%	39%	113%
ES	2090	RCP 6.0	-64%	-51%	-37%	-36%	-28%	16%	80%
ES	2090	RCP 8.5	-90%	-77%	-64%	-67%	-58%	4%	94%

Notes: DE: Germany. DK: Denmark. ES: Spain.

Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
FI	2055	RCP 2.6	-32%	-10%	3%	5%	13%	56%	88%
FI	2055	RCP 4.5	-44%	-25%	-1%	-7%	6%	95%	139%
FI	2055	RCP 6.0	-39%	-27%	0%	-4%	18%	62%	101%
FI	2055	RCP 8.5	-60%	-23%	-11%	-17%	-1%	45%	105%
FI	2090	RCP 2.6	-33%	-16%	-2%	-7%	13%	39%	71%
FI	2090	RCP 4.5	-54%	-24%	-5%	-5%	17%	41%	95%
FI	2090	RCP 6.0	-53%	-31%	-11%	-19%	8%	37%	90%
FI	2090	RCP 8.5	-79%	-52%	-29%	-30%	-12%	36%	115%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
FR	2055	RCP 2.6	-48%	-18%	-11%	-5%	0%	5%	53%
FR	2055	RCP 4.5	-61%	-26%	-12%	-12%	0%	42%	103%
FR	2055	RCP 6.0	-48%	-15%	-9%	-5%	3%	22%	70%
FR	2055	RCP 8.5	-68%	-43%	-28%	-29%	-10%	6%	74%
FR	2090	RCP 2.6	-56%	-15%	-6%	-2%	7%	28%	84%
FR	2090	RCP 4.5	-64%	-34%	-19%	-17%	-5%	31%	94%
FR	2090	RCP 6.0	-69%	-39%	-24%	-22%	-9%	23%	92%
FR	2090	RCP 8.5	-87%	-62%	-47%	-54%	-30%	20%	107%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
GR	2055	RCP 2.6	-57%	-41%	-27%	-35%	-14%	36%	93%
GR	2055	RCP 4.5	-68%	-48%	-31%	-38%	-18%	33%	101%
GR	2055	RCP 6.0	-61%	-39%	-31%	-35%	-20%	-7%	54%
GR	2055	RCP 8.5	-72%	-60%	-44%	-49%	-34%	-1%	71%
GR	2090	RCP 2.6	-59%	-39%	-25%	-33%	-20%	71%	130%
GR	2090	RCP 4.5	-79%	-56%	-40%	-48%	-21%	18%	98%
GR	2090	RCP 6.0	-74%	-58%	-46%	-51%	-41%	6%	80%
GR	2090	RCP 8.5	-95%	-84%	-73%	-78%	-67%	-22%	73%

Notes: FI: Finland. FR: France. GR: Greece.

Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
IE	2055	RCP 2.6	-35%	-12%	4%	0%	18%	49%	84%
IE	2055	RCP 4.5	-26%	-2%	8%	7%	18%	53%	79%
IE	2055	RCP 6.0	-23%	-2%	9%	9%	23%	31%	55%
IE	2055	RCP 8.5	-28%	-6%	4%	3%	15%	32%	60%
IE	2090	RCP 2.6	-43%	-2%	6%	4%	15%	45%	89%
IE	2090	RCP 4.5	-34%	-4%	7%	7%	20%	33%	67%
IE	2090	RCP 6.0	-34%	-8%	2%	1%	14%	34%	68%
IE	2090	RCP 8.5	-35%	-11%	4%	4%	22%	53%	88%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
IT	2055	RCP 2.6	-40%	-32%	-17%	-23%	-9%	36%	77%
IT	2055	RCP 4.5	-62%	-40%	-23%	-27%	-7%	34%	96%
IT	2055	RCP 6.0	-50%	-36%	-22%	-24%	-7%	1%	52%
IT	2055	RCP 8.5	-64%	-50%	-35%	-36%	-26%	9%	73%
IT	2090	RCP 2.6	-51%	-30%	-15%	-19%	3%	38%	89%
IT	2090	RCP 4.5	-63%	-46%	-28%	-31%	-13%	30%	94%
IT	2090	RCP 6.0	-59%	-49%	-34%	-39%	-22%	9%	68%
IT	2090	RCP 8.5	-89%	-75%	-58%	-64%	-54%	30%	119%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
LU	2055	RCP 2.6	-41%	-14%	-5%	-1%	7%	21%	62%
LU	2055	RCP 4.5	-47%	-19%	-9%	-9%	4%	30%	76%
LU	2055	RCP 6.0	-50%	-22%	-7%	-5%	7%	28%	78%
LU	2055	RCP 8.5	-65%	-38%	-22%	-21%	-3%	13%	78%
LU	2090	RCP 2.6	-57%	-16%	-2%	-3%	13%	46%	104%
LU	2090	RCP 4.5	-62%	-33%	-16%	-11%	1%	21%	83%
LU	2090	RCP 6.0	-64%	-34%	-17%	-10%	-3%	24%	88%
LU	2090	RCP 8.5	-86%	-57%	-39%	-44%	-21%	34%	120%

Notes: IE: Ireland. IT: Italy. LU: Luxemburg.



Min

-34%

Q1

-14%

Mean

-5%

Median

-6%

Q3

5%

Max

21%

Scenario

RCP 2.6

Year

2055

Region

NL

NL	2055	RCP 4.5	-43%	-13%	-5%	-6%	2%	40%	83%
NL	2055	RCP 6.0	-39%	-16%	-4%	-2%	14%	23%	61%
NL	2055	RCP 8.5	-52%	-26%	-16%	-17%	-4%	8%	60%
NL	2090	RCP 2.6	-42%	-16%	-2%	-3%	13%	43%	86%
NL	2090	RCP 4.5	-45%	-19%	-10%	-11%	4%	24%	69%
NL	2090	RCP 6.0	-40%	-24%	-11%	-8%	-3%	34%	74%
NL	2090	RCP 8.5	-71%	-43%	-28%	-32%	-15%	33%	104%
Region	Vear	Scenario	Min	01	Mean	Median	03	Max	Range
PT	2055	BCP 2.6	-51%	-27%	-9%	-15%	11%	44%	95%
PT	2055	RCP 4 5	-68%	-27%	-14%	-16%	0%	49%	117%
PT	2055	RCP 6.0	-35%	-25%	-3%	-10%	12%	66%	101%
PT	2055	RCP 8.5	-69%	-44%	-27%	-21%	-12%	30%	99%
PT	2090	RCP 2.6	-58%	-26%	-6%	-14%	16%	79%	137%
РТ	2090	RCP 4.5	-62%	-35%	-18%	-22%	0%	30%	92%
РТ	2090	RCP 6.0	-61%	-43%	-26%	-28%	-16%	22%	83%
РТ	2090	RCP 8.5	-86%	-66%	-51%	-54%	-36%	4%	90%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
SE	2055	RCP 2.6	-20%	-11%	5%	9%	16%	38%	58%
SE	2055	RCP 4.5	-32%	-16%	0%	-3%	14%	44%	76%
SE	2055	RCP 6.0	-37%	-11%	5%	0%	22%	51%	88%
SE	2055	RCP 8.5	-36%	-20%	-7%	-10%	6%	50%	86%
SE	2090	RCP 2.6	-38%	-10%	3%	1%	13%	44%	82%
SE	2090	RCP 4.5	-44%	-18%	-3%	0%	13%	26%	71%
SE	2090	RCP 6.0	-41%	-20%	-2%	-4%	12%	53%	94%
SE	2090	RCP 8.5	-58%	-34%	-20%	-22%	-3%	38%	96%
Region	Year	Scenario	Min	Q1	Mean	Median	Q3	Max	Range
UK	2055	RCP 2.6	-27%	-7%	4%	9%	15%	34%	61%
UK	2055	RCP 4.5	-26%	-3%	7%	4%	15%	66%	92%
UK	2055	RCP 6.0	-29%	-5%	6%	3%	18%	40%	69%
UK	2055	RCP 8.5	-37%	-10%	1%	4%	13%	36%	73%
UK	2090	RCP 2.6	-30%	-7%	8%	4%	23%	45%	75%
UK	2090	RCP 4.5	-28%	-8%	7%	4%	20%	55%	82%
UK	2090	RCP 6.0	-35%	-9%	0%	6%	15%	36%	71%
UK	2090	RCP 8.5	-43%	-21%	-1%	2%	12%	53%	95%

Notes: NL: Netherlands. PT: Portugal. SE: Sweden. UK: United Kingdom.

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