Les Cahiers du GERAD ISSN: 0711–2440

Will adaptation delay the transition to clean energy systems? An analysis with AD-MERGE

O. Bahn, K.C. de Bruin,
C. Fertel

G–2015–79

September 2015
Revised: November 2017

Citation suggérée: Bahn, Olivier; de Bruin, Kelly C.; Fertel, Camille (Septembre 2015). Will adaptation delay the transition to clean energy systems? An analysis with AD-MERGE, Rapport technique, Les Cahiers du GERAD G-2015-97, GERAD, HEC Montréal, Canada. Révisé: November 2017

Suggested citation: Bahn, Olivier; de Bruin, Kelly C.; Fertel, Camille (September 2015). Will adaptation delay the transition to clean energy systems? An analysis with AD-MERGE, Technical report, Les Cahiers du GERAD G-2015-97, GERAD, HEC Montréal, Canada. Revised: November 2017

Avant de citer ce rapport technique, veuillez visiter notre site Web (https://www.gerad.ca/fr/papers/G-2015-97) afin de mettre à jour vos données de référence, s'il a été publié dans une revue scientifique.

Before citing this technical report, please visit our website (https://www.gerad.ca/en/papers/G-2015-97) to update your reference data, if it has been published in a scientific journal.

La publication de ces rapports de recherche est rendue possible grâce au soutien de HEC Montréal, Polytechnique Montréal, Université McGill, Université du Québec à Montréal, ainsi que du Fonds de recherche du Québec – Nature et technologies.

The publication of these research reports is made possible thanks to the support of HEC Montréal, Polytechnique Montréal, McGill University, Université du Québec à Montréal, as well as the Fonds de recherche du Québec – Nature et technologies.

Dépôt légal – Bibliothèque et Archives nationales du Québec, 2017
– Bibliothèque et Archives Canada, 2017

Legal deposit – Bibliothèque et Archives nationales du Québec, 2017
– Library and Archives Canada, 2017

GERAD HEC Montréal
3000, chemin de la Côte-Sainte-Catherine
Montréal (Québec) Canada H3T 2A7

Tél. : 514 340-6053
Téléc. : 514 340-5665
info@gerad.ca
www.gerad.ca

Will adaptation delay the transition to clean energy systems? An analysis with AD-MERGE

Olivier Bahn [a]
Kelly C. De Bruin [b]
Camille Fertel [c]

[a] *GERAD & Department of Decision Sciences, HEC Montréal, Montréal (Québec) Canada*

[b] *ESRI, Dublin, Ireland*

[c] *GERAD, HEC Montréal, Montréal (Québec) Canada*

olivier.bahn@hec.ca
kelly.debruin@esri.ie
camille.fertel@gerad.ca

September 2015
Revised: November 2017
Les Cahiers du GERAD
G–2015–79

Abstract: Climate change is one of the greatest environmental challenges facing our planet in the foreseeable future, yet, despite international environmental agreements, global GHG emissions are still increasing. In this context, adaptation measures can play an important role in reducing climate impacts. These measures involve adjustments to economic or social structures to limit the impact of climate change without limiting climate change itself. To assess the interplay of adaptation and mitigation, we develop AD-MERGE, an integrated assessment model that includes both reactive ("flow") and proactive ("stock") adaptation strategies as well as a range of mitigation (energy) technologies. We find that applying adaptation optimally delays but does not prevent the transition to clean energy systems (carbon capture and sequestration systems, nuclear, and renewables). Moreover, applying both adaptation and mitigation is more effective than using just one.

Keywords: Climate change, climate policy mix, adaptation, mitigation, integrated assessment

Acknowledgments: Olivier Bahn acknowledges support from the Natural Sciences and Engineering Research Council of Canada. Research assistance from Radia Benheddi is also gratefully acknowledged.

1 Introduction

Climate change is one of the greatest environmental challenges facing our planet in the foreseeable future. According to the Intergovernmental Panel on Climate Change (IPCC), climate change is expected to impact both ecosystems and the environmental services they provide (e.g., biodiversity) and human societies (e.g., affecting human health). This is expected to result in economic damage of approximately 2%[1] of GDP per year for a temperature increase of 2.5°C (Arent et al., 2014).

To address this issue, one policy option is the mitigation approach, which aims to reduce anthropogenic greenhouse gas (GHG) emissions. To be effective, such a strategy needs to be implemented globally by the major emitters. The Kyoto Protocol to the United Nations Framework Convention on Climate Change (United Nations, 1997) set emission reduction targets for the developed countries. More recently, the Paris Agreement has recognized the importance of drastically reducing GHG emissions to limit the global temperature rise to 2°C, where nations submit their own emission-reduction targets named Individually Nationally Determined Contributions (INDCs). These INDCs, however, are voluntary and not binding and are expected to lead to significantly higher climate change than the proposed 2°C target (Rogelj et al., 2016). Furthermore, the withdrawel of the US will likely decrease the effectiveness of the agreement. the All in all, global GHG emissions continue to increase, adding to atmospheric GHG concentrations (Victor et al., 2014).

An additional policy option is the use of adaptation. Adaptation measures adjust economic or social structures to limit the impact of climate change at a given level of temperature, i.e. without limiting climate change itself. They can be implemented in an array of sectors and can take on many forms. Examples include crop modifications in agriculture, the building of sea walls, and medical precautions against pandemics. In the literature a common distinction is made of two types of adaptation strategies (Smit et al., 2000; Lecocq and Shalizi, 2007). Reactive strategies (or "flow" adaptation)[2] are measures implemented in reaction to climate change stimuli. Proactive strategies (or "stock" adaptation)[3] are preventive measures that must be taken in advance through the build up of adaptation stock. A further description of these two forms of adaptation will be given in the next section. Certain characteristics of adaptation are favourable as compared to mitigation . First, many adaptation measures have immediate benefits or benefits in the short term, whereas most mitigation benefits occur after several decades. Second, mitigation needs global cooperation to be effective, whereas adaptation can generally be implemented regionally. Adaptation also has some less favourable characteristics. For higher increases in temperature, the uncertainty range of the expected climate change damage is larger (Adger et al., 2005). Mitigation limits climate change and hence limits the uncertainty associated with living in an unkown climate, whereas adaptation shields us from the impact of climate change without affecting temperature. Furthermore, adaptation itself is likely less effective at higher temperatures, where the severe change in climate makes it harder to adapt.

Until recently, the focus in the climate-change literature and policy arena has been on mitigation. Adaptation is now attracting more attention, both in the scientific community with increased research and in the policy arena where funding has been made available (Pielke et al., 2007). Prominent examples are the IPCC's Fifth Assessment Report, which has four chapters that analyze adaptation, including Chambwera et al. (2014), and the Adaptation Fund,[4] which supports adaptation projects in developing countries. Also the recent Paris Agreement includes funding for adaptation (and mitigation) in developing regions. Though both adaptation and mitigation by themselves can reduce climate change impacts, addressing climate change most effectively will require a combination of both. The question then arises how much resources should be allotted to consumption, investments in capital, investments in adaptation capital, adaptation costs and mitigation efforts. One way to find the optimal balance of the mitigation and adaptation, is to use an integrated assessment approach that combines social economic elements with geophysical and environmental elements. Due to among others the large uncertainties involved in the issue of climate change, these models have important limitations, which should be considered when interpreting their results. IAM results should

[1]With an uncertainty range of 0% to 2.5%.

[2]This is a generalisation as not all flow adaptation options are reactive or vice versa, however the bulk of flow adaptation measures considered here are reactive.

[3]This is a generalisation as not all stock adaptation options are reactive or vice versa, however the bulk of stock adaptation measures considered here are proactive.

[4]See www.adaptation-fund.org.

be viewed as thought experiments, where the precision of their numerical magnitudes should not be overestimated. They are aggregate models that simplify reality and do not include many important details. Given these drawbacks, IAM results remain relevant in creating a better understanding of the future impacts of climate change and the interactions between climate policies.

Examples of integrated assessment models (IAMs) include DICE (Nordhaus, 1994, 2014), FUND (Anthoff and Tol, 2013), MERGE (Manne and Richels, 1992; Manne et al., 1995; Manne and Richels, 2005), RICE (Nordhaus and Yang, 1996; Nordhaus, 2011), and WITCH (Tavoni et al., 2006). Mitigation policies have been widely studied with IAMs, but adaptation strategies have only recently been explored. The first model to include adaptation was the PAGE model (Hope et al., 1993; Hope, 2006). PAGE modeled adaptation in a simplistic manner: for a small adaptation fee 90% of the climate-change damage could be eliminated. Later models have included a more comprehensive approach to adaptation. We distinguish these models based on the type of adaptation they include. Models include either reactive adaptation or proactive adaptation or both. Reactive adaptation refers to adaptation taken in reaction to climate change such as farmers changing their harvesting time. Proactive adaptation refers to adaptation taken in anticipation of future climate change, such as e.g. the building of seawalls for future protection against sea-level rise. Several models include only reactive adaptation, such as early versions of AD-DICE (Bruin et al., 2009b) and AD-RICE (Bruin et al., 2009a). FEEM-RICE (Bosello, 2008) and the first version of Ada-BaHaMa (Bahn et al., 2012) include only proactive adaptation. Other models include both reactive and proactive adaptation, such as later versions of AD-DICE (de Bruin and Dellink, 2011), AD-RICE (de Bruin, 2011, 2014), and Ada-BaHaMa (Bahn et al., 2015), as well as AD-WITCH (Bosello et al., 2010, 2013). AD-WITCH also includes adaptive capacity, where GDP growth enhances a region's capacity to adapt. The FUND model also includes sector-specific adaptation options, which depending on the sector are either proactive or reactive.

The aim of this paper is twofold. First, we contribute to the adaptation modeling literature,[5] which relies on a limited number of IAMs, by introducing in the MERGE model both reactive and proactive adaptation. In the process, we also recalibrate the MERGE damage function. Second, we use the resulting model (AD-MERGE) to study in detail the impact of adaptation on the implementation of mitigation measures in the energy sector. Such analyses are possible because MERGE includes a distinct energy module that details different technological options to curb energy-related GHG emissions and for this reason was chosen for this analysis. In terms of mitigation modeling, AD-MERGE provides a more detailed representation of mitigation options than existing IAMs (with adaptation) provide. In the DICE/RICE approach, energy use and the corresponding emissions are directly derived from economic production, and mitigation options are aggregated into a single mitigation cost function. Ada-BaHaMa distinguishes between a "carbon" sector and a "carbon-free" sector, where mitigation consists of replacing the former sector with the latter. AD-WITCH includes a bottom-up representation of the energy sector that distinguishes among seven energy technologies, whereas AD-MERGE has a more detailed representation with close to 40 technologies. In terms of adaptation modeling, AD-MERGE includes the latest developments in the literature. AD-MERGE thus enables a more comprehensive analysis[6] of the impact of adaptation on specific mitigation technologies.

One reason why studying the interactions between adaptation and mitigation in an IAM framework is important is to ensure mitigation results are not biased. Generally, IAMs assume adaptation strategies will be applied at their optimal level. However, examining the real-world adaptation shows that adaptation is not applied at its optimal level. There are many restrictions to adaptation, such as lack of knowledge or lack of funding, that lead to a lower level of adaptation than what is optimal (de Bruin and Dellink, 2011). IAM suggested optimal mitigation strategies should account for this and present mitigation results for varying adaptation assumptions and not simply rely on optimal adaptation. Not accounting for the interactions of adaptation and mitigation can lead to biased results, specifically when the underlying adaptation assumptions are not communicated.

The remainder of this paper is organized as follows. In Section 2, we describe the main characteristics of the MERGE model and describe the damage module; we discuss the adaptation options and the calibration of

[5]Note that in the theoretical literature, several studies investigate the interactions of adaptation and mitigation, e.g. (Brechet et al., 2013; Zemel, 2015)

[6]There exists of course models (such as bottom-up energy models.) that contain much more technological details, but they do not explicitly consider adaptation options.

the module. Section 3 presents the numerical results, and Section 4 provides a sensitivity analysis. Section 5 gives a discussion and a comparison with existing studies, and Section 6 presents concluding remarks.

2 Model description

In this section we will describe the AD-MERGE model applied in this paper. This model includes various regions, where a single decision maker for each regions makes policy decision to maximise that regions utility. Each region chooses how much of its production to use for consumption purposes, investment in capital (to increase future production), investments in energy technologies (to decrease emissions and hence climate change), investments in adaptation capital (to reduce future climate damages) or adaptation expenses (to reduce climate change damages now).

2.1 MERGE description

The Model for Evaluating the Regional and Global Effects of GHG Reduction Policies (MERGE) distinguishes among nine geopolitical regions: Canada, Australia and New Zealand (CANZ); China; Eastern Europe and the Former Soviet Union (EEFSU); India; Japan; Mexico and OPEC (MOPEC); the USA; Western Europe (WEUR); and the rest of the world (ROW). MERGE is composed of four interlinked modules that enable an integrated assessment of climate policies.

The first module (ETA) describes the energy supply sector of each region using a bottom-up engineering approach. More precisely, ETA distinguishes between electricity generation and the production of nonelectric energy (fossil fuels, synthetic fuels, hydrogen, and renewables). GHG emission reduction can be achieved by substitution between electricity generation technologies (e.g., using renewable power plants instead of fossil plants) and nonelectric energy carriers (e.g., switching to low-carbon fossil fuels).

The second module (MACRO) describes the other economic sectors using a top-down macroeconomic (Ramsey–Solow) approach. MACRO relies on a nested constant elasticity of substitution (CES) production function that includes as production factors capital, labor, and electric and nonelectric energy. MACRO captures economic feedback between the energy supply sector and other economic sectors in particular through energy prices that respond to climate policies.

The resulting regional ETA-MACRO models maximize the net present value of regional consumption (i.e., regional welfare). Each region has initial endowments of capital, labor, and fossil fuels (considered as exhaustible resources). MERGE links the regional ETA-MACRO models by aggregating the regional welfare functions into a Negishi weighted global welfare function. A balanced international trade of oil, gas, energy-intensive goods, and an aggregate good in monetary units (the "numéraire" good) further links the regional ETA-MACRO models.

Furthermore, the ETA-MACRO models compute the anthropogenic emissions of the main GHGs, namely CO_2 (carbon dioxide), CH_4 (methane), N_2O (nitrous oxide), HFCs (hydro-fluorocarbons), and SF_6 (sulfur hexafluoride). The third module, the climate module, describes how GHG emissions contribute to GHG concentrations in the atmosphere and how these in turn affect atmospheric temperatures through changes in radiative forcing.

Finally, the last (damage) module quantifies the economic losses caused by temperature changes. It considers both market damage (valued by market prices) and nonmarket damage (estimated by a willingness-to-pay approach). In this paper, we have replaced the original market damage function of MERGE with a new function based on the AD-RICE damage module that integrates reactive and proactive adaptation; see Section 2.2 below.

The MERGE model focuses on mitigation in the energy sector which is the largest source of anthropogenic GHG emissions. Other mitigation options such as non-energy consumer choices (e.g. dietary changes) and land-use changes are not included endogenously given that the modeling literature on these options is still somehow in its infancy.

2.2 Adaptation and damage modeling

The original MERGE model includes both market and nonmarket climate change damage. For market damage, MERGE assumes that a 2.5°C temperature increase will yield an economic loss of 0.25% of GDP in high-income regions and 0.5% in low-income regions. Furthermore, market damage increases proportionally with temperature. For nonmarket damage, MERGE assumes a willingness to pay the equivalent of 0.8% of consumption in high-income regions and 0.4% in low-income regions to avoid nonmarket damage associated with a 2.5°C temperature increase. A quadratic relationship between temperature increase and nonmarket damage is assumed.

In AD-MERGE, we retain the nonmarket damage of the original MERGE model, but we replace the market damage function with a series of functions describing climate damage. Our damage description includes the use of adaptation as a policy option to reduce damage. This new damage module is based on the AD-RICE-2012 model[7] (de Bruin, 2014). We distinguish between gross damage, which represents damage before adaptation, and residual damage, which represents damage after adaptation. Gross damage as a percentage of output ($GD_{j,t}$) is defined for each region j and each time period t as a function of the temperature change (T):

$$GD_{j,t} = \alpha_{1,j} T_t + \alpha_{2,j} T_t^{\alpha_{3,j}}. \tag{1}$$

This is the most commonly used form for damage costs in IAMs, where $\alpha_{1,j}$, $\alpha_{2,j}$, and $\alpha_{3,j}$ are calibration parameters, with $\alpha_{3,j}$ generally taking a value between 1 and 3 (Tol et al., 1998). Residual damage as a percentage of output ($RD_{j,t}$) is a function of total adaptation ($PT_{j,t}$) and gross damage ($GD_{j,t}$):

$$RD_{j,t} = \frac{GD_{j,t}}{1 + PT_{j,t}}. \tag{2}$$

The functional form of Equation (2) has been chosen because it limits between 0% (without any adaptation) and 100% (with infinite adaptation) the amount by which the gross damage can be reduced. This functional form also ensures decreasing marginal benefits of adaptation, i.e., the more adaptation is used, the less effective additional adaptation will be. This is because more cost-effective measures will be applied first.

AD-MERGE distinguishes between reactive and proactive adaptation. These two forms can have different characteristics and hence should be modeled differently. Reactive adaptation occurs as a reaction to an experience of climate change. For example, farmers may notice that rainfall patterns are changing and adjust their crop planting times to optimize the harvest. The main characteristic of reactive adaptation is that we assume that its costs and benefits fall within the current period and have no effect in the next period, i.e., reactive adaptation is a flow variable. This form of adaptation is often undertaken by individuals and does not need large investment, so it can be considered autonomous[8] and private. Proactive adaptation on the other hand is undertaken in anticipation of climate change. For example, one may build a seawall in anticipation of a rise in the sea level. The necessary investment (costs) will pay off in the future (benefits). Furthermore, the investment builds up a stock of adaptation, which has an impact in future periods too (just as a capital stock does). Because of the large-scale nature of proactive adaptation, it can be considered public. Table 1 gives several examples of different adaptation options considered in the calibration of this model and under which category of adaptation they fall.

Table 1: Adaptation measures.

Sector	Reactive adaptation	Proactive adaptation
Agriculture	Adjusted crop circulation	Increased irrigation infrastructure
Sea level rise	Beach Nourishment	Sea wall construction
Health	Use of mosquito nets	Increased health infrastructure
Energy market	Increased energy demand for cooling	Increased energy infrastructure
Extreme events	Migration	Development of early warning systems

[7]Note that we do not include catastrophic and sea level rise damage (which are included in the RICE model) because we assume that these elements are represented by MERGE's nonmarket damage.

[8]Autonomous adaptation refers to adaptation undertaken by individuals autonomously without government or other intervention.

Proactive and reactive adaptation are aggregated using a CES function, as follows:

$$PT_{j,t} = \beta_{1,j} \left(\beta_{2,j}\, SAD^{\rho}_{t,j} + (1-\beta_{2,j}) FAD^{\rho}_{t,j}\right)^{\beta_{3,j}/\rho} \tag{3}$$

where $\beta_{1,j}$, $\beta_{2,j}$, and $\beta_{3,j}$ are calibration parameters; $SAD_{t,j}$ is the total quantity of adaptation capital stock; $FAD_{t,j}$ is the amount spent on reactive adaptation; and ρ is given by $\frac{\sigma-1}{\sigma}$ with σ the (constant) elasticity of substitution; see de Bruin (2014) for more details. This elasticity is chosen to reflect the observed relationship between the two forms of adaptation, which are imperfect substitutes, with ρ set to 0.5. Adaptation capital stock is built up as follows:

$$SAD_{j,t+1} = (1-\delta_k) SAD_{j,t} + IAD_{j,t} \tag{4}$$

where δ_k is a depreciation rate and $IAD_{j,t}$ are the investments in adaptation stock. We set δ_k to the value used for the capital depreciation rate in the RICE model. The total adaptation costs ($PC_{j,t}$) in each period are hence the sum of the reactive adaptation costs and the investments in stock adaptation:

$$PC_{j,t} = FAD_{j,t} + IAD_{j,t}. \tag{5}$$

The market damage is the sum of the residual damage and the adaptation costs, and this damage function is calibrated to replicate the net damage computed by the RICE/AD-RICE damage function:

$$D_{j,t} = RD_{j,t} + PC_{j,t}. \tag{6}$$

We calibrate the adaptation costs and benefits based on the adaptation literature as described in de Bruin (2011). Specifically, we used the AD-RICE regional adaptation costs and benefits to calibrate the parameters of the gross damage function (Equation (1)) and the adaptation function (Equation (3)). Table 2 shows the calibrated regional gross damage in AD-MERGE.

Table 2: Regional gross damage (in % of GDP) as function of temperature increase.

δT	USA	WEUR	JAPAN	CANZ	EEFSU	CHINA	INDIA	MOPEC	ROW
1°C	0.14%	0.15%	0.06%	0.14%	0.10%	0.19%	0.55%	0.35%	0.31%
2.5°C	1.59%	1.25%	0.52%	1.25%	0.99%	2.18%	2.16%	2.43%	1.70%

3 Numerical results

This section presents our policy scenarios, which apply different adaptation strategies, as well as the results of our analyses.

3.1 Scenario characterization

The AD-MERGE database corresponds to version 5 of the MERGE model with two important exceptions: i) some key parameters of the climate module correspond to the revision of Bahn et al. (2011); and ii) the damage module has been revised and recalibrated as explained in Section 2.2.

The database is characterized by a rich description of the regional energy sectors, with many mitigation options. In terms of electricity-generation technologies, the model considers four types of coal power plants (two with carbon capture and sequestration, i.e., CCS); one type of oil power plant; three types of gas power plants (one with CCS); a generic low-cost renewable power plant (hydroelectric);[9] a power plant using existing nuclear technology;[10] and a generic advanced "high-cost" power plant. The advanced plant is called LBDE. It relies on biomass, nuclear, solar, and/or wind[11] and corresponds to a "backstop" technology with

[9] This technology has limited capacity reflecting the (limited) potential of the low-cost renewables that it represents.

[10] This technology also has limited capacity, reflecting the current public acceptance of this energy carrier. The model also considers advanced nuclear energy power plants through a generic technology that does not have a limited capacity.

[11] This corresponds to the modeling philosophy of MERGE that avoids *picking specific winners* (Manne and Richels, 2004) among advanced carbon-free technologies, but it does not allow for a distinction between nuclear and renewable energies.

unlimited capacity. In terms of nonelectric energy supply, the model considers 24 options: the direct use of coal; 10 cost categories for oil supply; 10 cost categories for gas supply; synthetic fuels; a limited supply of low-cost renewables (such as ethanol from biomass); and an unlimited carbon-free supply of nonelectric energy. The carbon-free energy is called LBDN. It is defined in a generic way; this could refer for instance to hydrogen production using carbon-free processes.[12]

The energy production costs are assumed to decline at an exogenous rate of 0.5% per year, except that for the LBDE and LBDN technologies, only a fraction of the cost is exogenously reduced. The remainder of the cost is reduced through the accumulation of knowledge in manufacturing and operation, which is measured by the cumulative installed capacities. This corresponds to the modeling of endogenous technological progress following a learning-by-doing approach (LBD); see for example Kypreos and Bahn (2003) and Manne and Barreto (2004).

We have analyzed several scenarios using AD-MERGE. The first is an artificial *Baseline* (used for comparison only), where regions do not consider climate change damages in their decision-making and consequently GHG emissions are not limited. This scenario assumes a world population level of 8.7 billion by 2050 and 9.5 billion by 2100. Between 2000 and 2100, the world GDP increases by a factor of 11 (to 382 trillion USD 2000), whereas primary energy supply and carbon emissions increase by a factor of 4 (to around 1600 EJ/year and 27 Gt C, respectively). In terms of primary energy supply and CO_2 emissions, our baseline scenario closely corresponds to the *high baseline emission* RCP8.5 scenario (Vuuren et al., 2011). In the following four scenarios, climate change damages are taken into account by decisionmakers and the regions react using different climate strategies following a cost-benefit approach. In these policy scenarios, mitigation is possible, but adaptation may be available only on a limited basis. Specifically, we consider a no-adaptation (*NoA*) scenario, where adaptation is not possible; a *Proactive* scenario, where only proactive adaptation is available; a *Reactive* scenario, where only reactive adaptation is available; and a optimal adaptation (*OptA*) scenario, where both forms of adaptation are available and applied at thier optimal levels.

3.2 Temperature and emission paths

Figure 1 presents the temperature increases (from the 2000 level). The temperature increases by almost 2.5°C by 2110 in the Baseline and by approximately 1.8°C in the other scenarios, with slightly higher values when adaptation is possible. When adaptation is applied, climate change damages decrease for a given level of temperature change, decreasing the benefits of mitigation, which decreases the level of mitigation applied, which in turn will yield higher temperatures. As can be seen in Figure 1, the temperature levels for the Proactive and Reactive adaptation scenarios lie between the No adaptation and Optimal adaptation levels. Applying only one form of adaptation will result in increased temperature levels compared to applying no adaptation, but does not decrease mitigation so much as to lead to the same temperature increase as in the Optimal adaptation case. This is due to the assumption in the model that proactive and reactive adaptation are not perfect substitutes, i.e. there are some damages that cannot be adapted to with only the one form of adaptation. An example of this is sea level rise, where no amount of beach nourishment (reactive adaptation) can result in the same amount of protection as a seawall (proactive adaptation). Note that all the scenarios miss the target of the Paris Agreement, which is an increase of 2°C compared to preindustrial levels.[13]

Figure 2 displays the world energy-related CO_2 emission paths that drive the temperature variations. In the policy scenarios, the implementation of mitigation options (discussed in Section 3.4) yields a peak in emissions by 2040 at around 9 Gt C. In the NoA scenario, where mitigation is the only policy available, a rather fast decarbonization path brings the emissions down to 3.1 Gt C by 2110. In this case, the lack of adaptation increases the damages associated with a certain level of temperature change, increasing the marginal benefits of mitigation, resulting in higher mitigation levels. When adaptation is available, the start of the fast reduction path is delayed by about 20 years. In the corresponding scenarios, the emission levels are reduced to around 4 Gt C by 2110. In other words, adaptation delays but does not prevent a (fast) transition

[12] E.g., biomass gasification, coal gasification with CCS, natural gas reforming with CCS, water electrolysis using renewable electricity or high-temperature water splitting using nuclear heat.

[13] The temperature increase between the preindustrial and the 2000 levels is estimated at 0.6°C (IPCC, 2014).

toward low-carbon energy systems; see also Section 3.4. Only applying one form of adaptation also results in a transition delay, but to a lesser degree than with Optimal adaptation.

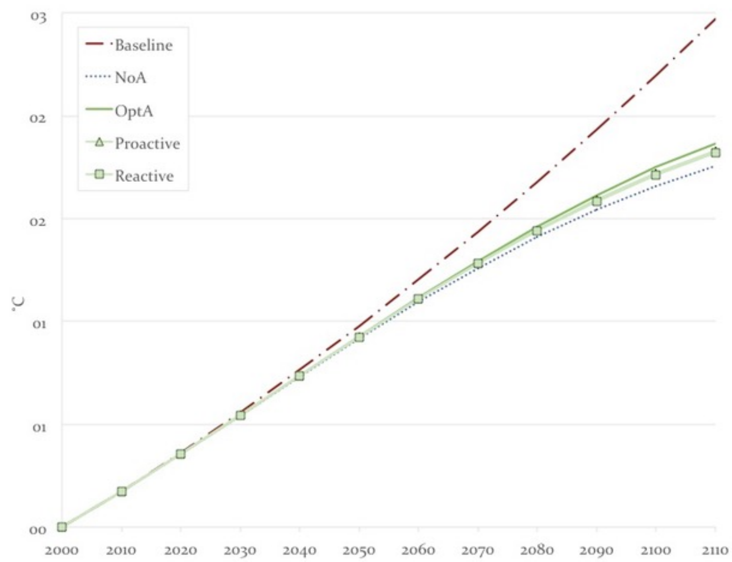

Figure 1: Temperature increase in °C compared to 2000.

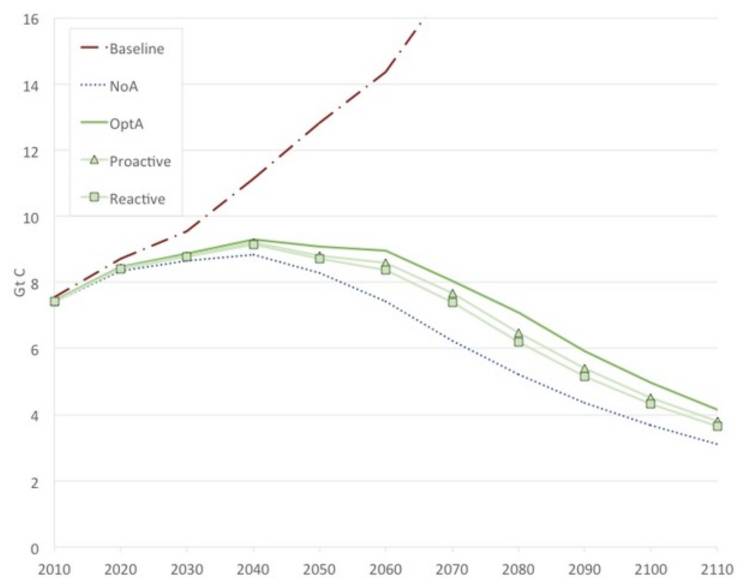

Figure 2: World energy-related CO_2 emission trajectories in Gt C .

3.3 Damage costs and adaptation measures

Figure 3 gives the global adaptation costs as a percentage of world GDP for our scenarios. It highlights some important trends. First, the adaptation costs increase over time with temperature increase; see again Figure 1. Second, due to a slowdown in the temperature increase, adaptation spending increases more slowly by the end of the 21st century. Mitigation benefits are only felt after a few decades due to the nature of the climate system. These benefits are discounted at a positive rate, which leads to a postponement of mitigation action. As can be seen in Figure 2, mitigation increases from around 2050, decreasing emissions. Increased mitigation decreases the benefits of adaptation, resulting in lower adaptation levels. This trend appears earlier with proactive adaptation spending (compared to reactive), due to the delayed effect of the former adaptation. Third, at a global level, spending on proactive adaptation is higher than on reactive adaptation up to 2100. This results generally holds at a regional level, with the exception of INDIA where spending on both forms of adaptation are approximately equal and in EEFSU where spending on reactive adaptation is higher (regional results are emitted here). Fourth, when only one form of adaptation is available (in the Proactive and Reactive scenarios), the fraction of GDP spent on that specific form increases compared to the case where both forms are available (in OptA, indicated by the dashed lines "Opt-adapt. (IAD)" and "Opt-adapt. (FAD)"). In these cases the one form of adaptation will increase to compensate for the lack of the other. However, there is less overall adaptation spending, i.e. the spending on the available form of adaptation is less than the spending on both forms of adaptation when these are available. This is because the two forms of adaptation are imperfect substitutes. Adaptation will thus be less cost-effective when only one form can be applied, resulting in lower marginal benefits and less adaptation will occur. This reflects the assumption that applying both forms of adaptation will be more effective in reducing damages than applying just one form.

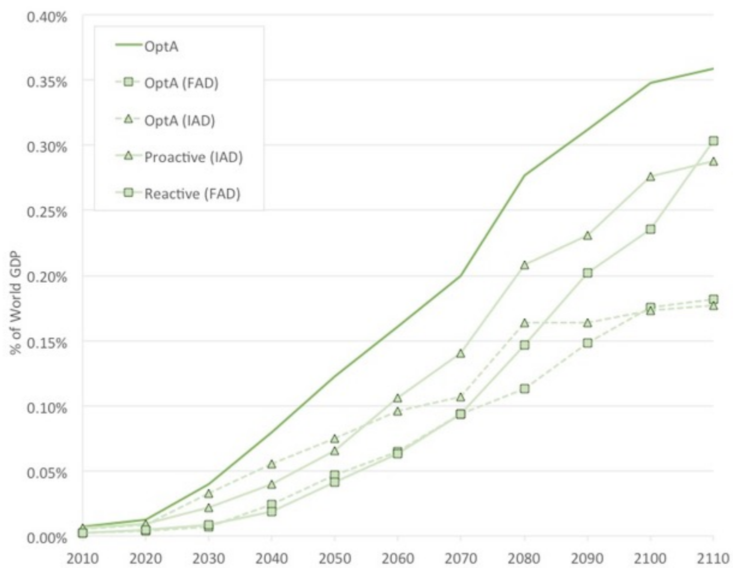

Figure 3: Total adaptation costs (proactive and/or reactive) over time, in % of world GDP. In the OptA scenario, the cost decomposition between proactive and reactive adaptation is given respectively by the dashed lines "OptA (IAD)" and "OptA (FAD)".

To illustrate the damage-reducing potential of adaptation, Table 3 presents the adaptation levels for the different regions in the OptA scenario, given as a percentage of the gross damage reduced through adaptation. Regional differences in the adaptation levels are quite large (up to 30%), reflecting adaptation possibilities that vary across regions. Moreover, these levels represent the optimal adaptation, as computed by the model. In reality, lower adaptation levels may be expected, especially in regions currently under development, because of the many constraints on adaptation not explicitly taken into account by AD-MERGE. In particular, lower income regions are likely to have less proactive adaptation, which entails large-scale funding and government planning (de Bruin and Dellink, 2011). This is discussed further in Section 3.5.

Table 3: Regional adaptation levels in the OptA scenario for 2050 and 2100, in % of gross damage reduced.

Year	USA	WEUR	JAPAN	CANZ	EEFSU	CHINA	INDIA	MOPEC	ROW
2050	43%	14%	36%	15%	30%	35%	22%	35%	17%
2100	57%	42%	68%	46%	48%	51%	39%	61%	41%

The net climate change damage (residual damage plus adaptation costs) is shown in Figure 4. The damage increases over time at a steeper rate than the temperature, due to the nonlinear relationship between temperature and damage. The damage associated with temperature change in the Baseline has been computed ex-post and is reported for comparison, reaching around 3.4% in 2110. A comparison of the Baseline and NoA scenarios shows that curbing GHG emissions can significantly reduce damage (to about 1.9% in 2110) by limiting temperature increase. Damage can be further reduced through adaptation, with reactive adaptation being slightly more effective than proactive. As seen in Figure 3 spending is less on reactive, this reflects the high damage reduction protential of less costly reactive measures. Applying both forms of adaptation leads to the lowest damage path (a level of about 1.4% in 2110), despite the slight temperature increase (see again Figure 1) due to adaptation substituting for some mitigation measures. This confirms the need for both adaptation and mitigation policies to best address climate change.

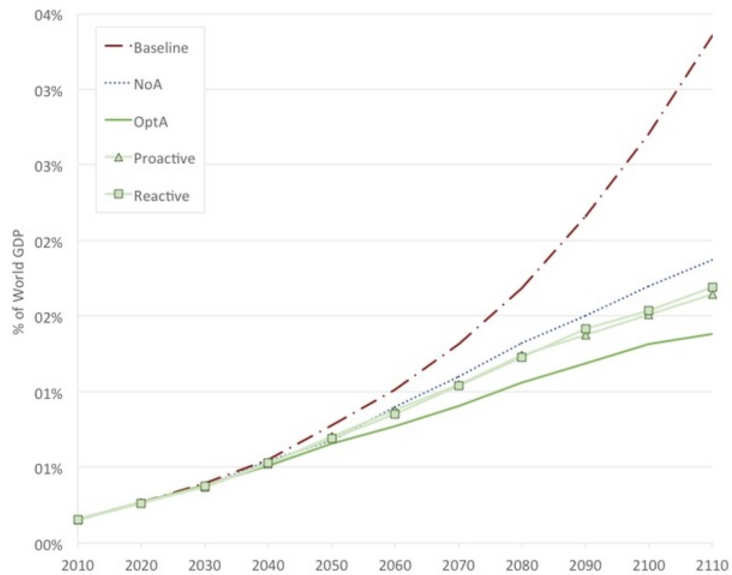

Figure 4: Net damage (sum of adaptation costs and residual damage), in % of world GDP.

3.4 Mitigation strategies

Figure 5 presents the world primary energy use in 2010 (for reference), 2050, and 2100. We will comment only on the 2100 situation, where the differences among the scenarios are the greatest, discussing both the total energy use and the energy mix.

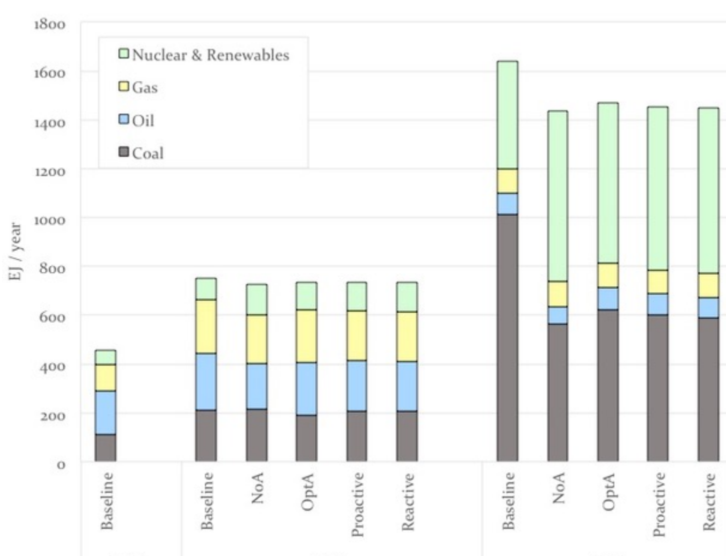

Figure 5: World primary energy use.

Compared to the Baseline, the other scenarios, which consider climate damages in the decisionmaking, require less energy to be supplied to the economy: the reductions are similar and vary between around 10% (in OptA) and 12% (in NoA). Furthermore, there are changes in the energy mix. In the Baseline, energy use is dominated by fossil fuels (especially coal, with a share of 62%). In the policy scenarios, GHG reduction is achieved (at the primary energy level) by the two following means. The first is an increased use of nuclear and renewables,[14] mostly at the expense of coal: the share of nuclear and renewables varies between 45% in OptA and 49% in NoA. NoA has a higher share because of the stronger need to curb emissions in the absence of adaptation in order to reduce damage. The second is inter-fossil substitution, mostly from coal to gas, again more so in NoA. Note also that in all the policy scenarios, coal is mainly used to generate electricity in power plants equipped with CCS systems (see below).

To illustrate the regional differences in primary energy use, Figure 6 presents the primary energy supply in 2100 for the different scenarios and three groups of regions. Following a World Bank classification,[15] these groups are defined as follows: *high income* refers to the OECD regions (USA, WEUR, CANZ, and JAPAN); *middle income* refers to EEFSU, CHINA, and MOPEC; and *low income* refers to INDIA[16] and ROW. The level of total primary energy use is highest in middle-income countries and lowest in high-income regions. Concerning the energy mix, the main differences among regions (across scenarios) is the share of nuclear and renewables. This ranges from 43% for middle-income regions in the OptA scenario and 50% for low-income regions in the NoA scenario. These differences are mainly due to regional energy endowments (that yield different mitigation costs from the baseline) and regional adaptation possibilities (in scenarios where adaptation is available). Besides, regions have different potential for economic and population growth. In particular, low-income countries have both an incentive and an opportunity to turn directly (to a large extent) in a mitigation context to clean energies and clean technologies.

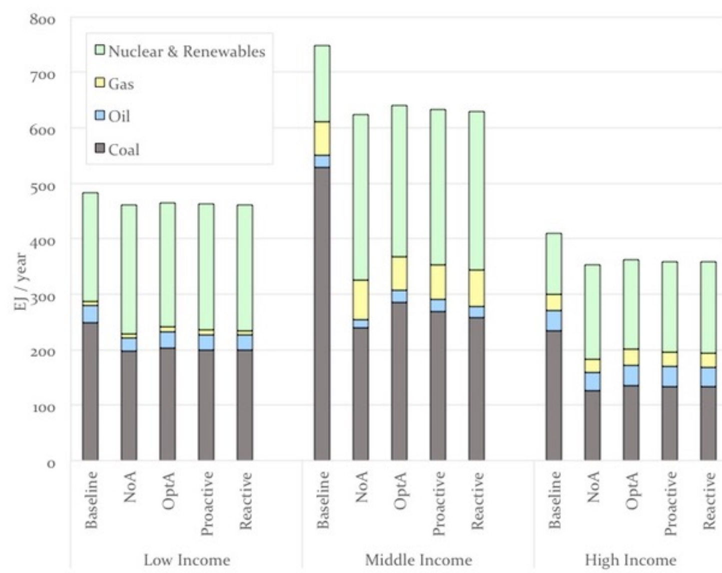

Figure 6: Regional primary energy use.

To further characterize the mitigation measures undertaken, Tables 4 and 5 present world electricity generation (by power plant type) and nonelectric energy production (by energy carrier) in 2100, respectively.

Compared to the Baseline, the mitigation strategies consist mainly, in all policy scenarios, of replacing coal power plants without CCS (COAL-N) by advanced coal power plants with CCS (COAL-A and IGCC).[17] Concerning nonelectric energy, the mitigation strategies are again rather similar with or without adaptation.

[14]Recall that MERGE does not distinguish between these two energy carriers.

[15]See http://data.worldbank.org/about/country-and-lending-groups.

[16]In the World Bank classification, India is a lower-middle income country. We group low income and lower-middle income together as low-income countries.

[17]Note that in all the scenarios, HYDRO and NUC are used at their full capacity by 2100.

Table 4: World electricity generation (in PWh per year) by power plant type: LBDE (advanced high-cost carbon-free technologies such as advanced nuclear, biomass, and solar), HYDRO (hydroelectric, geothermal, and other existing low-cost renewables), NUC (existing nuclear technology), GAS-A & COAL-A & IGCC (advanced gas and coal plants respectively with CCS), GAS-N (advanced gas combined cycle without CO_2 recovery), and COAL-N (pulverized coal plant without CO_2 recovery).

	Baseline	NoA	OptA	Proactive	Reactive
LBDE	1	2	2	2	2
HYDRO	3	3	3	3	3
NUC	3	3	3	3	3
GAS-A	0	5	0	1	2
COAL-A	0	52	44	50	50
IGCC	6	16	27	21	20
GAS-N	10	8	10	10	10
COAL-N	80	0	0	0	0
Total	103	89	90	90	90

Table 5: World nonelectric energy production (in EJ per year) by energy carrier: LBDN (advanced high-cost clean carriers such as hydrogen produced using carbon-free processes), RNEW (low-cost renewables such as ethanol from biomass), SYNF (synthetic fuels), GASNON (gas for nonelectric use), OILNON (oil for nonelectric use), and CLDU (coal for nonelectric use).

	Baseline	NoA	OptA	Proactive	Reactive
LBDN	172	417	374	386	395
RNEW	196	196	196	196	196
SYNF	160	0	0	0	0
GASNON	36	27	33	33	28
OILNON	88	69	91	86	82
CLDU	57	26	37	31	31
Total	710	735	732	732	733

Compared to the Baseline, the use of fossil fuels and especially synthetic fuels (SYNF) is much reduced in favor of advanced high-cost clean carriers such as hydrogen (LBDN);[18] in the absence of adaptation, this effect is slightly more pronounced.

3.5 Adaptation effects on mitigation strategies

In this section, we take a closer look at how adaptation impacts world energy-related CO_2 emission levels. In the previous results, we examined two extreme adaptation scenarios: No adaptation and Optimal adaptation. No adaptation refers to the case where decision makers do not apply either proactive or reactive adaptation. Optimal adaptation refers to the case where decision makers have full information on adaptation costs and benefits and apply adaptation at the optimal level where marginal costs equate marginal benefits. In reality, actual adaptation strategies are not likely to fall in either of these extremes, but somewhere in between. Here, we examine several additional adaptation scenarios to further investigate the impacts of adaptation on mitigation. As discussed previously, there are many barriers and restrictions to adaptation, hence in these scenarios we restrict adaptation to levels beneath the optimal adaptation level. We run nine additional restricted adaptation scenarios where the level of adaptation investments and costs are fixed between 90% and 10% of the optimal level.

In Figure 7 the world energy-related CO_2 emission trajectories are given for the various restricted adaptation scenarios over time. The figure illustrates that the more adaptation is restricted, the more emissions decrease. With lower levels of adaptation, residual damages are higher, which increases the benefits of mitigation and in turn increases mitigation efforts, resulting in lower emissions.

[18] Note that in all the scenarios, traditional renewables such as biomass (RNEW) are used at their full potential by 2100.

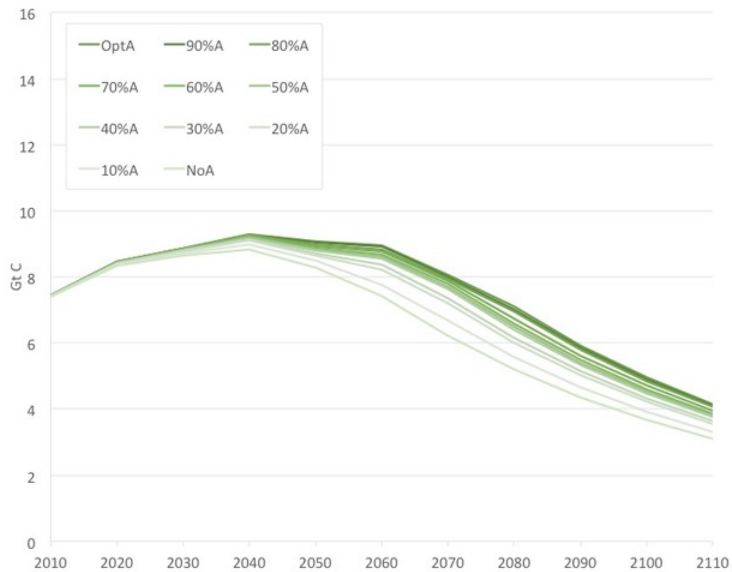

Figure 7: World energy-related CO_2 emission trajectories for various restricted adaptation scenarios.

4 Sensitivity analysis

To investigate the robustness of our results, this section presents a sensitivity analysis. Specifically, we examine how varying the climate sensitivity and the effectiveness of adaptation impacts the interplay of adaptation and mitigation strategies, comparing the OptA and NoA scenarios. This analysis can give us a better picture of how given other parameter assumptions our results may differ.

4.1 Climate sensitivity

There remains a high level of uncertainty concerning the precise temperature effect of GHG emissions. To analyze this, we explore different levels of climate sensitivity (CS), following Bahn et al. (2011). We consider our original parameterization with medium CS[19] (3°C) and a mean lag for ocean warming[20] (57 years), a case with low CS (1.5°C) and a short lag (45 years); and a case with high CS (4.5°C) and a long lag (77 years). The resulting temperature increases for these cases under the OptA and NoA scenarios are given in Figure 8. The temperature differences between the two scenarios increase slightly with CS: 0.03°C by 2110 for low CS, 0.11°C for medium CS, and 0.15°C for high CS.

The temperature variations are driven by GHG emissions (CO_2, in particular). Again, the differences between the OptA and NoA scenarios increase with CS. In particular, under high CS, world energy-related CO_2 emissions reduce to 1.9 Gt C by 2110 in NoA and to 3.1 Gt C in OptA (a level comparable with that of the NoA scenario under medium CS). However, in this case, adaptation delays by only 10 years the transition toward cleaner energy systems (compared to 20 years in our original medium CS case). The emission levels are driven by the mitigation efforts undertaken, in particular in the energy sectors. Figure 9 presents the global primary energy consumption. In the long run (2100), both the total energy consumption and the energy mix vary notably with and without adaptation under high CS. Without adaptation, the higher temperature increase would trigger higher damage in the NoA scenario. This yields a greater need for mitigation. Nuclear and renewables then become the dominant primary energy sources by 2100 with a share of 83% (compared to 49% in OptA). One of the main differences is the dominant use of the LBDE technology for electricity generation instead of coal power plants with CCS (IGCC and COAL-A). The considerable introduction of LBDE in NoA is associated with cost reductions for this advanced learning technology due to the (long-run)

[19]The CS parameter corresponds to the long-term equilibrium temperature for a doubling of preindustrial atmospheric GHG concentrations.

[20]This parameter corresponds to the lag between the observed surface temperature and the equilibrium temperature. It is essentially controlled by the uptake and transport of heat by the global ocean circulation.

effects of endogenous technological progress. Cost reductions (in the long run) for electricity generation also induce higher primary energy use in NoA compared to OptA.

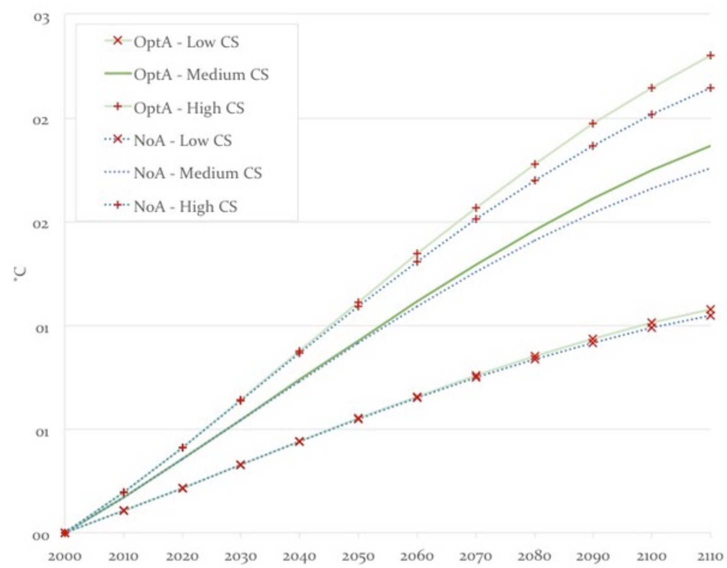

Figure 8: Temperature increase for low, medium, and high CS levels in the OptA and NoA scenarios in °C compared to 2000.

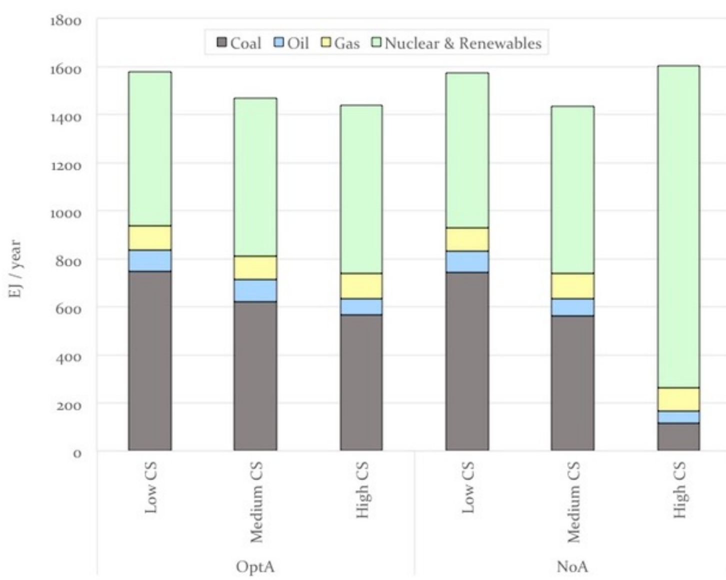

Figure 9: Global primary energy use for low, medium, and high CS levels in the OptA and NoA scenarios.

4.2 Adaptation effectiveness

Since this paper investigates the influence of adaptation on mitigation choices, it is important to also investigate the sensitivity of our results to the parameterization of adaptation. To assess this, we vary parameter $\beta_{1,j}$ from Equation (3), which reflects the effectiveness of adaptation. Compared to our original setting, we choose a lower (respectively, higher) adaptation effectiveness (AE) such that the same adaptation costs will result in a 50% lower (respectively, higher) adaptation level (fraction of gross damage reduced). We return to our original (medium) CS setting. Table 6 presents the adaptation levels in 2100 for the different regions in the OptA scenario for our three AE cases. As expected, the levels for each region vary significantly with the AE.

Table 6: 2100 regional adaptation levels in the OptA scenario for low, medium, and high AE levels, in % of gross damage reduced.

AE	USA	WEUR	JAPAN	CANZ	EEFSU	CHINA	INDIA	MOPEC	ROW
Low	25%	7%	47%	8%	18%	20%	11%	23%	5%
Medium	57%	42%	68%	46%	48%	51%	39%	61%	41%
High	82%	62%	78%	67%	70%	74%	59%	84%	61%

Higher AE levels reduce mitigation needs: by 2100, world energy-related CO_2 emissions are 3.5 Gt C for low AE (compared to 3.1 Gt C in NoA), 4.1 Gt C for medium AE, and 4.5 Gt C for high AE. In all these cases, adaptation delays by 20 years the transition toward cleaner energy systems (compared to NoA). However, for low AE, the emission path is closer to that of the NoA scenario. Figure 10 presents the global primary energy consumption. In contrast to CS, AE has less impact on primary energy. The main difference is the use of nuclear and renewables: their share is 47% for low AE (compared to 49% in NoA), 45% for medium AE, and 43% for high AE.

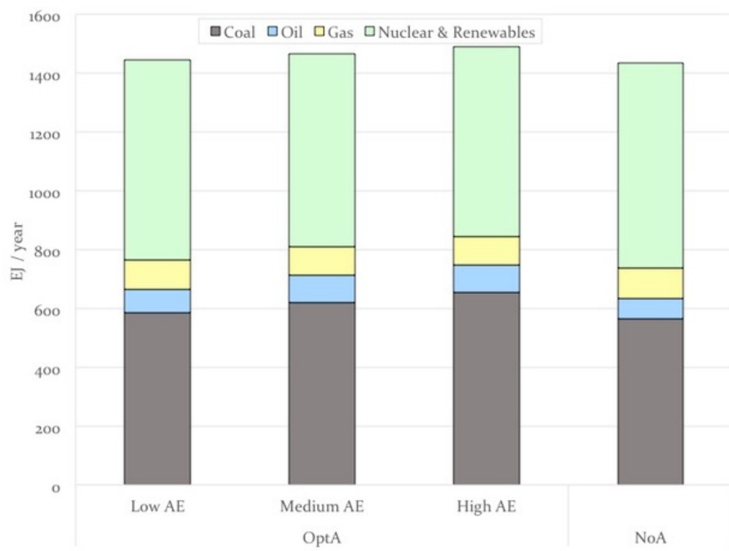

Figure 10: Global primary energy use for low, medium, and high AE levels in the OptA and NoA scenarios.

5 Discussion

It has been argued (e.g., Pindyck, 2013; Stern, 2013) that the uncertainties surrounding climate change render current IAMs useless. There is indeed much uncertainty involved in estimating the relationships between climate, the economy, and energy use. IAMs typically run one or two centuries into the future, making (long-term) assumptions and estimations very uncertain. This is an important drawback of IAMs that should be kept in mind when interpreting the results. Another important issue that should be considered in this context is that of climate thresholds. It is often argued that once certain temperature thresholds are passed, disastrous climate change damages may occur. In our analysis (as in most IAMs) we do not include thresholds, which would most likely strengthen the recommendation of a fast transition to clean energy systems, see e.g. Bahn et al. (2011). Furthermore, due to the complexity of IAMs, aggregations and simplifications are needed. Important sectoral and regional details of (among others) adaptation and mitigation cannot be all included. In AD-MERGE, many forms of adaptation have been aggregated and included. However, the representation of adaptation in the model will obviously not fully replicate all the options available. Finally, IAMs do not consider the practical side of implementing climate policies, which can prove very complex and difficult in reality. We believe however that with a cautious interpretation of the results, IAMs can yield useful insight into long-term climate change polices.

Only two other IAMs include explicit adaptation measures and mitigation options: Ada-BaHaMa and AD-WITCH. AD-WITCH has a detailed description of different energy carriers and technologies, but this does not feature in the analyses reported by Bosello et al. (2010, 2013). These studies set a stabilization target for GHG concentrations. When adaptation is applied, GDP increases (through reduced damage), translating into higher energy demands, thus leading to slightly higher mitigation costs to achieve the same target. There is no further discussion of which energy technologies are used to reach the concentration target. In Ada-BaHaMa, as reported by Bahn et al. (2015), adaptation delays the start of the transition toward clean energy systems by 10 years (2055 instead of 2045). Afterward, the transition occurs rapidly as in the case where only mitigation is possible. In AD-MERGE, adaptation delays the rapid transition toward low-carbon energy systems by 20 years (2060 instead of 2040), as reported in Figure 2 for the OptA scenario in our standard parametrization.[21] After 2060, the transition occurs at the same speed as in the case where only mitigation is possible (NoA scenario). In our sensitivity analyses, we find that adaptation always delays the transition by 20 years, except under high CS where the delay is only 10 years. The finding that adaptation delays but does not prevent the transition toward clean energy systems thus appears robust.

Recalling once more the many uncertainties inherent to IAMs, we recommend interpreting the results of AD-MERGE with caution. We can, however, make some general policy conclusions based on our analysis. First, adaptation and mitigation are important components of an optimal climate policy. They are imperfect substitutes, and an optimal policy should include both. To effectively deal with climate change, governments should formulate local adaptation plans as well as mitigate emissions, where collaboration on a global level is necessary. Second, both forms of adaptation have an important role to play in reducing climate damages. Reactive adaptation will largely need to be undertaken by individuals, though policymaking can increase the (correct) application of this form of adaptation through knowledge building and support. Proactive adaptation often requires large timely investments, which will need to be coordinated in the public sector. Third, an emphasis on adaptation (as in the high AE case) could lead to a situation where the use of mitigation options is reduced. Most IAMs assume an optimal adaptation level. Therefore, these models may understate the optimal mitigation, given that adaptation levels are bound to be suboptimal because of the many real-world constraints (de Bruin and Dellink, 2011). This could have important implications mainly for developing regions, where adaptation plays a more important role in reducing damages and is likely to be suboptimal. And fourth, although adaptation can considerably reduce climate change damage, a transition toward clean energy systems is still warranted in the long run. Indeed, our results show that even with optimal adaptation such systems will be adopted on a large scale, albeit with a delay of up to two decades compared to the situation where adaptation is not available. Given the real-world constraints on adaptation and the high uncertainties involved in assessing climate change effects, an early transition to clean energy systems seems warranted and policymaking should focus on this transition.

6 Conclusion

This paper has examined the interactions between adaptation and mitigation policies using an IAM approach. Only a few IAMs include both mitigation and adaptation, and to date there has been no detailed analysis of the interaction between these strategies. Our contribution is the exploration of different mitigation technologies and how adaptation may affect their deployment. To do this, we have proposed the AD-MERGE model based on the MERGE and AD-RICE models. AD-MERGE includes close to 40 energy technologies as well as reactive and proactive adaptation.

Our results show that the optimal levels of reactive and proactive adaptation (and hence adaptation costs) increase over time, as temperature increases. By the end of the century, however, mitigation efforts will reduce the rate of the temperature increase and hence the use of adaptation strategies. This shows the trade-off between mitigation, which limits temperature increases in the long run, and adaptation, which reduces the damage for a given temperature increase and is effective in the short run.

[21] Recall however that emissions peak by 2040 in all the policy scenarios.

We find that either mitigation or adaptation will significantly decrease the impact of climate change. The best approach is to apply both strategies. Our results also show that proactive adaptation is more effective than reactive adaptation.

Concerning energy use, our results show that, when climate change damages are not considered by decisionmakers (in our artificial Baseline), fossil fuels (especially coal) dominate the total primary energy supply. When only mitigation strategies are used, there is a transition to CCS systems, nuclear, and renewables. When adaptation is applied in combination with mitigation, this transition still takes place but is delayed by up to 20 years. In other words, adaptation may delay investment in mitigation options, but a transition to low-emitting energy systems appears inevitable in the long run. Our sensitivity analyses show that the configuration of the energy system is quite sensitive to the climate sensitivity parameter but less so to the adaptation effectiveness parameter.

Our results show that adaptation changes the optimal mix of energy technologies. Generally IAMs assume optimal adaptation, as adaptation is likely to be below its optimal level in reality, this leads to biased results. As adaptation is assumed to be higher than is likely to occur, IAMs will underestimate the optimal level of low-emitting energy systems.

Although we have conducted sensitivity analyses and compared our results to existing studies, our findings should be interpreted with caution. IAMs are complex and inherently include many uncertainties. AD-MERGE could be improved: we could, for example, develop better damage estimates, include non-energy mitigation and enhance the treatment of uncertainty. Our results are not definitive, but they may be indicative of future adaptation and mitigation interaction.

References

Adger, W Neil, Nigel W Arnell, and Emma L Tompkins (2005) Successful adaptation to climate change across scales, Global environmental change, 15, 77–86.

Anthoff, David and Richard S.J. Tol (2013) The uncertainty about the social cost of carbon: A decomposition analysis using fund, Climatic Change, 117, 515–530.

Arent, Douglas J., Richard S.J. Tol, Eberhard. Faust, Joseph P. Hella, S.urender Kumar, Kenneth M. Strzepek, Ference L. Toth, and Denghua Yan (2014) Key economic sectors and services, in Christopher B. Field, Vicente R. Barros, David J. Dokken, Katharine J. Mach, Michael D. Mastrandrea, T. Eren Bilir, Monalisa Chatterjee, Kristie L. Ebi, Yuko Otsuki Estrada, Robert C. Genova, Betelhem Girma, Eric S. Kissel, Andrew N. Levy, Sandy MacCracken, Patricia R. Mastrandrea, and Leslie L. White eds. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 659–708.

Bahn, Olivier, Marc Chesney, and Jonathan Gheyssens (2012) The effect of proactive adaptation on green investment, Environmental Science & Policy, 18, 9–24.

Bahn, Olivier, Marc Chesney, Jonathan Gheyssens, Reto Knutti, and Anca Claudia Pana (2015) Is there room for geoengineering in the optimal climate policy mix? Environmental Science & Policy, 48, 67–76.

Bahn, Olivier, Neil R. Edwards, Reto Knutti, and Thomas F. Stocker (2011) Energy policies avoiding a tipping point in the climate system, Energy Policy, 39, 334–348.

Bosello, Francesco. (2008) Adaptation, Mitigation, and Green R&D to Combat Global Climate Change: Insights from an Empirical Integrated Assessment Exercise,Technical Report 20, CMCC Research Paper.

Bosello, Francesco, Carlo Carraro, and Enrica de Cian (2010) Climate policy and the optimal balance between mitigation, adaptation and unavoided damage, Climate Change Economics, 01, 71–92.

——— (2013) Adaptation can help mitigation: An integrated approach to post-2012 climate policy, Environment and Development Economics, Vol. 18, 270–290.

Brechet, Thierry, Natali Hritonenko, and Yuri Yatsenko (2013) Adaptation and Mitigation in Long-term Climate Policy, Environmental and Resource Economics, 55(2), 217–243.

de Bruin, Kelly C. (2011) Distinguishing Between Proactive (Stock) and Reactive (Flow) Adaptation, Working Paper 8, CERE.

——— (2014) Calibration of the AD-RICE 2012 model, Working Paper 3, CERE.

de Bruin, Kelly C. and Rob B. Dellink (2011) How harmful are restrictions on adapting to climate change? Global Environmental Change, 21, 34–45.

de Bruin, Kelly C., Rob B. Dellink, and Shardul Agrawala (2009a) Economic Aspects of Adaptation to Climate Change: Integrated Assessment Modelling of Adaptation Costs and Benefits, Vol. 6 of OECD Working Papers: OECD Publishing Paris.

de Bruin, Kelly C., Richard S. J. Tol, and Rob B. Dellink (2009b) AD-DICE: An Implementation of Adaptation in the DICE Model, Climatic Change, 95, 63–81.

Chambwera, Muyeye, Geoffrey Heal, Carolina Dubeux, Stephane Hallegatte, Liza Leclerc, Anil Markandya, Bruce A. McCarl, Reinhard Mechler, and James E. Neumann (2014) Economics of adaptation, in Christopher B. Field, Vicente R. Barros, David J. Dokken, Katharine J. Mach, Michael D. Mastrandrea, T. Eren Bilir, Monalisa Chatterjee, Kristie L. Ebi, Yuko Otsuki Estrada, Robert C. Genova, Betelhem Girma, Eric S. Kissel, Andrew N. Levy, Sandy MacCracken, Patricia R. Mastrandrea, and Leslie L. White eds. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 945–977.

Hope, Chris W. (2006) The Marginal Impact of CO_2 from PAGE2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern, Integrated Assessment Journal, 6, 19–56.

Hope, Chris W., J. Anderson, and P. Wenman (1993) Policy Analysis of the Greenhouse Effect: An Application of the PAGE Model, Energy Policy, 15, 328–338.

IPCC (2014) Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva, Switzerland: IPCC, pp.151 pp.

Kypreos, Socrates and Olivier Bahn (2003) A MERGE model with endogenous technological progress, Environmental Modeling & Assessment, 8, 249–259.

Lecocq, F. and Z. Shalizi (2007) How Might Climate Change Affect Economic Growth in Developing Countries? A Review of the Growth Literature with a Climate Lens,Technical report, World Bank.

Manne, Alan and Richard Richels (2004) The impact of learning-by-doing on the timing and costs of CO 2 abatement, Energy Economics, 26, 603–619.

Manne, Alan S and Leonardo Barreto (2004) Learn-by-doing and carbon dioxide abatement, Energy Economics, 26, 621–633.

Manne, Alan S., Robert O. Mendelsohn, and Richard G. Richels (1995) MERGE: A Model for Evaluating Regional and Global Effects of GHG Reduction Policies, Energy Policy, 23, 17–34.

Manne, Alan S. and Richard G. Richels (1992) Buying Greenhouse Insurance: The Economic Costs of CO_2 Emission Limits, Cambridge: The MIT Press.

——— (2005) MERGE: An integrated assessment model for global climate change, in R. Loulou, J.-P. Waaub, and G. Zaccour eds. Energy and Environment. GERAD 25th Anniversary Series: Springer, 175–189.

Nordhaus, William D. (1994) Managing the Global Commons: The Economics of Climate Change, Cambridge: The MIT Press.

Nordhaus, William. D. (2011) Estimates of the social cost of carbon: Background and results from the RICE-2011 model,Technical Report 1826, Cowles Foundation Discussion Paper.

Nordhaus, William D. (2014) Estimates of the Social Cost of Carbon: Concepts and Results from the DICE-2013R Model and Alternative Approaches, Journal of the Association of Environmental and Resource Economists, 1, 273–312, URL: http://www.jstor.org/stable/10.1086/676035.

Nordhaus, William D. and Zili Yang (1996) RICE: A Regional Dynamic General Equilibrium Model of Optimal Climate-Change Policy, American Economic Review, 86, 741–765.

Pielke, Roger, Gwyn Prins, Steve Rayner, and Daniel Sarewitz (2007) Climate change 2007: Lifting the taboo on adaptation, Nature, 445, 597–598.

Pindyck, Robert S. (2013) Climate change policy: What do the models tell us? Journal of Economic Literature, 51, 860–872.

Rogelj, Joeri, Michel den Elzen, Niklas Hohne, Taryn Fransen, Hanna Fekete, Harald Winkler, Roberto Schaeffer, Fu Sha, Keywan Riaha, and Malte Meinshausen (2016) Paris Agreement climate proposals need a boost to keep warming well below 2°C, Nature, 534, 631–639.

Smit, Barry, I. Burton, Richard J. T. Klein, and Johanna Wandel (2000) An Anatomy of Adaptation to Climate Change and Variability, Climatic Change, 45, 223–251.

Stern, Nicholas (2013) The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models, Journal of Economic Literature, Vol. 51, 838–859, URL: http://www.aeaweb.org/articles.php?doi=10.1257/jel.51.3.838, DOI: http://dx.doi.org/10.1257/jel.51.3.838.

Tavoni, Valentina Bosetti, Carlo Carraro, Marzio Galeotti, and Massimo Emanuele Massetti (2006) A World induced Technical Change Hybrid Model, The Energy Journal, 13–38.

Tol, Richard S. J., Samuel Fankhauser, and Joel B. Smith (1998) The Scope for Adaptation to Climate Change: What Can We Learn from the Impact Literature? Global Environmental Change, 8, 109–123.

United Nations (1997) Kyoto Protocol to the United Nations Framework Convention on Climate Change: Climate Change Secretariat, Bonn.

Victor, David G., Dadi Zhou, Essam H.M. Ahmed, Pradeep K. Dadhich, Jos G.J. Olivier, H-Holger Rogner, Kamel Sheikho, and Mitsutsune Yamaguchi (2014) Introductory Chapter, in Ottmar Edenhofer, Ramon Pichs-Madruga, Youba Sokona, Ellie Farahani, Susanne Kadner, Kristin Seyboth, Anna Adler, Ina Baum, Steffen Brunner, Patrick Eickemeier, Benjamin Kriemann, Jussi Savolainen, Steffen Schlömer, Christoph von Stechow, Timm Zwickel, and Jan C. Minx eds. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 111–150.

van Vuuren, Detlef P., Jae Edmonds, Mikiko Kainuma, Keywan Riahi, Allison Thomson, Kathy Hibbard, George C. Hurtt, Tom Kram, Volker Krey, Jean-Francois Lamarque, Toshihiko Masui, Malte Meinshausen, Nebojsa Nakicenovic, Steven J. Smith, and Steven K. Rose (2011) The representative concentration pathways: An overview, Climatic Change, 109, 5–31.

Zemel, Amos (2015) Adaptation, mitigation and risk: An analytical approach., Journal of Economic Dynamics and Control, 51, 133–147.