Expanding Integrated Assessment Modelling: Comprehensive and Comprehensible Science for Sustainable, Co-Created Climate Action

29/02/2024

D5.6 Behaviour, social and disruptive innovation

WP5 – Expanding – Resilient, inclusive, sustainable development

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Responsible Author	Natasha Frilingou	**Email**	nfrilingou@epu.ntua.gr	
	NTUA	**Phone**	+30 210 772361	
Contributors	Evelina Trutnevyte, Nik Zielonka [UNIGE]; Alaa Al Khourdajie [Imperial]; Dirk-Jan van de Ven, Clàudia Rodés Bachs, Russell Horowitz [BC3]; Nikos Kleanthis [UPRC]; Thomas Nikolakakis, Anastasios Karamaneas, Alexandros Nikas, Konstantinos Koasidis [NTUA]; Glen Peters, Shivika Mittal [CICERO]; Mohamed Lifi, Jaime Nieto, Gonzalo Parrado-Hernando, Iñigo Capellán-Pérez, David Alvarez-Antelo, Juan Pérez-Marcos [UVa]; Adrián Mateo-Martínez, Noelia Ferreras-Alonso [CARTIF]			
Reviewer(s)	Clàudia Rodés Bachs [BC3], Panagiotis Fragkos [E3M], Sara Giarola [Imperial]			
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EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA.

2. Dissemination and uptake

This report will be used by the project to assess the impact of multiple policy objectives to mitigation pathways, as prescribed in Task 5.4 - Disruptive innovation in models and off-model/qualitative socio-technical analyses and Task 5.5 - The role of behavioural change and social innovation in the transition of the Grant Agreement. The report also addresses research questions derived from the first cycle of the Policy Response Mechanism of IAM COMPACT and can be used to inform stakeholders (technical policymakers, industry representatives, and civil society actors) and researchers on policy-relevant topics. Part of the work will also be submitted for publication in peer-reviewed literature.

3. Short summary of results (<250 words)

This deliverable covers two different tasks of WP5, aiming to expand aspects of Integrated Assessment Models (IAMs), and address related questions received from our Policy Response Mechanism. The first task (Task 5.4) aims to capture key disruptive innovations and technologies currently underrepresented in IAMs and includes four modelling studies. Section 2 presents probabilistic projections of the diffusion of solar photovoltaics, wind power, biogases, heat pumps, and three types of low-carbon passenger cars in 39 European countries for 2023-2050 and compares the projected capacities against the quantities required for the energy transition. Section 3 examines how maximal effort across all sectors to reduce gross, in addition to net emissions, might contribute to a reduced role of CDR in deep mitigation. Section 4 then explores the impact of future interest rates in decarbonisation pathways, by applying an empirical dataset of estimated cost of capital differentiated by technology and country in two global IAMs and one electricity-system model. Section 5 explores the impacts of climate scenarios on adjustment in firms' credit risk and financial valuation and highlights the critical role of the financial sector in influencing the pace of the transition to net zero emissions, and finally Section 6 investigates the economic implications of considering the adoption rates of clean technologies in the context of heterogeneous discount rates across consumer categories and explores the potential of behavioural change and social innovation in climate action.

4. Evidence of accomplishment

This report.

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Preface

IAM COMPACT supports the assessment of global climate goals, progress, and feasibility space, and the design of the next round of Nationally Determined Contributions (NDCs) and policy planning beyond 2030 for major emitters and non-high-income countries. It uses a diverse ensemble of models, tools, and insights from social and political sciences and operations research, integrating bodies of knowledge to co-create the research process and enhance transparency, robustness, and policy relevance. It explores the role of structural changes in major emitting sectors and of political, behaviour, and social aspects in mitigation, quantifies factors promoting or hindering climate neutrality, and accounts for extreme scenarios, to deliver a range of global and national pathways that are environmentally effective, viable, feasible, and desirable. In doing so, it fully accounts for COVID-19 impacts and recovery strategies and aligns climate action with broader sustainability goals, while developing technical capacity and promoting ownership in non-high-income countries.

NTUA – National Technical University of Athens	EL
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Executive Summary

This deliverable covers two different tasks of WP5, aiming at expanding different aspects of Integrated Assessment Models (IAMs), as well as addressing related questions received from our Policy Response.

The first task (Task 5.4) aims to capture key disruptive innovations and technologies currently underrepresented in IAMs, and include the following chapters:

- To support discussions around the feasibility of the energy transition, Section 22 presents probabilistic projections of the diffusion of solar photovoltaics, wind power, biogases, heat pumps, and three types of low-carbon passenger cars in 39 European countries for 2023-2050 and compares the projected capacities against the quantities required for the energy transition. We create these projections using 72 different variants of diffusion models that we test using hindcasting (2012-2022) and weigh according to their performance. We find that the projected diffusion of all these technologies will most likely lead to an uneven distribution of capacities across Europe. Most countries are likely to reach numbers of battery-electric vehicles required for the energy transition with high uncertainty, but unlikely to reach the required level of onshore and offshore wind power and biogases with high confidence. Probabilities and uncertainties of reaching required numbers of solar photovoltaics and heat pumps vary the most between countries.
- Focusing on CDR, Section 33 examines how maximal effort across all sectors to reduce gross, in addition to net, emissions might contribute to a reduced role of CDR in deep mitigation.
- Both Sections 4 and 5 are driven by our PRM and explore the impact of financing risks at the firm, technology, or regional level. Section 44 examines exploratory future pathways of the cost of capital for renewable generation, fossil fuel, and green hydrogen technologies in different regions, to explore how their variation could affect decarbonisation pathways. We apply an empirical dataset of estimated cost of capital differentiated by technology and country in two global IAMs and one electricity-system model and explore stakeholder-driven pathways of de-risking clean energy technologies and risking fossil fuels. Section 5 links a processed-based IAM to a climate financial risk (CFR) model across a wide range of energy supply technologies and climate scenarios. It aims to explore the impacts of climate scenarios on adjustment in firms' credit risk and financial valuation and highlights the critical role of the financial sector in influencing the pace of the transition to net zero emissions.

The second task (Task 5.5) explores bahavioural aspects related to mitigation, and their role in post-2030 climate action. It starts with a qualitative mapping of such dimensions already captured in models and, drawing from inputs of the policy dialogue, co-develops joint qualitative narratives of behavioural change and societal innovation to quantify them as drivers of mitigation (Section 66). Adding to Task 5.4, multi-modelled scenarios with complementary storylines will describe the potential of these aspects in climate action, including conflicting approaches to energy transition.

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1 Introduction

This IAM COMPACT Deliverable, D5.6 - Behaviour, social and disruptive innovation, presents the project's mid-term results related to countries' uptake of key disruptive innovations in the form of differentiated interest rates, deviations from cost-optimisation rationales, enhanced technological and behavioural changes, and the inclusion of investors' expectations and climate risk assessment on mitigation scenarios.

The IPCC AR6 reported large investment gaps between the recent average investment levels (2017–2020) and cost-effective investment needs over the decade 2020–2030 to ensure alignment with Paris-compatible pathways. Pauchauri et al. showed that inter-regional financial flows will increase to meet fair share regional contributions in 1.5ºC (Pachauri et al., 2022).

First, we focus on granular energy technologies, such as solar photovoltaics (PV), wind power, heat pumps or electric vehicles, as they are foreseen to play a key role for the energy transition in Europe and elsewhere (Victoria et al., 2022). Due to comparatively small, modular capacities, lower risk, and investment barriers, these technologies can diffuse faster than centralised technologies and can thereby accelerate the energy transition. In Section 2 we investigate how granular energy technologies can be expected to grow in European countries until 2050 and what the associated probabilities and uncertainties are, especially if we compare the expected growth against the levels that are required for the energy transition.

We then move onto the required capacity of Carbon Dioxide Removal (Section 3), as achieving the 2˚C and especially the 1.5˚C long-term temperature goals will be infeasible without CDR either as an enhanced land sink (e.g., reforestation) and/or dedicated technologies (e.g., direct air capture or Biomass with CCS) (IPCC, 2022), and explore how enhanced mitigation efforts can miminise CDR reliance and thus increase the likelihood of reaching ambitious mitigation targets, given the high-costs of CDR technologies and their limited scale.

As underinvestment is partly caused by the large disparities in financing conditions and higher-risk profiles of developing countries (Ameli et al. 2021), in Section 4 we apply an empirical dataset of estimated cost of capital differentiated by technology and country in two global IAMs and one electricity-system model and explore stakeholder-driven pathways of de-risking clean energy technologies and risking fossil fuels.

Investors' expectations about the impact of climate risks, and of climate policies on economic activities are likely to play a key role in the reallocation of capital into the low-carbon economy (Kreibiehl et al., 2022). Thus, by integrating climate considerations into their financial risk assessment, investors can influence firms' investment decisions and foster the structural change in the economy that is needed to achieve ambitious climate mitigation goals. In Section 5, we define different narratives reflecting the interplay of investors' expectations and climate policy credibility within the transition process and map the revision in interest rates as a result of investors' expectations from the narratives into a wider set of scenarios with various carbon budgets.

Finally, Section 6 uses inputs from the policy dialogue and aims to address research questions generated within the PRM, namely "What are the economic impacts (rather than the cost or effectiveness of policy implementation) of a given behavioural change?" and "How do heterogeneous discount rates across consumer categories affect the adoption rates of clean technologies?", by investigating the economic implications of considering the adoption rates of clean technologies in the context of heterogeneous discount rates across consumer categories. It also includes a qualitative mapping exercise to understand what relevant dimensions are already considered in models, as part of Task 5.5.

Despite the heterogeneity of its contents, this deliverable and the corresponding project tasks (Task 5.4 and Task 5.5) were explicitly designed to feature both Grant Agreement-prescribed work (Sections 2 and 7) and research conducted in response to the Listening mechanism of the project (Sections 2, 4, 5 and 6)—much like several other tasks and deliverables in IAM COMPACT.

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2 Probabilities of reaching required capacities of granular energy technologies in European countries

Authors: *Nik Zielonka, Evelina Trutnevyte [University of Geneva]*

This Section will be submitted to a peer-reviewed journal.

2.1 Introduction

Granular energy technologies, which are at a more individual rather than institutional level (Wilson et al., 2020), such as solar photovoltaics (PV), wind power, heat pumps or electric vehicles, are expected to play a key role for the energy transition in Europe and elsewhere (International Energy Agency, 2022; Shivakumar et al., 2019; Victoria et al., 2022). Due to comparatively small, modular capacities, lower risk and investment barriers, these technologies can diffuse faster than centralised technologies and can thereby accelerate the energy transition (Vinichenko et al., 2023; Wilson et al., 2020). Consequently, the diffusion is more dynamic, complex, and dependent on diverse non-technical factors that vary across countries (International Energy Agency, 2022; Shivakumar et al., 2019), resulting in higher variations that make the growth of these technologies particularly hard to project. Uncertainties increase even further if the technologies are at an early phase of diffusion and the availability of historical time series data is limited (Debecker & Modis, 1994; Zielonka et al., 2023), which applies to granular energy technologies in Europe (Eurostat, 2023a, 2023e).

Projections of future diffusion of granular energy technologies are key for policymaking and infrastructure planning (Shivakumar et al., 2019; Victoria et al., 2022). Currently, projections oftentimes describe optimal pathways that energy system models determine for specific techno-economic, environmental, and policy conditions (International Energy Agency, 2022; U.S. Energy Information Administration, 2023; Victoria et al., 2022). Although modelers aim to create projections that are as realistic as possible from today's point of view, they often fail to describe the actual future state of an energy system (Gilbert & Sovacool, 2016; Trutnevyte, 2016). Recent research hence increasingly explores ways to conceptualise and quantify real-world feasibility of future projections for energy transitions (Brutschin et al., 2021; Jewell & Cherp, 2023; Wang et al., 2022). One way to model feasible projections is to adopt probabilistic methods by empirically learning from historical data (Trutnevyte et al., 2022; Way et al., 2022; Zielonka et al., 2023). Such probabilistic projections do not describe discrete future scenarios anymore, but rather a range of possible future outcomes and thereby combine predictive thinking (forecasting) with in-depth uncertainty quantification (Kaack et al., 2017; Morgan & Keith, 2008; Trutnevyte et al., 2022). In addition to informing about probabilities and uncertainties that help policy discussions and decision-making (Stirling, 2010; Shlyakhter et al., 1994; Raiffa, Howard, 1968), probabilistic projections can also often provide projections with higher real-world accuracy than deterministic methods (Zielonka et al., 2023). Studies make first efforts in creating probabilistic projections for granular energy technologies in European countries (Odenweller et al., 2022; Trutnevyte et al., 2022). However, there is no study that comprehensively creates and compares probabilistic projections over a range of granular energy technologies across Europe and against required quantities for the energy transition to inform policymaking.

While there is a wide range of methods to create probabilistic projections, their use for modeling energy technology diffusion is still limited. For instance, Bayesian, regression, or system dynamics models rely on the availability of vast datasets that help to predict a quantity using conditional probabilities (Guidolin & Mortarino, 2010; Hoffreumon, 2022; Jeon & Shin, 2014). Autoregressive models and neural networks rely on the availability of long time series data with repeating patterns to learn from (Alderete Peralta et al., 2022; Kumar & Saravanan, 2017). The use of empirical prediction intervals also requires sufficiently long time series data to quantify hindcasting

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errors between the projections and historically observed values (Kaack et al., 2017; Lee & Scholtes, 2014; Wachtmeister et al., 2018). Such error-based methods also mostly create symmetric intervals and only show uncertainty bounds without probabilities. Alternatively, many projections use random sampling, like Monte Carlo simulations, to generate a range of possible projections (Kroese et al., 2014; Odenweller et al., 2022). Assigning ranges and probability distributions to parameters from random sampling is a challenging or even impossible task due to limited knowledge (Morgan, 2014), whereas the generated forward-looking projections are rarely evaluated based on their accuracy and uncertainty performance. Yet, evaluation is key to close the gap between the modeled projections and the feasible real-world transitions (Trutnevyte, 2016; Wen et al., 2023) and it is particularly crucial when uncertainty intervals are narrow or the projection model is prone to overfitting, e.g., S-curve models (Höök et al., 2011; Zielonka et al., 2023). Thus, Zielonka et al. (2023) have recently combined sampling with hindcasting-based model evaluation to create probabilistic projections of granular energy technologies at a national and sub-national scale. Yet, this method relies on large numbers of historical time series.

In this work, we investigate how granular energy technologies can be expected to grow in European countries until 2050 and what the associated probabilities and uncertainties are, especially if we compare the expected growth against the levels that are required for the clean energy transition towards net-zero greenhouse gas emissions by 2050. We investigate eight granular energy technologies at national level in 39 European countries, including four electricity generation technologies (solar PV, onshore and offshore wind power, and biogases), one heating technology (heat pumps), and three types of passenger cars (Battery Electric Vehicles (BEVs), hybrid vehicles, and fuel cell electric vehicles (FCEVs)). Provided that historical time series data is available, for each technology and country we create and evaluate up to 72 different probabilistic projections from six different S-curve models, three variants of Near-Optimal Differential Evolution (NODE), and four numbers of historical data years, using an adjusted version of the Zielonka et al. (2023) approach, called PROWIDE (see *Experimental procedures*). Using hindcasting-based evaluation of the projections between the years 2012 and 2022, we weight and combine these 72 projections for each technology and country to create probabilistic projections until 2050. We then compare our probabilistic projections against the installed capacities of these technologies required for the European energy transition at national level according to the European Green Deal policy package "Fit for 55" (FF55) (European Commission, 2021b) and the Ten Year Network Development Plan (ENTSOG & ENTSO-E, 2022) (see *Experimental procedures*). We show that the numbers of electric vehicles will most likely increase sufficiently in most European countries, although uncertainties are high. While solar PV and heat pumps show a notable growth in most countries, the probability of reaching the respective levels required for the transition towards net-zero varies between countries. Future capacities of biogas and wind power will likely remain lower than the estimated transition needs with high certainty.

2.2 Results

Diffusion of technologies will most likely be uneven across Europe

Our probabilistic projections reveal a notable variation among the European countries in terms of which granular energy technologies are more likely to grow and at what rate (Figure 2-1). For example, in Germany, the only country with projections for all eight investigated technologies, solar PV will most likely double in capacity by 2050, heat pumps will triple (see median in Figure 2-1). In contrast, the capacities of biogases and offshore wind power will remain relatively low given the current circumstances of diffusion. Unless further promoted or restricted, the numbers of BEVs can be expected to grow similarly than hybrid vehicles, whereas the numbers of FCEVs will remain comparatively low over the next decades. This relation between electric vehicles can be observed for almost all European countries. The trend in solar PV capacities is also representative for most European countries, except for the United Kingdom (UK), for instance. Here, however, offshore wind power will

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likely grow faster than in all other countries. The probabilistic projections for biogases and onshore wind power show a diffuse picture where, for example, biogases increase for Cyprus, Greece, and Turkey, and onshore wind power for Belgium, Finland, Ireland, and Netherlands, while the capacities remain close to current levels, for example, for Luxembourg, Portugal, and Spain. For heat pumps, the projections estimate a notable increase in capacity for most countries until 2050, except for Norway and Sweden.

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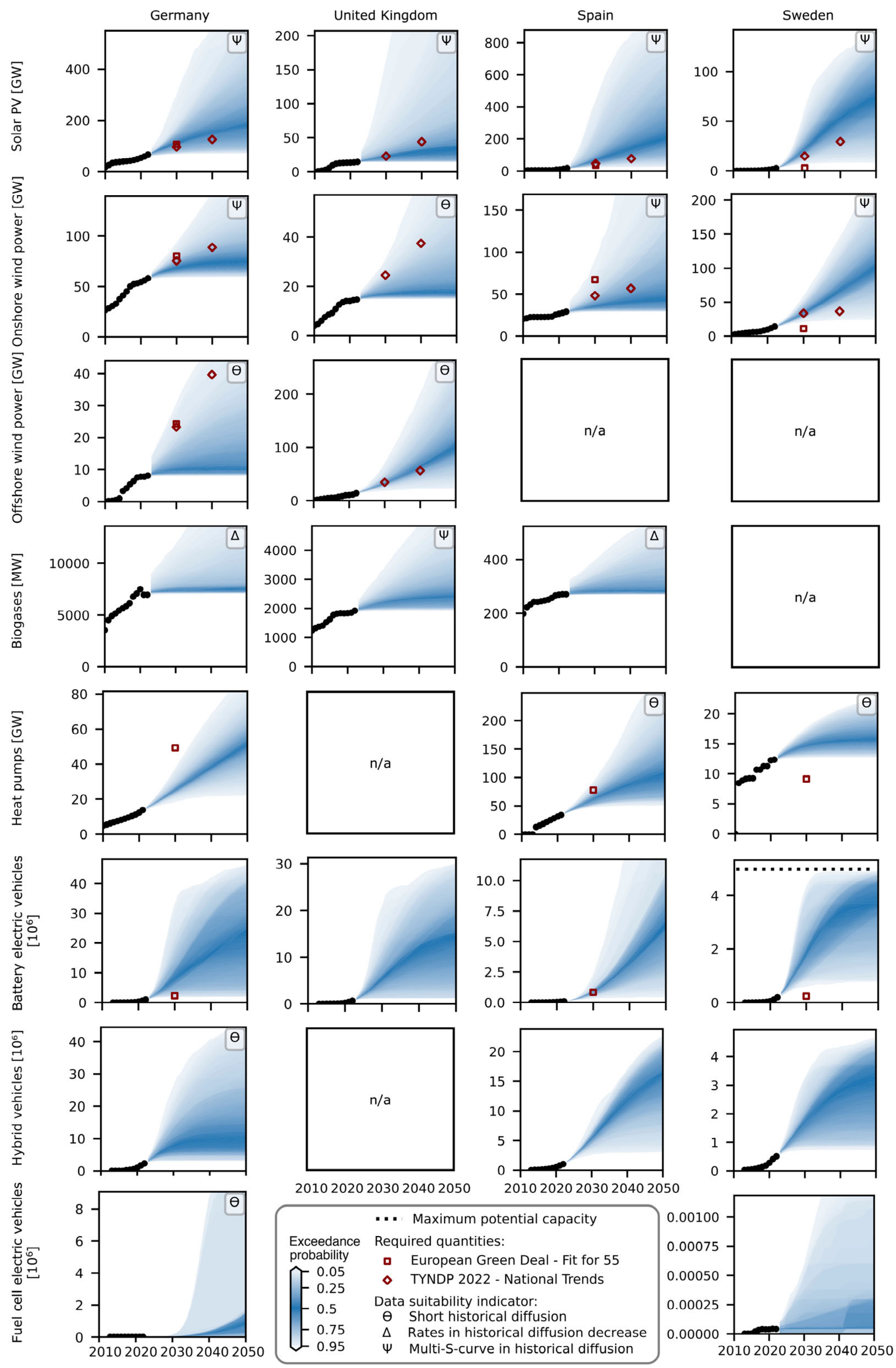

Germany
United Kingdom
Spain
Sweden
Solar PV [GW]
Onshore wind power [GW]
Offshore wind power [GW]
Biogases [MW]
Heat pumps [GW]
Battery electric vehicles [10^6]
Hybrid vehicles [10^6]
Fuel cell electric vehicles [10^6]
n/a
2010 2020 2030 2040 2050
Maximum potential capacity
Exceedance probability
0.05
0.25
0.5
0.75
0.95
Required quantities:
European Green Deal - Fit for 55
TYNDP 2022 - National Trends
Data suitability indicator:
Θ Short historical diffusion
Δ Rates in historical diffusion decrease
Ψ Multi-S-curve in historical diffusion

Figure 2-1: Probabilistic projections for all eight investigated technologies exemplarily in Germany, the United Kingdom, Spain, and Sweden, including training data until 2022, respectively 2021 for heat pumps. The probabilistic density intervals show the probability that a quantity will be reached or exceeded. The color gradient describes the quantiles of the projected capacities: the darker the color, the closer the capacity is to the median. The black dots show historical capacities and the black dotted lines, if visible, the maximum potential capacity that a country can install. The red squares and diamonds show required quantities for the energy transition, estimated in scenarios of European Commission (2021b) and Ten Year Network Development Plan (ENTSOG & ENTSO-E, 2022) that are consistent with the European Green Deal policy package "Fit for 55", national energy and climate policies (see *Experimental procedures*). The Greek letters Θ, Δ, and Ψ indicate the suitability of the historical time series data for projecting probabilistic growth (see *Experimental procedures*).

The projected diffusion of granular energy technologies will most likely lead to a very uneven distribution of capacities in 2050 in Europe (Figure 2-2). Germany, the country with the largest number of inhabitants, will most likely be among the countries with the largest installed capacities of solar PV, wind power, and biogases and the largest number of electric vehicles by 2050. In the UK, the comparatively small projected growth in solar PV but high growth in offshore wind power can be expected in absolute values of installed capacities. This relation is compatible with the capacity factors in the UK which are comparatively low for solar PV and high for wind power (Kies et al., 2021). The offshore wind power capacities also remain one of the highest in the UK when scaled by capita, while the distribution of onshore wind power and solar PV across Europe becomes evener. In absolute capacities, the distribution of onshore wind power and solar PV is diffuse across European countries. Besides Germany, highest capacities are projected for solar PV in France, Netherlands, Poland, and Spain, and for onshore wind power in the Nordic countries, France, Spain, and Turkey. Sweden stands out with high shares per capita for both solar PV, onshore wind power, BEVs and hybrid vehicles. Both in relative and absolute terms, the highest capacities of heat pumps are projected in France, followed by Portugal and Spain, and biogases in Germany, Turkey, and the UK. All other countries will likely have low capacities of both technologies. Like with Germany, the highest projected numbers of electric vehicles are where most people live, e.g., in the UK (BEVs), Spain, France, and Italy (hybrid). Besides Sweden, the numbers per capita are highest for Norway and Switzerland (BEVs), and Belgium, Luxembourg, Italy, Spain, and Switzerland (hybrid).

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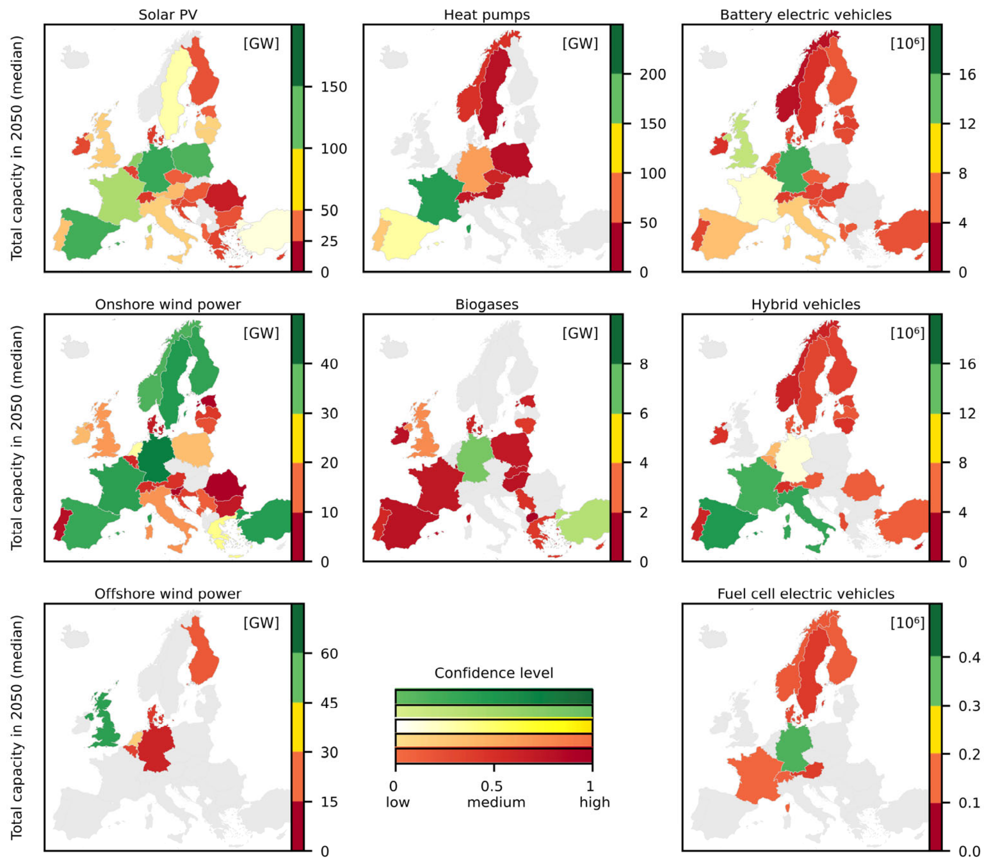

Figure 2-2. Distribution of capacities of all eight investigated technologies across Europe in 2050. The colors group countries according to the total capacity estimated by the median in the probabilistic projections. The color gradient indicates the confidence level: the darker the color, the higher the confidence. The confidence level describes the width of a probabilistic projection and is defined as the share of quantiles that covers a ±25% deviation from the projected median quantity (see *Experimental procedures*). The lower the share, the broader is the probabilistic projection. Countries in grey have no projection.

While the magnitude by which a technology is projected to grow varies notably between technologies and countries, our probabilistic projections most often show similar levels of confidence on the projected capacities for the same technology (Figure 2-2). Consequently, high confidence means that the inner probabilistic projection intervals are sharp, whereas the overall range of uncertainty can remain high, e.g., see the example of offshore wind power in the UK (Figure 2-1 and Figure 2-2). For most countries, the confidence is comparatively high in the projections of biogases and onshore wind power and medium in the projections of solar PV, offshore wind power, and heat pumps (Figure 2-2). Compared to the other technologies, the historical time series of electric vehicles are short and hence lead to higher uncertainties and consistently lower confidence. The historical time series also reflect the way that the confidence reduces the further away the projected year is from today. For instance, the historical diffusion of heat pumps is relatively steady in most countries and the probabilistic projections hence form a relatively regular cone (Figure 2-1). In contrast, if the historical diffusion is unsteady, the width of the probabilistic density intervals evolves rapidly and into irregular shapes, e.g., biogases and wind power.

Most countries are likely to reach BEV numbers required for the transition, but not wind power and biogases

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When comparing the probabilistic projections against capacities that European countries need for the energy transition for 2030 and 2040 according to FF55 (European Commission, 2021b) and TYNDP (ENTSOG & ENTSO-E, 2022) (see *Experimental procedures*), we find that most countries are unlikely to reach the required quantities of biogases and wind power, while most are likely to reach the ones for BEVs (Figure 2-4). For solar PV and heat pumps, the probabilities vary the most among countries. For solar PV, countries in north-eastern Europe, Netherlands, Portugal, and Spain are likely to reach the required capacities, while countries from southern Europe and Ireland are likely to miss them. For heat pumps, Austria, Czech Republic, Portugal, and Sweden are likely to reach the required capacities, while Germany, Poland, and Spain are likely to miss them. In most cases, our findings are consistent with the results from both considered transition scenarios of FF55 and TYNDP. However, for some countries where the estimated capacities required for the transition diverge notably, the probabilities of reaching the required capacities can diverge too. For example, FF55 provides a comparatively low value for offshore wind power in Denmark that our projected diffusion will very likely reach by 2030, whereas Denmark is unlikely to reach the high value from TYNDP. Consequently, drawing universal conclusions on the feasibility of the energy transition is limited in such cases. At the same time, the required quantities for some countries are comparatively low and thus require only small growth in capacities. For heat pumps in Sweden, for example, the capacity required for the transition by FF55 is even lower than the current capacity (Figure 2-1), which may result from erroneous assumptions for that country.

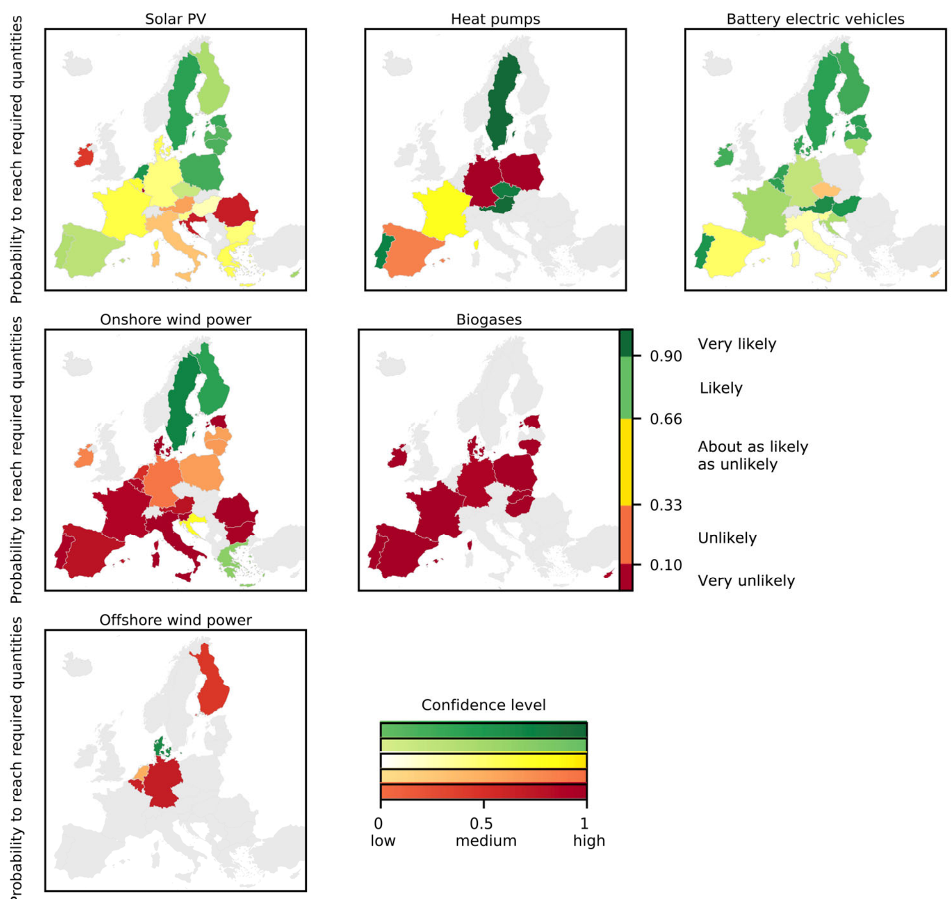

Figure 2-3. Map showing the exceedance probability of countries to reach required quantities in 2030. The required quantities are estimated by European Commission (2021b) in scenarios that are consistent with the European Green Deal policy package "Fit for 55" (see *Experimental procedures*). The colors group all countries according to level of probability and translate into likelihoods in line with IPCC (Frame et al., 2010). The color gradient indicates the confidence level: the darker the color, the higher the confidence. The confidence level describes the width of a probabilistic projection and is defined as the share of quantiles that covers a ±25% deviation from the projected median quantity (see *Experimental procedures*). The lower the share, the broader is the probabilistic projection. Countries in grey have either no projection or values of required quantities.

The confidence for reaching or missing the required quantities for the energy transition is transferable from the confidence on the projected quantities for each technology and country (Figure 2-2 and Figure 2-3). Consistently, confidence is generally high for biogases and wind power, and low for BEVs. Also, the confidence levels related to reaching the necessary quantities of heat pumps are rather high, while confidence levels related to solar PV vary the most between countries. Overall, the comparison against required quantities shows that if the probability of reaching a required quantity is either very high or very low, the confidence of reaching or missing a required quantity is high. With median levels of probability, the confidence is more diffuse.

Choice of best-performing variants of diffusion models varies across technologies and countries

From the methodological point of view, we find that the 72 variants of diffusion models that we use for our projections (a combination of six S-curves, three NODE variants with and without historical rates, and four numbers of historical data years; see *Experimental procedures*) show hindcasting performance in projecting the future that varies notably across technologies and countries. At the same time, there is no single best model variant that scores consistently better than others (Figure 2-4). However, we observe among the S-curves (Bass, Bertalanffy, Gompertz, logistic, Richards-4p, and Richards-5p), variants using the logistic model perform worst on average, while there is no clear over- or underperforming NODE variant or number of historical data years for creating the projections. Overall, the projections for heat pumps receive lowest scores in comparison to the other technologies and are therefore comparatively reliable. In contrast, the projections for solar PV, wind offshore, and FCEVs often receive comparatively high penalties and therefore tend to be less reliable.

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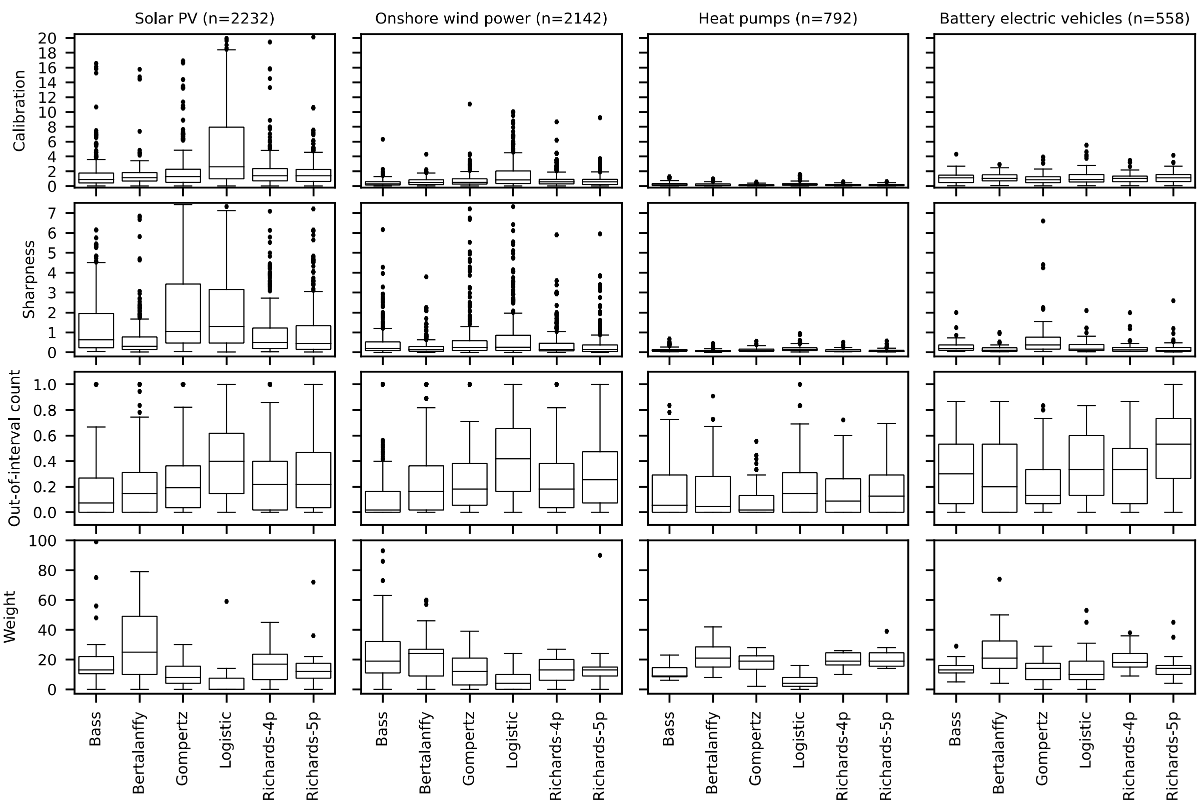

Figure 2-4. Box plots showing the distribution of calibration and sharpness penalties, out-of-interval count, and weights across all countries exemplarily for solar PV, onshore wind power, heat pumps, and battery electric vehicles (BEVs), grouped by S-curve models. The penalties of calibration, sharpness, and out-of-interval count are means over all hindcasting years and method variants. The resulting weights based on the inverse of the squared weighted sum of the three scores are sums over all method variants. The sample size n is the number of countries with projections for the technology times the number of method variants (maximum 72).

We measure the performance in projecting the future with three scores, which are calibration and sharpness penalties of the weighted interval score that approximates the continuous ranked probability score (Bracher et al., 2021), and out-of-interval count (OC). Based on the sum of the three scores, we weight all 72 variants (see *Experimental procedures*). We see that all 72 variants get comparable calibration penalties across most technologies and countries and thereby project future technology diffusion with comparable accuracy. Only the logistic model stands out in solar PV and offshore wind power, where a larger share of projections is less accurate compared to the other models. All variants also mostly share comparable sharpness in the probabilistic density intervals. However, Bass, Gompertz, and logistic models have a larger share of sharpness penalties in projections of solar PV, which is also the case for the Bertalanffy and Gompertz models for FCEVs and there is a tendency that the two NODE variants that use historical rates (NODE-RR and NODE-RR) have higher sharpness penalties. Having low sharpness penalties translates into a risk that the probabilistic projections are so sharp that future capacities can lay outside the probabilistic density intervals as we see in comparatively high OCs for Bertalanffy and Richards-5p models. However, the logistic model has high OCs, although its sharpness is comparatively low. NODE-RR and NODE-DR have higher sharpness penalties and consequently lower out-of-interval count.

2.3 Discussion

Our probabilistic projections of granular energy technologies in Europe until 2050 reveal different types of growth

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that can roughly be divided into three groups: (1) high growth with low levels of confidence, (2) low growth with comparatively medium to high confidence, and (3) medium to high growth with comparatively medium confidence. Although it varies country by country in which group the projections of each technology fall, there is a tendency for BEVs and hybrid vehicles to fall into the first group, biogases and wind power falling into the second, and solar PV and heat pumps falling into the last. Reasons for this tendency are manifold. For example, diffusion of biogases and wind power has recently slowed down in many countries while the diffusion of electric vehicles gathered speed. Nevertheless, the tendency from our findings still indicates that more granular technologies like electric vehicles and solar PV tend to diffuse faster with lower confidence than less granular technologies, as suggested in literature (Vinichenko et al., 2023; Wilson et al., 2020).

The projected growth in granular energy technologies will not only lead to an uneven spatial distribution of capacities across Europe but also to uneven extent and confidence with which countries will likely reach or miss the levels required for the energy transition. Only the diffusion of BEVs is an exception as all countries are likely to reach the levels required, except for Cyprus and Czech Republic that are likely to miss them and for Italy, Slovenia, and Spain where the outcome is about as likely as unlikely. The new regulation of the European Union that allows new registrations only for emission-free passenger cars from 2035 on (Regulation (EU) 2023/851 of the European Parliament and of the Council of 19 April 2023, 2023) would further strengthen this trajectory as our projections do not consider new policies. On the contrary, almost all countries that need higher capacities of biogases and wind power for the transition must intensify their efforts towards higher diffusion. For solar PV, the southern European countries, except for Portugal, Spain, and Turkey, are particularly the ones that should increase their efforts not only since they are likely to miss the quantities required but also as they have higher capacity factors (Kies et al., 2021) and can therefore profit from higher PV output and thereby cheaper PV electricity than northern European countries. The conclusions for heat pumps are less evident since the quantities required for the transition are less clearly defined, if at all, and can lay close or even below current values.

From the methodological point of view, there are three main implications for decision-makers and modelers. First, our approach for now does not allow analysing how contextual factors like policy decisions, technological developments or society drive the diffusion. At the same time, recent changes in contextual factors may show no direct effect on the projected diffusion due to lag (Polzin et al., 2015) and if there are no comparable changes in the historical time series data. Accordingly, reasons remain undisclosed why specific countries are likely to reach the technology levels required for the transition while others are not and how contextual changes may disrupt the projected diffusion. The investigation of decisions and contextual factors in hindsight and in forward-looking sense (Horschig & Thrän, 2017; Liu & Feng, 2023; Polzin et al., 2015) should ideally be coupled with probabilistic projections. Second, our projections neglect energy system effects in which the diffusion of one technology accelerates or inhibits the diffusion of another one (e.g., the diffusion of heat pumps or electric vehicles would lead to higher uptake of solar PV and wind to generate the required electricity), which is an important subject of future work. Third, probabilistic projections should always use and test multiple S-curve models as the hindcasting performance in terms of accuracy and uncertainty varies highly from case to case, as also shown in previous work (Zielonka et al., 2023). When computational or other constraints limit the number of S-curve models that can be used, modelers should provide compelling reasons for their selection. In contrast to common practice (Geroski, 2000; Höök et al., 2011; Young, 1993), the logistic model should be the first model to drop. However, modelers can consider limiting computational costs in many cases by selecting one NODE variant or reducing the number of historical years they use for curve fitting. Reducing the number of historical years has the additional advantage of providing diffusion models more flexibility in accounting for recent contextual changes and projecting more diverse levels of diffusion.

In terms of policy implications, our probabilistic projections emphasise that decision-makers in European countries must consider additional policies to speed up the diffusion of the granular energy technologies to reach the levels required for the energy transition, especially for wind power, biogases, and in some countries also for solar PV and heat pumps. Our projections provide country-specific information on probabilities and confidence of future technology growth and thereby can direct attention to the most problematic issues and hence support policy debates and decision-making. Our findings are generally in line with some earlier projections and examinations in literature (International Energy Agency, 2024; International Renewable Energy Agency, 2022), although we provide more detailed, quantitative evidence. As next step, the decision-makers could investigate alternative technology mixes that advance the energy transition if supported by studies that combine our probabilistic technology diffusion projections with different scenarios or energy system models of the whole energy system. Doing so would help to explore different energy futures while having information on which futures are more feasible than others and what the associated uncertainties are.

2.4 Experimental procedures

2.4.1 Methods

Creation and evaluation of probabilistic projections – PROWIDE method

We create our probabilistic projections for each technology and country by applying an extended version of the four-step method of Zielonka et al. (2023) that we now call PROWIDE (PRObabilistic projections using Weighted models and Iterative hindcasting for empirically based DEnsity intervals). The original method (Zielonka et al., 2023) has been developed to model probabilistic projections at a subnational level and hence requires data from many regions to create meaningful projections. Tests of the method showed that it can project national-level diffusion with comparable levels of accuracy, but it needs alternative ways to provide probabilities (Zielonka et al., 2023). Consequently, we apply PROWIDE to create probabilistic projections based solely on historical time series data of the considered country.

After data preparation, PROWIDE consists of two main parts in which it follows four major steps (Figure 2-5). In the first part, represented by steps 1 and 2, we first exclude quasi-static and highly fluctuating historical time series as they do not record a diffusion that we can project and test empirically. We include time series if at least three most recent data points are non-zero, not more than five (three for electric vehicles) consecutive capacities are the same, and there is no drop in the time series from one year to another by more than 30%. Although we choose these inclusion criteria deliberately, time series might still pass through for which projections are meaningless and could be excluded visually, e.g., solar PV in Bosnia and Herzegovina. In step 1, we create probabilistic projections for each technology and country using up to 72 method variants. Each method variant creates 450 deterministic projections and is a combination of one S-curve model (Bass, Bertalanffy, Gompertz, logistic, Richards-4p, and Richards-5p as in Zielonka et al. (2023), one curve fitting variant that uses NODE to create projections with and without the consideration of historical diffusion rates (NODE, NODE-RR, NODE-DR), and a number of historical data years (5 years, 10 years, 15 years, and full history). In step 2, we calculate the quantiles q of all 450 deterministic projections to describe probabilistic projections of each method variant. We limit the number of deterministic projections to 450 to save computational costs and since we find that the resulting projections are comparable to the ones with 200 parametrization that we create in prior tests of our methods.

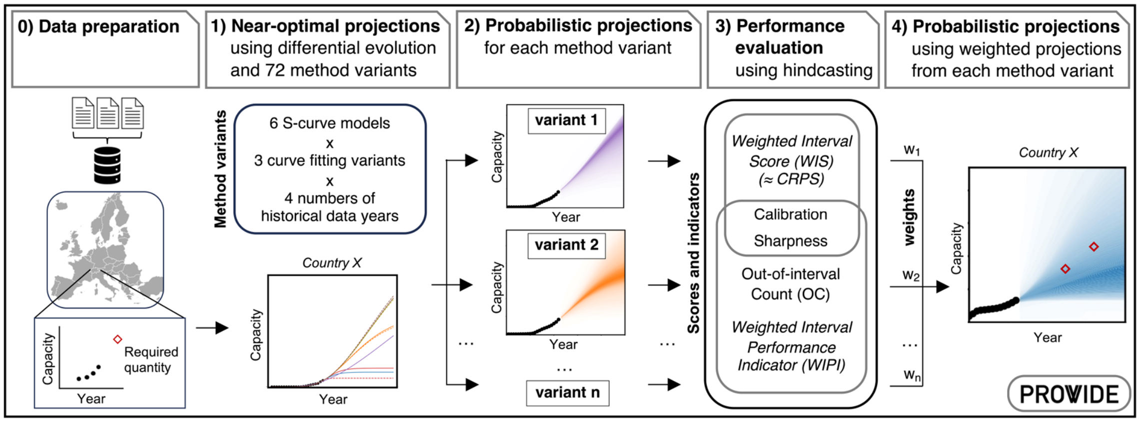

Figure 2-5: Flow chart of the PROWIDE (PRObabilistic projections using Weighted models and Iterative hindcasting for empirically based DEnsity intervals) method, extended from Zielonka et al. (2023), to create probabilistic projections of granular energy technology diffusion at national level. Each hindcasting iteration repeats steps 1 and 2 using one share of the historical time series data for training and the remaining share of up to 10 years for evaluation. Calibration and sharpness penalties are part of the WIS that approximates the Continuous Ranked Probability Score (CRPS) (Bracher et al., 2021). The WIPI sums calibration, sharpness, and OC.

For each of the 72 method variants, we fit one S-curve model to the historical time series data of a technology in a country using differential evolution (Phillips, n.d.; Storn & Price, 1997), which randomly explores different parametrizations of the S-curve. S-curves describe the three historically observed (Geroski, 2000; Odenweller et al., 2022; Wilson et al., 2013) technology diffusion of three phases (formation, exponential and stable growth, and saturation) using different parameters specific to each S-curve and including various contextual factors (Höök et al., 2011; Lekvall & Wahlbin, 1973). We repeat the curve fitting 225 times and, in each repetition, randomly select two parametrizations that the differential evolution explores until it finds an optimum parametrization for the S-curve that fits the data best. As doing so generates a collection of 450 projections around the optimum, we call this curve fitting method near-optimal differential evolution (NODE). As curve fitting is prone to overfitting (Höök et al., 2011; Zielonka et al., 2023), we use two additional variants of NODE that increase the width of the probabilistic projections in years of the near future. We do so by adding a data point to the end of the time series which is assumed to be the capacity of that year, before we fit curves again. In the variant with Recent Rates (NODE-RR), we multiply each annual diffusion rate of the five most recent years of the historical time series rate with the capacity of the latest year to create five assumed capacities and eventually five different time series. In the variant with historical Diffusion of Rates (NODE-DR), we create capacities based on the last rate, and ±1 and ±2 standard deviations of all historical rates, centered around the last rate. In addition to fitting the S-curves to the full historical time series, we limit the use of the historical capacities to ranges of the most recent 5, 10, and 15 years. We do so since historical diffusion can show patterns of multiple S-curves that uniform S-curves may not represent properly and bi-S-curves are computationally expensive to fit and have a high risk to overfit or replicate the uniform curves (Zielonka et al., 2023). As the historical diffusion of electric vehicles is comparatively short, we do not limit the number of historical data years for such technologies.

In the second part, represented by steps 3 and 4, we evaluate the probabilistic projections of all method variants separately for all technologies and countries using hindcasting. In each hindcasting iteration, we split the historical time series data into a training set with which we repeat steps 1 and 2, and an out-of-sample evaluation set which we use to evaluate the created probabilistic projections in terms of performance scores. After each iteration, we remove one more year from the evaluation set and add it to the training set. We do hindcasting for the last ten years for the power generation technologies and heat pumps, and for the last five years for the electric vehicles. In hindcasting, we evaluate the probabilistic projections based on the unitless Weighted Interval Performance

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Indicator (WIPI) that we eventually use to weigh the probabilistic projections of all method variants separately for all technologies and countries to create our final probabilistic projections in step 4. We define the unitless weights *w* for each method variant using an equation adapted from Sun et al. (2017) and Zielonka et al (2023):

$$w = 1/mean(WIPI^2) \quad (1)$$

Here, WIPI sums three performance scores, that we normalise from 0 to 1, using equal weights. The first two scores are calibration and sharpness penalties of the weighted interval score that approximates the continuous ranked probability score (Bracher et al., 2021). While calibration evaluates the accuracy of a probabilistic projection to a real data point, sharpness reflects the width of probabilistic density intervals. The third score is the out-of-interval count that counts how many data points lay outside the probabilistic density intervals of a projection (Lison, Adrian, 2020), that we bound between quantiles 0.01-0.99.

The quantiles that define the probabilistic density intervals translate into probabilities and confidence of a probabilistic projection. We define the exceedance probability p_{ex} that describes the probability that a future quantity will be reached or exceeded as the opposite of a quantile q:

$$p_{ex} = 1 - q. \quad (2)$$

The median (i.e., 50% quantile or 50% probability of exceedance) shows the center of a probabilistic projection at which it is equally likely that the real quantity will lay above or below. We define the level of confidence on a projected quantity as the width of the probabilistic density intervals that covers a ±25% deviation from the median of a projection and thereby reflects the sharpness of the probability projection. The confidence can vary between 0, where both the upper and the lower bound of the ±25% deviation lay between the same quantiles, and 1, where the width of the entire probabilistic projection is equal or smaller than the difference between the upper and the lower bound of the deviation. In line with IPCC (Frame et al., 2010), we show increasing confidence with increasing strength of shading when comparing probabilistic projections between countries, e.g., in Figure 2-2 and Figure 2-3.

2.4.2 Data

Historical time series

To create our probabilistic projections, we take historical time series data of cumulative installed capacities for each technology and country from Eurostat (2023a, 2023b, 2023e) and fill data gaps for power generation technologies with values from IRENA (2023), for battery electric vehicles in United Kingdom from SMMT (2023), and add heat pump capacities in Switzerland from Swiss Federal Office of Energy (2023). Heat pumps include aerothermal, geothermal, and hydrothermal technologies. Hybrid vehicles include plug-in and full hybrid vehicles with petrol or diesel. Altogether, the historical time series data ranges from 1990-2022 for the power generation technologies, 1990-2021 for heat pumps, and 2013-2022 for electric vehicles. To indicate the suitability of the historical time series data and thereby the probabilistic projections, we add one of the following labels to the projections:

- "Short historical diffusion" if hindcasting is not possible for all years due to the exclusion criteria in step 1. Consequently, projections are less reliable as empirical testing is comparatively short.
- "Rates in historical diffusion decrease" if the historical diffusion rates do not monotonically increase. Consequently, the diffusion models may interpret saturation and project no future growth.
- "Multi-S-curve in historical diffusion" if the historical diffusion rates increase after a previous decrease.

Consequently, the diffusion models may capture only the first growth phase and underestimate possible future growth unless the number of historical data years is reduced enough to skip the first growth phase.

Maximum potential capacities

For each technology and country, we limit the potential of maximum installable capacities not to be exceeded in S-curve fitting. For solar PV and wind, we use the upper quartile of potentials provided across literature (Dupré La Tour, 2023). For biogases, we assume that all national capacities can increase by a factor of 15 to give enough space to grow as the European Biogas Association (2023) estimates an increase in production of at least fivefold by 2050. For other power generation technologies that have a historical time series but no potential in some countries (e.g., Albania, Malta, and Turkey for solar PV and Montenegro, Serbia, and Turkey for onshore wind power), we add the average ratio between potential and currently installed capacity of all countries. For heat pumps, we assume that the share of heat pumps in space heating can increase to 100%. Accordingly, we approximate the resulting potentials by dividing the current capacities by the current share of heat in space heating given by Eurostat (2023c), IDEA (2022), and SEAI (2023) and assume that a future increase in the share is equivalent to an increase in heat pump capacity of the same magnitude. For Cyprus, Luxembourg, and Malta, we assume current shares of heat pumps at 1%. For electric vehicles, we set the limit to the current total number of passenger cars in each country.

Technology quantities required for the energy transition

To assess whether the current diffusion of the granular energy technologies is on track to reach future capacities required for the European energy transition, we compare projections against three values. The first value is the mean of three scenarios of the European Commission that are consistent with the European Green Deal policy package of reaching 55% reductions in greenhouse gas emissions in the European Union by 2030 ("Fit for 55") (European Commission, 2021b). While we directly use the estimated net installed capacities for solar PV and wind power, we derive the capacities for heat pumps and BEVs from the final energy consumption of ambient heat and the share of electricity in road transport, respectively. We assume that the change in ambient heat from 2020 to 2030 approximates the factor by which the heat pump capacity needs to change. For BEVs, we assume that the share of electricity in road transport approximates the share of BEVs over all road vehicles (Eurostat, 2023d) as the share of electric vehicles in non-passenger vehicles will remain comparatively negligible according to the report that provides the basis for the "Fit for 55" scenarios (European Commission, 2021a). The second and third values of quantities required are estimates for 2030 and 2040 from the TYNDP scenario "National Trends" (ENTSOG & ENTSO-E, 2022) that is consistent with national energy and climate policies and with long-term strategies in line with European targets.

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3 Minimising the use of carbon dioxide removal while still achieving net-zero emissions

Authors: *Jay Fuhrman [JGCRI], Glen P. Peters [CICERO], Haewon McJeon [JGCRI]*

This Section is a summary of a preprint currently in review: "Ambitious Efforts on Residual Emissions can Reduce CO_2 Removal and Lower Peak Temperatures in a Net-Zero Future" by Jay Fuhrman, Simone Speizer, Seth Monteith, Patrick O'Rourke, Glen P. Peters, Laura Aldrete, Frances Wang, Haewon McJeon

3.1 Introduction

Achieving the 2˚C and especially the 1.5˚C long-term temperature goals will be infeasible without Carbon Dioxide Removal (CDR) via an enhanced land sink (e.g., reforestation) and/or dedicated technologies (e.g., direct air capture).(IPCC, 2022b) CDR plays three key roles in mitigation pathways (Figure 3-1**Error! Reference source not found.**). First, CDR helps reduce emissions in the short term, but this effect is only small in relation to emission reductions. Second, around the point of net zero emissions (CO_2 or GHG), counterbalance ongoing residual 'hard-to-abate' emissions(G. Iyer et al., 2021). Third, after the point of net zero emissions, exceed the level of ongoing residual emissions to produce net negative emissions, thereby leading to a net removal of CO_2 from the atmosphere leading to temperature overshoot.(Prütz et al., 2023) In light of sustainability and feasibility concerns of large-scale CDR, several recent IAM studies have evaluated the role of reduced energy and material demand, electrification, agricultural improvements, and reduced non-CO_2 emissions in limiting the need for CDR.(Fuhrman et al., 2019; Gambhir et al., 2022; Grubler et al., 2018b; Smith et al., 2016; van Vuuren et al., 2018) However, as IAM modelling groups have expanded the portfolio of CDR options that they represent, the additional CDR capacity has often allowed for increased residual emissions and/or delays in net emissions reductions.(Fuhrman et al., 2020, 2021; Realmonte et al., 2019; Strefler et al., 2018)

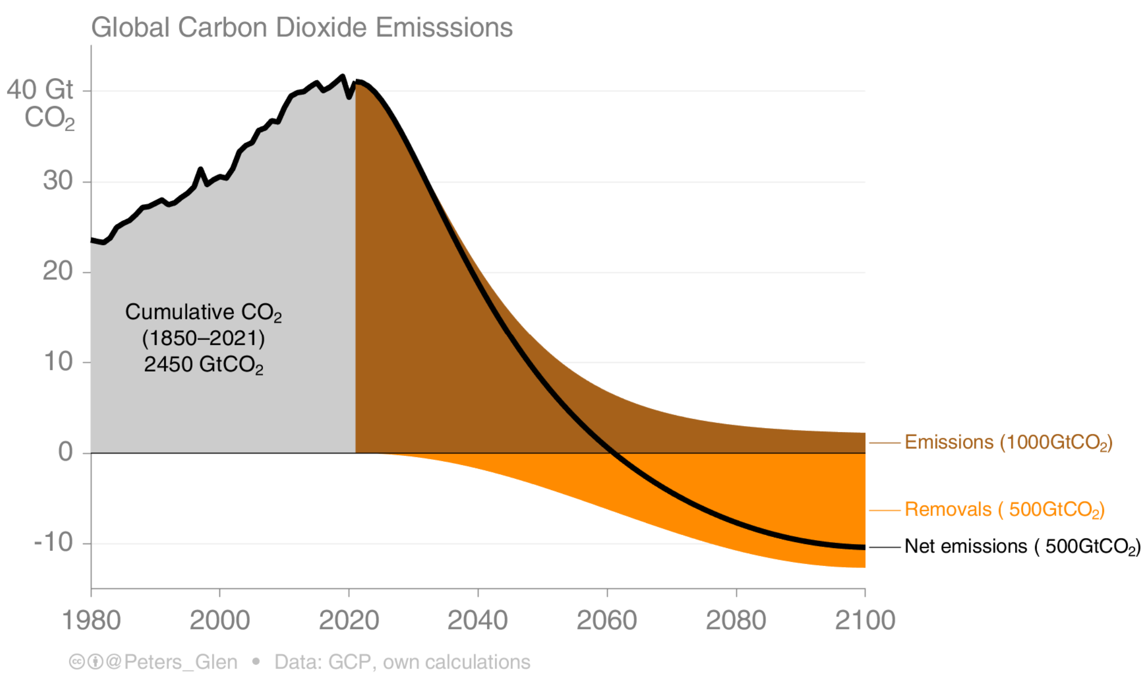

Figure 3-1: A stylised CO_2 emission pathway showing continued residual emissions (brown), CDR (orange), and net emissions (black line). CDR essentially has three roles: 1) help reduce emissions (today towards net zero), 2) counterbalance residual emissions (around net zero), 3) help produce net-negative emissions and temperature overshoot (after net zero).

As nations have strengthened their commitments to reduce emissions, international organizations and trade

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groups, including for the most difficult-to-abate sectors have announced plans to bring their industries in-line with these efforts.(Aspen Institute, 2021; International Air Transport Association, 2022; International Chamber of Shipping, 2021; International Civil Aviation Organization, 2022) There are numerous studies and modelling exercises on deep emissions reductions pathways for individual sectors (e.g., electricity, industry, transportation, agriculture and land-use) aiming to reduce their CO_2 emissions (Cao et al., 2021; Davis et al., 2018; IEA, 2020; Kyle & Kim, 2011; Roe et al., 2019). Efforts to reduce non-CO_2 emissions may come with disproportionate climate benefits but be extremely challenging to fully eliminate (Ou et al., 2021). To our knowledge, no IAM study to date has examined how maximal effort across all sectors to reduce gross, in addition to net emissions, might contribute to a reduced role of CDR in deep mitigation.

3.2 Method

We used the Global Change Analysis Model (GCAM), a technology-rich IAM with detailed treatment of climate and global energy, land, and water systems, to evaluate the extent to which maximal effort to reduce residual emissions from electricity, fuel supply, transportation, buildings, industry, and agriculture could minimise the requirement for CDR in reaching net-zero and eventually net-negative emissions (Calvin, Patel, Clarke, Asrar, Bond-Lamberty, Cui, et al., 2019a). To do this, we further extended the "sectoral strengthening" scenario used in our recent work on diverse CDR approaches (Fuhrman et al., 2023). That "orderly yet ambitious transition" scenario was first developed by (Gambhir et al., 2021) and included demand reductions through behavioral changes, higher energy and material efficiency, rapid electrification of end-uses, reductions in non-CO_2 GHGs, and restrictions on both bioenergy and geologic carbon storage (Gambhir et al., 2021). For this work, we further limited bioenergy and implemented additional assumptions regarding the full phase-out of unabated fossil power plants, petroleum-derived liquid transportation fuels, electrification of buildings, transport, and industrial sectors not requiring combustion-grade heat, and accelerated compliance with the Kigali Amendment to reduce fluorinated gas emissions. We also developed the capability to model carbon capture for cement process heat, hydrogen combustion turbines for peaking power, and synthetic liquid fuels production using CO_2 from direct air capture. Nevertheless, the scenarios still has the full set of CDR options, including bioenergy with carbon capture and storage, afforestation, direct air capture with carbon storage, enhanced weathering, biochar and direct ocean capture with carbon storage (Fuhrman et al., 2023).

3.3 Results

We find that combined, these enhanced technological and behavioral changes can reduce the requirement for CDR by over 50% compared to a global carbon emissions constraint alone and substantially increase the role of the land sink in removing CO_2 from the atmosphere (Figure 3-2). The full implementation of zero or low-carbon technologies in electricity, transportation, buildings, and most industrial sectors may enable the near-elimination of residual CO_2 emissions by the end of the century, substantially reduce residual non-CO_2 emissions, and enable net-zero GHG emissions by mid-century. Additionally, the distribution of CDR is shifted away from countries such as China and the United States with large prospective geologic storage capacity in favor of a more equal distribution across regions (Figure 3-3).

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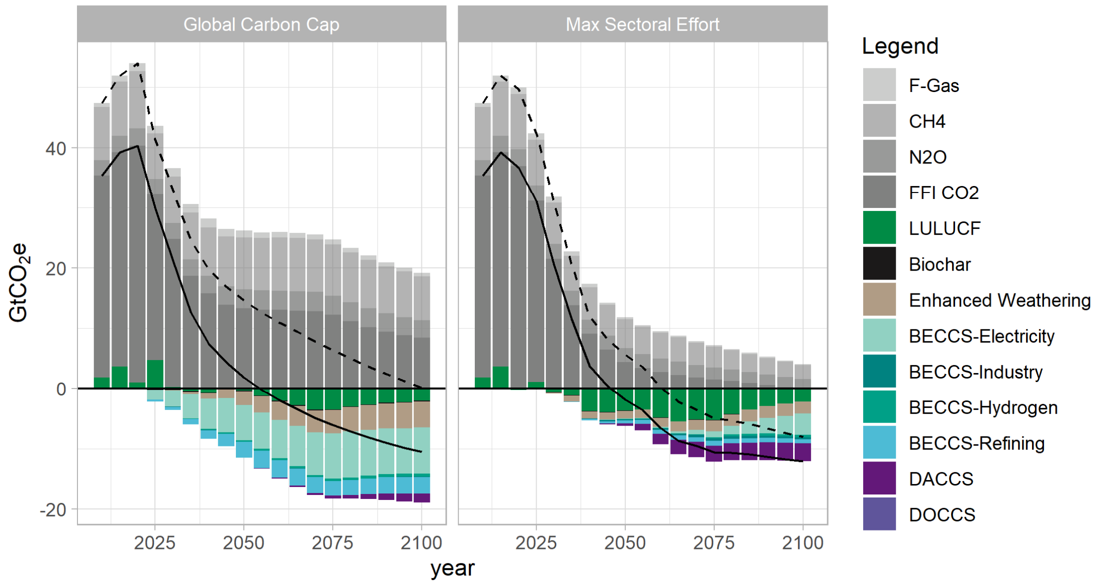

Figure 3-2: Gross and net GHG emissions, include CDR by type in the standard Global Carbon Cap and the Max Sectoral Effort.

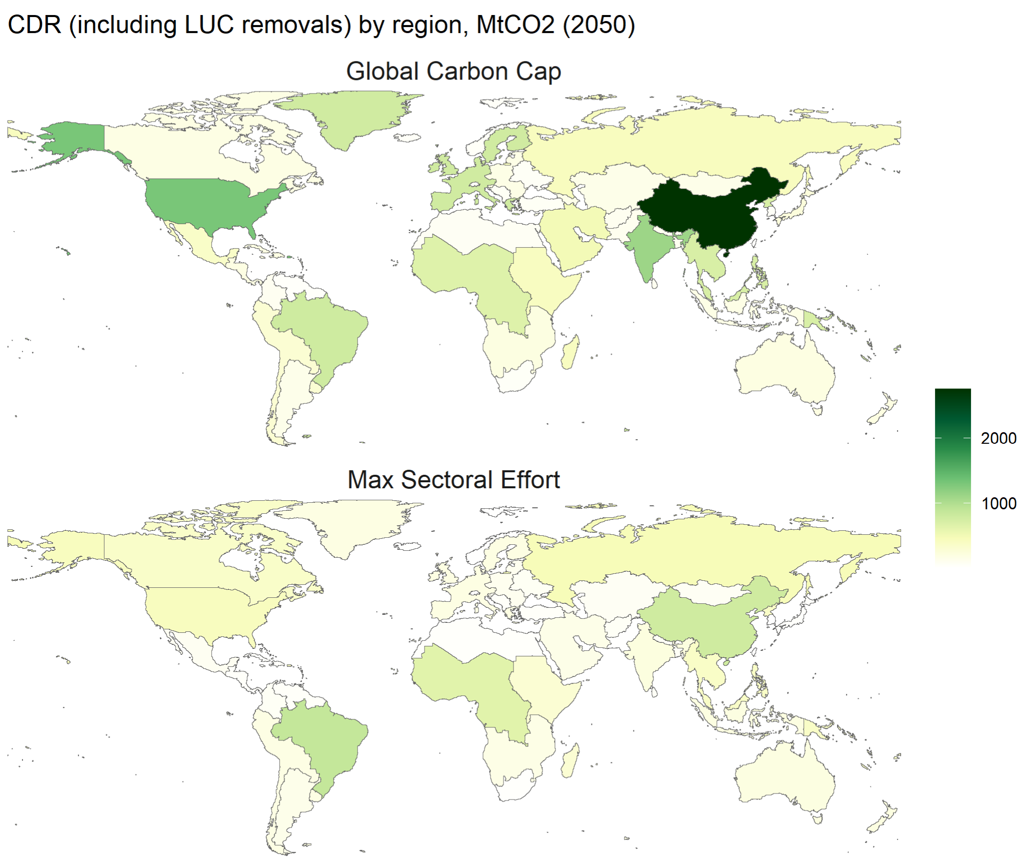

Figure 3-3: The distribution of regional CDR by scenario in 2050 for the Global Carbon Cap and the Max Sectoral Effort scenarios.

Many sectors contribute to reduced residual emissions. Shifted dietary preferences including reduced ruminant meat and dairy demand, along with fossil fuel phase-outs can reduce but not eliminate non-CO_2 GHG emissions from these sources. Zero-carbon fuel and vehicle standards in transportation, a reduced emphasis on CCS, and improved grid management could drastically limit CO_2 emissions from the top six residual CO_2 sources under a carbon emissions constraint alone.
Trajectories for both net and residual positive GHG emissions from our maximum sectoral effort scenario are near the lower bound of 1.5°C scenarios in the IPCC's 6th assessment report (AR6) scenario database (**Error! Reference source not found.**), while gross CO_2 removals remain towards the middle of the distribution of emissions trajectories. Under CO_2 emissions constraints alone, both gross CDR and residual emissions increase towards the upper bound of the trajectories in the AR6 due to our recently expanded CDR capacity going largely towards allowing reduced abatement effort on residual emissions.

3.4 Discussion

As reliance on CDR grows to achieve the Paris goals amid slow efforts to drastically reduce net emissions, our results highlight the importance of maximising the extent to which any CDR that is deployed is going towards drawing down CO_2 over time rather than offsetting residual emissions to reduce tradeoffs. Including more behavioral and technological options in models helps reduce reliance on CDR, indicating that modelers should ensure they can capture that latest technological and behavioral options, some of which may be more advanced than CDR. Policy makers need to ensure a sharp focus on short-term emissions reductions with low or even negative costs compared to fossil fuels, encompassing simple behavioral changes, while ensuring investments in the so-called 'hard-to-abate' sectors. Given the high-costs of many types of CDR and their limited scale, minimising residual emissions from 'hard-to-abate' sectors increases the likelihood of reaching ambitious mitigation targets, or opens options for lower temperature outcomes.

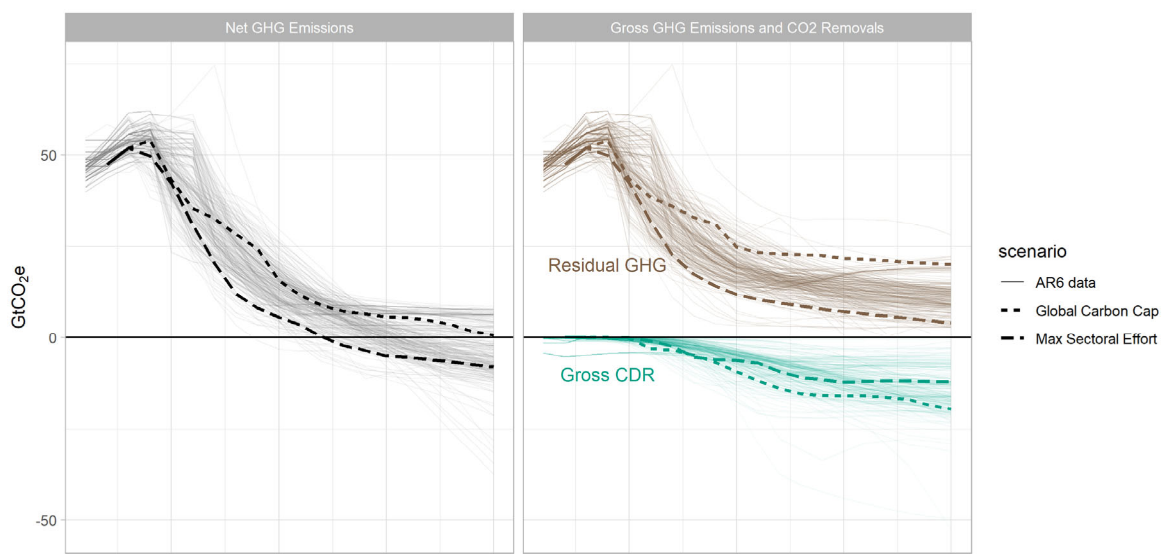

Figure 3-4: Comparison to AR6 results for net and gross GHG emissions and CDR. Due to reductions in net GHG emissions, peak global average temperature in the max sectoral effort scenario is reduced by approximately 0.1 °C, to 1.6 °C, and the temperature in 2100 is reduced by 0.4 °C, to 1.1 °C above the pre-industrial average.

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4 The impact of interest rates on decarbonisation pathways

Authors: *Natasha Frilingou, Anastasios Karamaneas, Thomas Nikolakakis, Alexandros Nikas, Konstantinos Koasidis [NTUA]; Dirk-Jan Van de Ven [BC3]; Shivika Mittal [Imperial]; Nikos Kleanthis, Vassilis Stavrakas, Alexandros Flamos [UPRC]; Ilkka Keppo [Aalto]*

Part of this Section will be submitted to a peer-reviewed journal.

4.1 Context within IAM COMPACT's PRM

As part of the IAM COMPACT Policy Response Mechanism, we have conducted numerous workshops with different Policy Steering Groups under four distinct policy-relevant themes (see D2.4 - Proceedings of Stakeholder Interactions). Overall, 23 questions emerged from these high-level exchanges, which we then grouped into proposals for seven modelling studies (for a full list of questions, see D4.5 - National, regional, global mitigation pathways). These proposals were in turn grouped into four overreaching themes and disseminated to a wider policy audience (forming the core working groups) from our database, selected on geographical and sectoral criteria. This consultative process helped us evaluate the relevance of policy issues, refine the scope of research questions, and establish a balanced group of stakeholders (core working group) to participate. We conducted one workshop under each theme and core working group to consult stakeholders on our scenario design and co-define desired outputs as well as a key set of joint input assumptions. The theme "Global Effects[1]", in particular, explored the impact of financial and political aspects on global decarbonisation, aiming to facilitate collaboration between the IAM COMPACT modelling teams and policymakers, other researchers, and industry representatives. The workshop sought feedback on the scenario design, inputs, and projections of two proposed modelling studies:

- How could geopolitics and technological limitations affect decarbonisation pathways? (addressed and documented in project deliverable D5.4 Modelling out-of-ordinary extremes)
- How could interest rates influence global decarbonisation pathways? (addressed and documented here)

The latter question on interest rates originated from our discussions with DG ECFIN and DG CLIMA, under the Policy Steering Group topic of "Global Green Investments" (see D2.2 - Scoping policy relevant research questions). Among others, we were asked to explore how hydrogen production can be made affordable and how the EU taxonomy can foster additional green investments. These questions were then grouped together in the present overarching study on interest rates.

4.2 Introduction

Decarbonising the economy necessitates global action to address fundamental economic disparities and overcome the climate investment trap faced by numerous developing nations (IPCC, 2023). It is estimated that USD 2.8 trillion was invested in energy in 2023, with more than 1.7 USD going to clean energy, while the remaining USE 1 trillion towards fossil fuel supply and power (IEA, 2023c). If the world is to meet the Paris Agreement global temperature goal of limiting warming to 1.5°C above pre-industrial levels, over USD 5 trillion in annual terms of additional investment will be required (IRENA, 2023). The climate financing gap reflects a persistent geographic misallocation of global capital, as almost all recent growth of investments in clean energy is directed towards advanced economies and China, while capital flows remain flat in emerging economies and developing countries, accounting only for 15% of clean energy investments despite encompassing two-thirds of the word population and contributing to one-third of global GDP (IEA, 2023b).

[1] https://iam-compact.eu/news-events/core-working-groups-workshop-global-effects

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Low-carbon technologies require large upfront investments, unlike fossil-fuel technologies where fuel costs are the dominant part of the lifecycle costs and upfront investment costs are relatively low (Hirth & Steckel, 2016). The private cost of capital (CoC), i.e., the discount rate employed in evaluating private investments, becomes essential to assessing the investment choices of companies that must decide between various alternatives, such as different power generation technologies (Steffen, 2020). The CoC is thus used in investment appraisals, such as in levelised cost of energy (LCOE) calculations, and the capital-intensive nature of low-carbon technologies implies that their LCOE is more sensitive to the CoC rate (Lonergan et al., 2023). The CoC is thus a major determinant of the cost of electricity from renewable power generation technologies and of their deployment.

An increase in the CoC raises financing expenses, posing challenges in achieving attractive risk-adjusted returns, particularly for clean energy technologies. In advanced economies, capital costs (e.g., land and equipment acquisition) typically constitute the most significant chunk of total clean energy project expenses, while in developing economies financing costs take the lead (IEA, 2023b). While clean energy technology costs have been decreasing in the last decades, in most developing economies political, regulatory, and macroeconomic risks lead to difficulties in securing the required finance (Ameli et al., 2021; Ondraczek et al., 2015). Reducing the CoC in developing economies will thus not only benefit investors but also enhance the overall affordability of energy transitions for consumers.

Reliable data and an improved understanding of the composition of the CoC and its drivers are essential to develop support mechanisms and market designs that appropriately consider varying technology and country risks (Anatolitis et al., 2023). These are commonly represented in the weighted average cost of capital (WACC), a special case of the CoC that considers the proportion of debt and equity in a company's capital structure. In essence, WACC is a weighted average of the cost of debt and the cost of equity, where the weights are determined by the proportion of each in the company's total capital (Breitschopf & Alexander-Haw, 2022). In case of energy projects characterised by elevated perceived risk, such as those in politically unstable regions or involving newer and highly uncertain technologies, the WACC is higher, signifying that investors require greater returns to offset the higher risk of potential financial losses (Ellenbeck & Lilliestam, 2019).

Most energy-economy models typically use uniform WACC values across regions over time, which can disproportionately impact mitigation pathways for developing economies (Ameli et al., 2021). There exist scarce datasets of empirically grounded WACC values for power-sector technologies; the International Renewable Energy Agency (IRENA) has put together such a dataset at the global level (Anatolitis et al., 2023), including green hydrogen (IRENA, 2022), while recent research efforts have focused on putting together regionally disaggregated WACC values for a subset of electricity production technologies, in the EU (Polzin et al., 2021), Africa (Sweerts et al., 2019), and globally (Ameli et al., 2021; Calcaterra et al., 2024).

In this study, we use empirically calibrated WACC values by region and technology taken from (Calcaterra et al., 2024) and (IRENA, 2022) in two global integrated assessment models (IAMs) and one electricity-system model and explore stakeholder-driven pathways of de-risking clean energy technologies and risking fossil fuels. As one of the largest uncertainties lies in the way WACC values will evolve over time, we combine the empirical estimates of baseline WACC values with an expert-based approach (Meng et al., 2021) to produce forward-looking scenarios of evolving WACCs over time.

Post-COVID debt, increased interest rates, and high inflation, along with the huge subsidies of the US Inflation Reduction Act (IRA) are currently driving clean energy investments out of developing countries (UNCTAD, 2023). The recent surge in energy prices has increased firms' input costs and households' energy expenditure and has led to substantial windfall profits in the energy and manufacturing sectors (IMF, 2022). Taxing windfall profit taxes on revenues from mega-corporations has been proposed as way to fund the financing cap through underwriting capital market low-carbon investments in emerging and developing economies (Grubb, 2023; Oxfam International, 2023). Indicatively, the oil and gas industry generated windfall profits of trillions of USD in 2022

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alone—considerably more than what would be needed to halve the emissions intensity of the industry's operations by 2030 (estimated at around USD 600 billion) (IEA, 2023a). Therefore, we additionally incorporate a corrective justice dimension (Zimm et al., 2024) in our narratives by assessing the impacts of risk underwriting for low-carbon investments through taxing those windfall profits and distributing the revenue as subsidies towards high-WACC regions.

4.3 Methods and tools

4.3.1 Expert elicitation

Expert inclusion in energy-economy modelling has been proven useful to maximise real-world feasibility of model insights from a societal perspective, and to improve model accuracy and relevance with inputs informed by stakeholder consultations (Nikas et al., 2023). Here, we turn to experts from academia, European, and national policy to elicit their knowledge and perceptions in the form of a survey[2] on how interest rates might develop in the future and, in turn, to co-design our study pathways.

Specifically, we draw experts' opinion on how much investment risks (e.g., risks in power markets, permits, social acceptance, resource and technology, currency, geo-/political) may change for a set of technologies in 2050 in high, middle, and low-income countries, considering possible finance and policy de-risking or divestment mechanisms that may play out, to determine the final risk percentage change. As a baseline, we provide empirically estimated WACC values from (Calcaterra et al., 2024) and (IRENA, 2022) by technology (coal, natural gas, nuclear, hydro, biomass, solar PV, onshore wind, offshore wind, and green hydrogen) and country-income classification (high, medium, low); baseline WACC values are provided in ANNEX D: Section 4 baseline WACC valuesand survey results in ANNEX E: Section 4 expert elicitation survey results.

After filling out the survey, in-depth discussions with the experts revealed their interest in the distributional impacts of technological change and affordability, the expansion of the empirically defined WACC values beyond power technologies—including technologies critical in the decarbonisation of hard-to-abate sectors—as well as the assessment of exploratory pathways of varying interest rates among regions to explore their impacts, without considering solely the cost effectiveness of investments. These discussions, in turn, informed our scenario protocol presented in Section 4.3.2.

4.3.2 Model ensemble

GCAM

The Global Change Assessment Model (GCAM[3]) is a global integrated assessment model that represents the behaviour of and interactions between five major systems—energy, land, water, the economy, and climate—at regional and global scales. GCAM is a recursive dynamic simulation model that has been widely used to explore low-carbon policies and mitigation scenarios. GCAM represents economic and energy systems in 32 geopolitical regions and reports demands for and supplies of energy forms as well as emissions of greenhouse gases, aerosols, and other short-lived species (Calvin, Patel, Clarke, Asrar, Bond-Lamberty, Yiyun Cui, et al., 2019).

The model solves for a set of market prices such that supplies and demands are equal for all markets in the model, iterating on these prices until equilibrium is reached. Markets exist for physical flows and other types of goods and services, such as tradable emissions permits. Representative agents interact through the markets, indicating their intended supply and/or demand for goods and services. The current version of GCAM used here

[2] https://sprw.io/stt-cuGGLq98ejqNDdC4Eb4eR9
[3] https://www.i2am-paris.eu/detailed_model_doc/gcam

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(v7[4]) operates from 1990 to 2100 in five-year timesteps, with 2020 as the final calibration year. Once the model solves for each period, it utilises the resulting state of the world, including decisions taken during that time and progresses to the next time step, repeating the process (JGCRI, 2023).

Economic choice

Most of the economic activities represented in GCAM present us with a choice among several ways to produce the result of the activity. The exact share a given option receives in GCAM depends on the logit exponent and the share weight:

$$s_i = \frac{a_i c_i{}^{\gamma}}{\sum_{j=1}^{N} a_j j^{\gamma}} \ (eq\ 5.1)$$

where s_i, c_i, and a_i are the share, cost, and share weight of technology i, respectively, and γ is the logit exponent. Logit exponents are exogenously specified and calculated in the historical period, prescribing the degree to which cost, or profit, determines the share; exponents that are larger in absolute magnitude result in a more "winner takes all" behaviour (Calvin, Patel, Clarke, Asrar, Bond-Lamberty, Yiyun Cui, et al., 2019).

Energy demand

Final energy demand includes buildings, transportation, and industry (aluminium, cement, chemicals, construction, fertiliser, iron and steel, mining and agricultural energy use, and other industry) and is driven by exogenous assumptions for income (GDP per capita) and population as well as endogenous changes in the cost of producing a service (O'Rourke et al., 2023).

Energy supply

GCAM models depletable resources (oil, unconventional oil, natural gas, coal, and uranium) using graded resource supply curves. The model's renewable resources include onshore and offshore wind, solar, geothermal, hydropower, biomass, and in some regions "traditional" biomass; except biomass, none of these resources are traded between regions. Wind and solar are considered as options for producing electricity or hydrogen, while geothermal and hydropower are only used as options for producing electricity. In contrast to the depletable resources, whose cumulative stocks are explicitly tracked, renewable resource quantities are indicated as annual flows.

Hydrogen can be produced from 10 central production technologies (biomass with or without CCS, natural gas steam reforming with and without CCS, thermal splitting, grid electrolysis, dedicated wind and solar electrolysis, nuclear high temperature electrolysis (HTE), and coal chemical with or without CCS) and industrial on-site production technologies (grid electrolysis, renewable electrolysis (green hydrogen), and natural gas with CCS)(O'Rourke et al., 2023) .

Electricity

Individual technologies compete for market share based on their technological characteristics, cost of inputs and price of outputs. The cost of a technology in any period depends on its exogenously specified non-energy cost, its endogenously calculated fuel cost, and any cost of emissions, as determined by an imposed climate policy:

$$C = t + \sum_{j=1}^{n} i_j + \sum_{k=1}^{m} g_k - \sum_{l=1}^{o} v_l \ \ (eq\ 5.2)$$

where c is the total cost, t ($) is the exogenously specified technology cost, i_j is the cost of input j (e.g., a fuel), g_k is the GHG value of gas k, and v_l is the value of secondary output l. Costs vary by region, technology, and year (JGCRI, 2023). Fuel or electricity costs depend on the specified efficiency of the technology and the cost of

[4] http://jgcri.github.io/gcam-doc/index.html

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the fuel or electricity. Non-energy costs represent capital, fixed, and variable O&M costs incurred over the lifetime of the equipment, excluding fuel or electricity costs. For electricity technologies, GCAM reads in each of these terms and computes the levelised cost of energy (LCOE) within the model:

$$LCOE = \frac{FCR \cdot CAPEX + FOM}{CF \cdot 8760(\frac{hours}{year})} + VOM \ (eq\ 5.3)$$

where FCR is the fixed charge rate, which is the amount of revenue per dollar of investment required that must be collected annually by an investor to pay the carrying charges on that investment, CAPEX is capital expenditures to achieve commercial operation, FOM the fixed operation and maintenance expenses, CF the capacity factor, and VOM the variable operation and maintenance (NREL, 2022).

Cost of capital

The overall cost of capital is derived from a weighted average of all capital sources (debt and equity), known as the weighted average cost of capital (WACC). The WACC serves as the discount rate, indicating that the value of a cash flow depends on the time in which the flow occurs. As the FCR represents all the fixed charges as an annual percentage of the original costs, it levelises the cost of capital (White, 1979). Here, we vary FCR across technologies, regions, and time:

$$FCR = \frac{WACC_{l,n,t}}{1-(1+WACC_{l,n,t})^{lifetime_l}} \times \frac{1-(T * PV_{depreciation})}{1-T} \ (eq\ 5.4)$$

where $WACC_{l,n,t}$ is the weighted average cost of capital of technology *l*, region *n*, and time *t*; T the marginal income tax rate; $lifetime_i$ the lifetime of technology *i*; and $PV_{depreciation}$ the present value of depreciation (G. C. Iyer et al., 2015). Country-WACC values are weighted by GDP for each aggregated GCAM region.

TIAM

The TIMES Integrated Assessment Model (TIAM[5]) is a multi-regional, inter-temporal partial equilibrium model of the entire energy/emission system of the world. It is a technology-rich, bottom-up model generator, which uses linear-programming to produce a least-cost energy system, optimised according to a number of user constraints, over medium- to long-term time horizons. Throughout the optimisation process, the model has the flexibility to select from various technologies, each characterised by specific attributes including capital and operational expenses, efficiency, fuel composition, etc., to attain its objective. TIAM includes all the steps from primary resources through the chain of processes that transform, transport, distribute, and convert energy into the supply of energy services demanded by energy consumers. The total energy system cost (including any losses to consumers' welfare as a result of energy price rises) is calculated as a net present value (NPV) cost of the energy system over the whole time period.

Energy demand

Through various energy carriers, energy is delivered to the demand side, which can be structured sectorally into residential, commercial, agricultural, transport and industrial sectors. The demand sector breakdown is completely flexible and adaptable in TIMES. The "agents" of the energy demand side are the "consumers". The mathematical, economic, and engineering relationships between these energy "producers" and "consumers" is the basis underpinning TIMES models. Demand drivers (population, GDP, households, etc.) and the assumed elasticities of the demands to their own prices are obtained externally (Loulou & Labriet, 2008).

Energy supply

On the energy supply side, it comprises fuel mining, primary and secondary production, and exogenous import

[5] https://www.i2am-paris.eu/detailed_model_doc/tiam

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and export. The "agents" of the energy supply side are the "producers".

Solution process

Once the model has incorporated all the inputs, constraints, and scenarios, it tries to solve and identify the energy system that satisfies the demands for energy services throughout the entire time horizon at the minimum cost. This involves making decisions on equipment investments, operations, primary energy supply, and energy trade concurrently, categorised by region. TIAM operates under the assumption of perfect foresight, meaning that investment decisions are made in each period with full awareness of future. The optimisation spans horizontally across all sectors and vertically across all imposed time periods. The outcome provides the optimal combination of technologies and fuels for each period, along with associated emissions to fulfil the demand.

The model configures the production and consumption of commodities (such as fuels, materials, and energy services) and their prices. Equilibrium is achieved when the model aligns supply with demand, matching energy producers with energy consumers. Mathematically, this entails maximising both producer and consumer surplus. The model is structured so that the price of producing a commodity influences its demand and, simultaneously, demand affects the commodity's price. A market is considered in equilibrium at prices 'p' and quantities 'q' when no consumer wants to purchase less than 'q,' and no producer wishes to produce more than 'q' at price 'p.' Total economic surplus is maximised when all markets are in equilibrium, representing the sum of producers' and consumers' surpluses[6].

Cost of capital

Financial hurdle rates, defined as an estimation of the WACC and expressing the cost of financing for a technology, can be applied in TIAM to undertake policy analysis where a policy choice may impact the revenue or cost positions of a technology or sector (Coleman, 2021). These hurdle rates are used for uplifting the capital costs in the model by increasing the total capital recovery over the project lifetime. The total discounted system cost, i.e., TIMES objective function, includes costs arising from the supply (production and import/export) and consumption of energy including fuel expenditures, investments in power plants, infrastructure, purchases of demand devices, and fixed/variable operating, and maintenance costs associated with all technologies. Here, we use a descriptive approach for discounting, expressing the cost of financing as a weighted average cost of capital (WACC) for a technology.

The regional disaggregation used in this study for both GCAM and TIAM is shown in Table 4-1.

Table 4-1: Regional disaggregation for GCAM & TIAM in this study

Code	Region	Countries
AFR	Africa	Algeria, Angola, Benin, Botswana, Cameroon, Congo, Democratic Republic of Congo, Côte d'Ivoire, Egypt, Eritrea, Ethiopia, Gabon, Ghana, Kenya, Libya, Morocco, Mozambique, Namibia, Nigeria, Senegal, South Africa, Sudan, United Republic of Tanzania, Togo, Tunisia, Zambia, Zimbabwe, and Other Africa
AUS	Oceania	Australia, New Zealand, Oceania
CAN	Canada	Canada
CHI	China	China
CSA	Central & South America	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay, Venezuela and Other Latin America
EEU	Eastern Europe	Albania, Bosnia-Herzegovina, Bulgaria, Croatia, Czech Republic, Hungary, Macedonia, Poland, Romania, Serbia and Montenegro, Slovenia, Slovakia

[6] https://github.com/etsap-TIMES/TIMES_model

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IND	India	India
JPN	Japan	Japan
MEA	Middle East	Bahrain, Islamic Republic of Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, United Arab Emirates, Yemen, and Turkey, Cyprus
MEX	Mexico	Mexico
FSU	Russia and Central Asia	Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Tajikistan, Turkmenistan, Ukraine, Uzbekistan, Russian Federation
SKO	Republic of Korea	Republic of Korea
ODA	(Other) South and Southeast Asia	Bangladesh, Brunei Darussalam, Cambodia, Taiwan (China), Indonesia, DPR of Korea, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, Vietnam and Other Asia
USA	United States of America	USA
WEU	Western Europe	Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Norway, Portugal, Spain, Sweden, Switzerland, The Netherlands, UK

OSeMOSYS-GR

The Open Source Energy MOdelling SYStem (OSeMOSYS) is an energy system model that identifies the least-cost decarbonisation pathway via the minimisation of the discounted energy system cost. In this process, OSeMOSYS identifies the optimal capacity and generation mix of energy technologies to cover the energy demand (Howells et al., 2011). OSEMOSYS-GR is a model implementation for the energy transition in the Greek power sector up to 2050. It includes different electricity supply technologies, i.e., importing and extraction technologies, fossil-fired power plants using lignite, natural gas, oil, renewable energy technologies (i.e., hydro, onshore and offshore wind, solar photovoltaic (PV), biomass, and geothermal), electricity storage (i.e., battery and pumped hydro), hydrogen production and consumption (namely electrolysers and fuel cells), transmission, and distribution systems, as well as interconnections with neighbouring countries. In the context of this modelling exercise, we used a parameter that allows the application of different discount rates for each technology. Consequently, the WACC of each technology could be represented by the respective discount rate. In this regard, OSEMOSYS-GR was modified to model technological vintages that differ in terms of the assumed WACC per technology that was linearly extrapolated for a specific timeframe. In total, six vintages for each power generation technology were used for the modelling horizon to cover intervals of five years each, namely [2021-2025], [2026-2030], [2031-2035], [2036-2040], [2041-2045], and [2046-2050]. It should be noted that the impact of the varying WACC of fossil-fuel technologies on fossil-fuel investments was captured via an exogenous technoeconomic assessment considering that these investments are articulated by the national planning in the Greek power sector and the respective policy documents.

4.3.3 Scenario protocol

Before running the numerous scenarios for different interest rates (see Table 4-2), a baseline was defined, against which each scenario is benchmarked/compared to allow quantifying the impact. The NDC scenario of IAM COMPACT is used as a baseline, in which current policies are explicitly represented, and National Determined Contributions are enforced on top of current policies until 2030, before then implementing long-term targets (LTTs). NDC targets are based on a direct interpretation of countries' unconditional Paris Agreement pledges, or the less ambitious range for pledges where NDC targets are given in ranges, as announced until mid-2023 (see D4.5 - National, regional, global mitigation pathways for details on the IAM COMPACT global scenario protocol). This scenario also includes empirical WACC values differentiated by region and technology to reflect non-uniform risk perceptions. The comparison among scenarios would thus reveal the impacts of varying WACC values over time via de-risking renewables ("IAMCOM_RES_Low_Risk"), fossil fuel divestment ("IAMCOM_FF_High_Risk") and their combination ("IAMCOM_Survey"), increasing differences of risk perceptions among high and medium/low income regions ("WACC_Fragmented"), as well as the impact of subsidies towards low-carbon technologies ("Windfall_allocation"; TIAM did not run this scenario).

Model assumptions have been updated to reflect latest trends, including population drawn from the EUROPOP2019 (Eurostat, 2022) database and the short-term economic outlook of the IMF WEO of October 2023 until 2027 (WEO, 2023), extrapolated to 2050 according to the SSP2 socioeconomic pathway reflecting historic trends, while demand projections for the EU are taken from the EU Reference scenario (European Commission, 2021) (in OSeMBE), according to deliverable D4.3 ('Broad Scenario Logic').

Table 4-2: Scenario protocol

#	Name	Scenario assumptions	Current polices till 2030	Climate Target
1	NDC_baselineWACC	We use baseline empirical WACC values, keeping these values fixed for the entire time horizon. The scenario is based on stated 2030 emission targets pledged in NDCs submitted or announced by June 2023, capturing all mitigation ambition updates during and after the COP26 in Glasgow, implemented on top of current policies. In model regions where current policies exceed the mitigation targets of NDCs, no additional emission constraints are applied. Emissions reductions in NDC scenarios are therefore never less ambitious than current policies imply. For regions that expressed an LTT, such as net-zero commitments or other targets for 2050 or later, emission constraints linearly decline from 2030 emissions from the NDC target towards the LTT. For regions without LTTs, post-2030 the applied policy targets are maintained as minimum levels beyond 2030 to avoid backtracking of achieved policies. This scenario provides the carbon price for the rest of scenarios.	Current Policies	NDC (on top of current policies), LTT
2a	IAMCOM_RES_Low_Risk	We use baseline empirical WACCs (2018), while future WACCs decrease for RES & green H_2 (see ANNEX F: Section 4 survey-based 2050 WACC values) according to IAM COMPACT survey results. Values between 2018 & 2050 change linearly. Carbon prices are taken from Scenario 1.	Current Policies	NDC (on top of current policies), LTT
2b	IAMCOM_FF_High_Risk	We use baseline empirical WACCs (2018), while future WACCs increase for fossil fuels and nuclear (and decreasing for CCS, see ANNEX F: Section 4 survey-based 2050 WACC values) according to IAM COMPACT survey results. Values between 2018 & 2050 change linearly. Carbon prices are taken from Scenario 1.	Current Policies	NDC (on top of current policies), LTT
3	IAMCOM_Survey	We use baseline empirical WACC values, while future WACCs change for all technologies according to IAM COMPACT survey results. Values between 2018 & 2050 change linearly (see ANNEX F: Section 4 survey-based 2050 WACC values). Carbon prices are taken from Scenario 1.	Current Policies	NDC (on top of current policies), LTT
4	WACC_Fragmented	We use baseline empirical WACC values, while for future WACCs we assume that differences between high-income & low-income countries intensify towards 2050. For high-income countries (incl. China), WACC values converge to the 25th percentile of the average baseline empirical WACC per technology. For middle- and low-income countries, WACC values converge to the 75th percentile of the average baseline empirical WACC per technology. Values between 2018 & 2050 change linearly (see ANNEX G: Section 4 diverging 2050 WACC values). Carbon prices are taken from Scenario 1.	Current Policies	NDC (on top of current policies), LTT
5	Windfall_allocation	We use baseline empirical WACC values, keeping these values fixed for the entire time horizon. We calculated the share of	Current Policies	NDC (on top of current

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		each country's GDP per capita to the total available subsidy (997.46 billion USD); countries with higher share would get a larger proportion of the subsidy. To account for countries with high GDP but low GDP per capita (e.g., India), we also compute the share of each country's GDP (PPP) to total GDP. Countries with higher share will also get a higher share of the subsidy. We then apply a penalty function to WACC values, excluding countries with average WACC for RES & green H2 below 6% (as they already have a relatively low WACC and therefore will not get a share of the subsidy). Countries with higher WACC get a higher share of subsidy. Finally, we combine these shares linearly (GDP per capita, GDP_PPP, WACC) and normalise them to find the final subsidy allocation by country (see ANNEX H: Section 4 windfall profits tax revenue allocation). Carbon prices are taken from Scenario 1.		policies), LTT

Figure 4-1 shows a representation of baseline and future aggregated WACC values by regions and technology for each scenario, along with the distribution of windfall profits allocation by regions. It is worth noting that "WACC_Fragmented" scenario (panel b) describes a clear divide among low/middle- and high-income regions compared to baseline (panel a), while in "IAMCOM_Survey" scenario (panel c) stakeholders indicated a substantial increase in future WACC values of both fossil fuels and nuclear power, and an overall decrease, albeit more moderate, in WACC values of renewable power sources, CCS, and green hydrogen. For the implementation of the scenario "Windfall_allocation" (panel d), we assumed a windfall tax revenue of 997,460,000,000 current USD globally (Oxfam International, 2023), 126,507,783,508 current USD for Europe (EU27, UK, Switzerland, Norway) (Tax Foundation, 2023), and 6,887,448,043 current USD for Greece (Reuters, 2022).

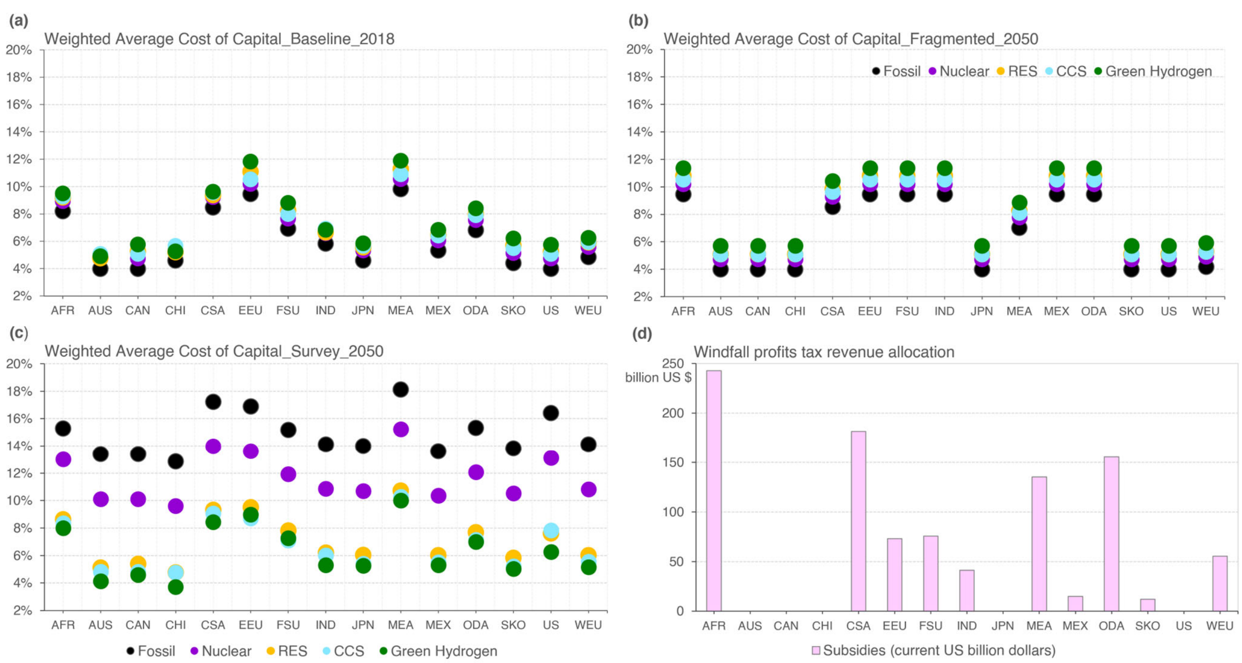

Figure 4-1: WACC values aggregated by region (AFR: Africa, AUS: Australia & New Zealand, CAN: Canada, CSA: Central & South America, EEU: Eastern Europe, FSU: Russia & Central Asia, IND: India, JPN: Japan, MEA: Middle East, MEX: Mexico, ODA: (Other) South & Southeast Asia, SKO: Republic of Korea, US: USA, WEU: Western Europe) and technology (fossil fuels, renewables, nuclear, CCS, and green hydrogen) **(a)** in the baseline year, **(b)** in 2050 for the WACC_fragmented scenario, **(c)** in 2050 based on survey results and **(d)** Windall profits tax revenues allocation by region in US current billion $.

Regarding the focus on Greece, its energy sector is in the middle of a transition towards renewable energy but is hindered by the high perceived risks and WACCs towards new investment (Polzin et al., 2021), making it an interesting case study (see Greek power sector impacts) for country-specific implementation of the scenario protocol within the EU.

4.4 Results and Discussion

4.4.1 Global and regional impacts

Carbon price

All scenarios apply the same climate policy intensity (i.e., the same level of carbon price) with the NDC_baselineWACC scenario, shown in Figure 4-2 for GCAM and TIAM across all regions. GCAM shows an incremental increase in carbon price, with the highest prices observed in 2050 for Western Europe (254 US$2010) and Republic of Korea (237 US$2010). TIAM generally shows higher carbon prices, which are introduced later (2040) than in GCAM in most regions, with the exception of Japan, South Korea, and WEU where carbon prices reach 100 US$2010 on average in 2030 either because current policies are insufficient to reach NDC targets (JPN, SKO), or because of highly ambitious 2030 targets (WEU) (den Elzen et al., 2022; van de Ven et al., 2023).

Models with perfect foresight like TIAM tend to have exponentially increasing carbon prices, as technology and investment choices among long-lived capital assets include knowledge of future prices. In anticipation of significantly higher future prices, this leads to emissions already being reduced in the short term, when the prices as still low (Guivarch & Rogelj, 2017). In contrast, GCAM is a recursive dynamic model with myopic foresight, and as such emissions reductions in the short term are only based on current prices and knowledge leading to incremental increase in carbon prices (Kaufman et al., 2020).

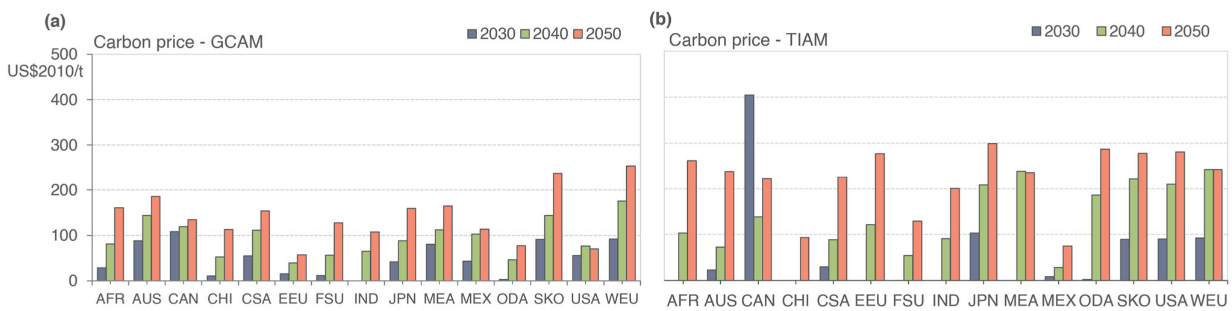

Figure 4-2: Carbon prices by region (US$2010/yr) for GCAM (**a**) and TIAM (**b**) in NDC_baselineWACC, kept constant in all other scenarios.

Changes in emissions

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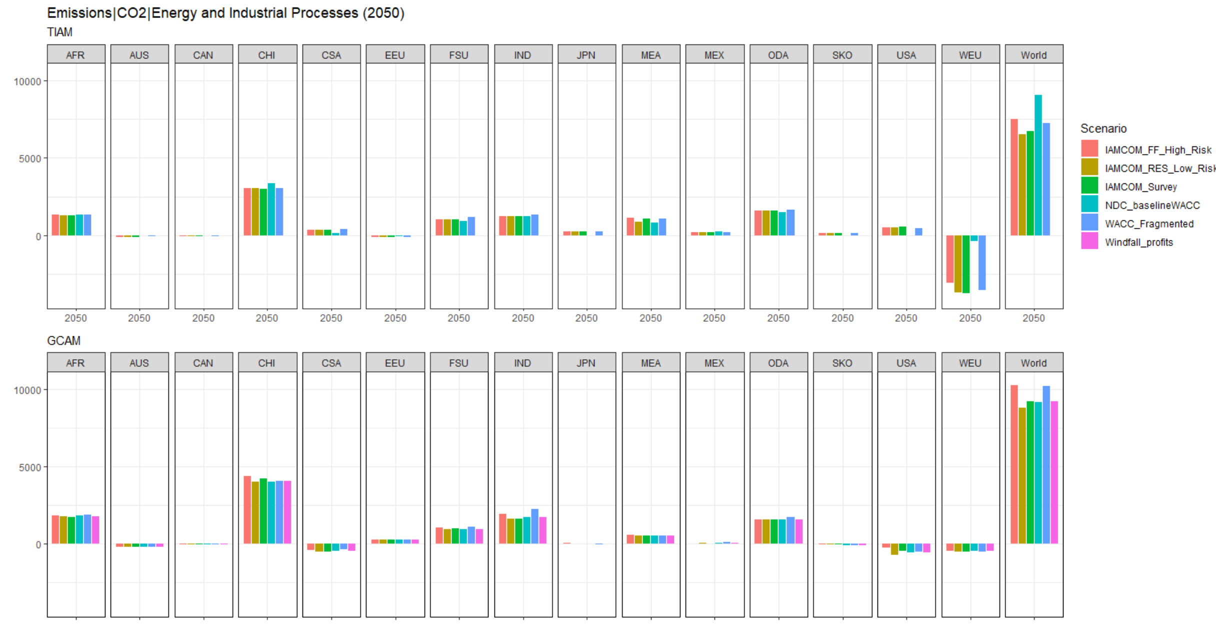

Figure 4-3: CO_2 emissions of energy and industrial processes in TIAM (up) and GCAM (down) by scenario and region.

Global CO_2 emissions pathways from energy and industrial processes are shown in **Error! Reference source not found.**. In TIAM, we observe that the highest emission reductions are achieved through de-risking clean energy technologies, as lower risk would enhance their deployment. Similarly, re-risking fossil fuels would also benefit emission reductions, but in a smaller extent, as investments would be allocated to lower-cost (clean) technologies. A fragmented world would also decrease emissions as it would generally de-risk investments across technologies in high-income countries and magnify risks in middle and low-income countries.

In GCAM, decisions about production, consumption, and investment are only based on the prices of that period, meaning that emission mitigation is proportional to investment, and thus scenarios facing significantly higher WACC values tend to mitigate less (G. C. Iyer et al., 2015). The highest emission increase is observed when fossil fuel and nuclear WACC increase over time (IAMCOM_FF_High_Risk) attributed mainly to the increasing risk of nuclear power, a CO_2-free tech with high upfront costs compared to fossil technologies, highly affected by the cost of capital, followed by a world where future WACC values drop in high-income regions but increase in medium- and low-income regions. Despite the moderate effect of de-risking renewables in 2050 global emissions, it seems that the decreased WACC almost offsets the emission increase caused by higher fossil fuel WACC in IAMCOM_Survey. Subsidies have a minimal impact on emissions in 2050, slightly decreasing for low and middle-income regions (AFR, ODA).

Changes in the energy system

<u>Capacity additions</u>

In terms of added capacity (Figure 5-5), a future pathway with increasing WACC trends in fossil fuels and nuclear and decreasing in renewables and CCS (IAMCOM_Survey) would expectedly lead to increased solar and wind compared to baseline in both models. TIAM directs capacity mostly to solar, followed by wind in all regions, and towards Gas w/o CSS in Europe and ODA while GCAM increases Biomass capacity in all regions instead. In a fragmented world, fossil fuels increase in high-income regions, and renewables decrease in low-middle income in GCAM, while in TIAM again Gas w/o CCS is added in Europe and ODA and Biomass w/ CCS in USA. Providing subsidies with fixed WACC values has a minor impact on capacity additions, but strangely in the years subsidies are provided (2025, and 2030), we observe a slight increase in renewables, especially in middle-income regions.

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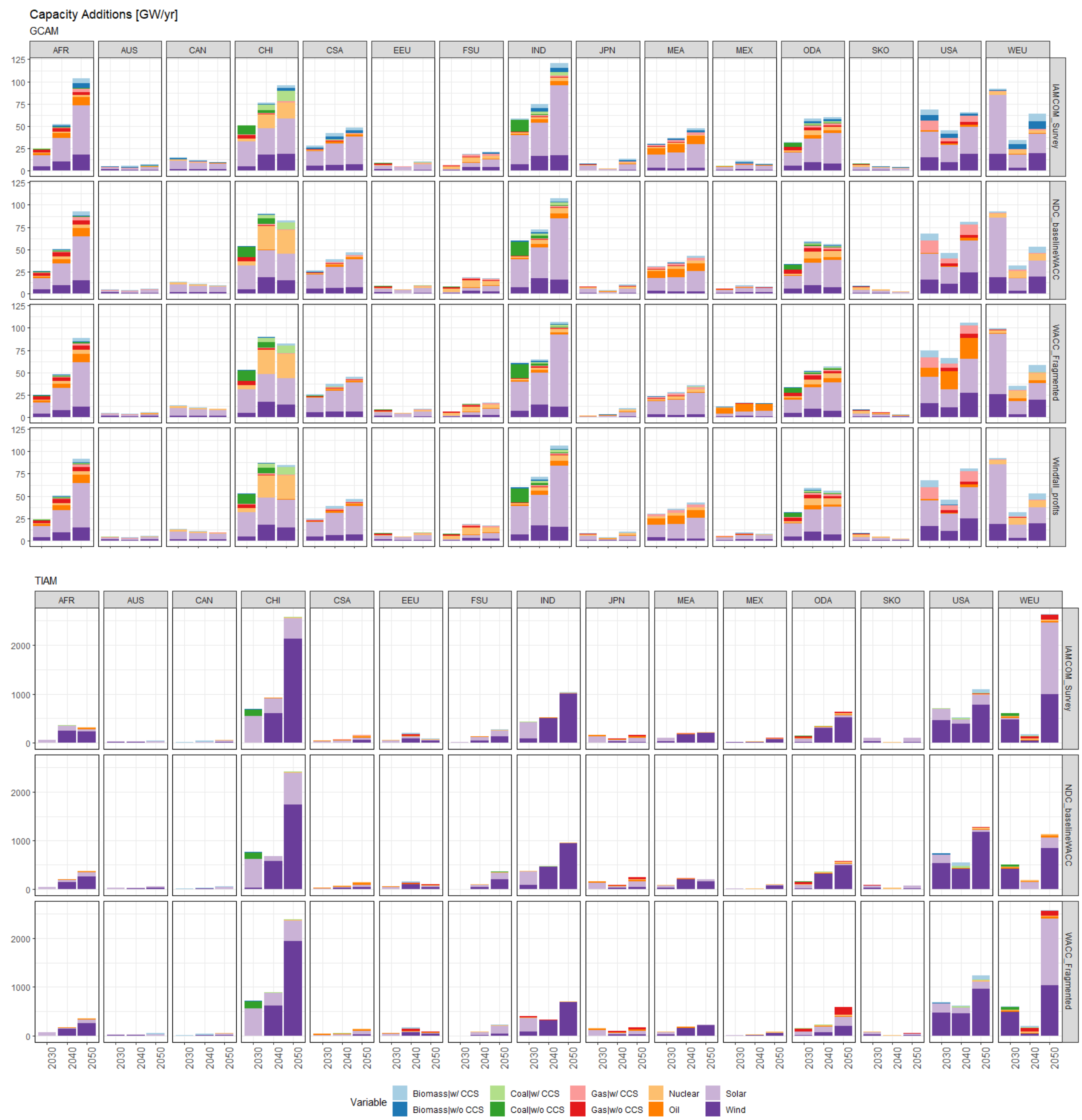

Figure 4-4: Capacity additions [GW/yr] by region and technology in CGAM (up) and TIAM (down) for all scenarios.

<u>Secondary energy</u>

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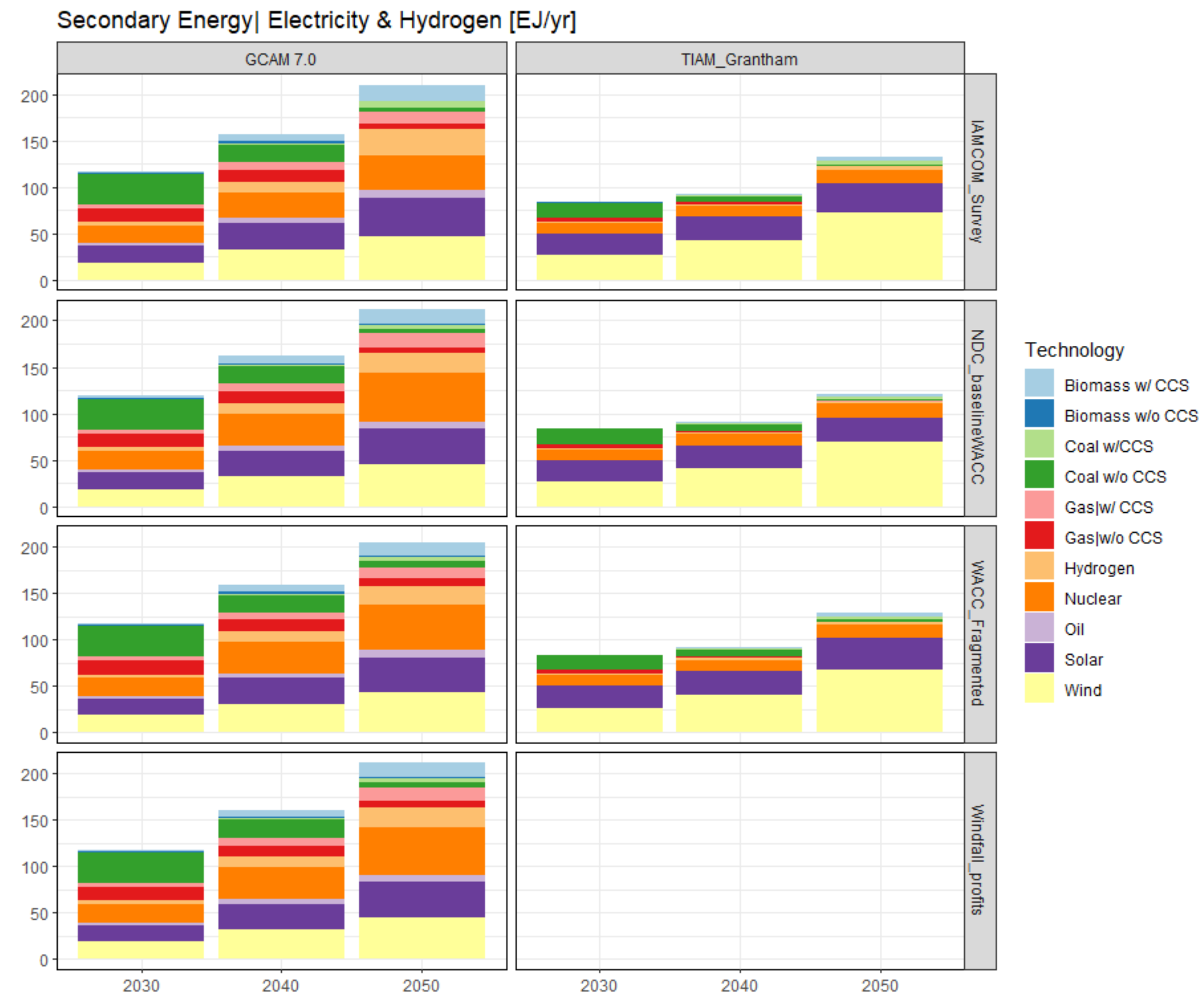

Figure 4-5: Absolute difference of global secondary energy by energy carrier (electricity, hydrogen) and source (wind, solar, biomass, coal, and gas with or without CCS, hydro, nuclear) compared to NDC_baselineWACC in GCAM (left) and TIAM (right) for all scenarios.

As investment risks across technologies increase (decrease) through higher (lower) cost of capital, the cost of electricity generation is higher (lower), and thus they get deployed less. In GCAM, when combining these trends (IAMCOM_Survey) nuclear power decreases electricity generation from nuclear substantially, shows a wider use of CCS in Biomass and Coal, and increases hydrogen electrolysis. TIAM also shows increased CCS in Biomass towards 2050, but the main effect is seen in solar & wind, which increase by 21% and 4% respectively.

In TIAM, a fragmented world shows minor differences to the baseline, the main effect being an increase of Biomass w/o CCS, Gas w/o CCS, and solar which wind and nuclear slightly decrease. In CGAM, coal also increases, as renewable risk in coal-dominated regions increase, encouraging coal use. Finally, subsidies towards high-risk regions have minimal impact on electricity generation, showing a slight increase in coal with and without CCS.

Distributional impacts

<u>Electricity prices</u>

Wholesale electricity prices in 2050 are increased in all regions in a scenario of higher fossil fuel WACC, ranging from 26% in Japan to 3% in Mexico. Despite the increased investments risks, fossil fuel technologies still get raising electricity prices. De-risking renewables would decrease electricity prices in all regions ranging from -4.5% in Africa to -1.95% in Japan, except for USA (1% increase) and South Korea (0.5%). Combining these pathways shows that, in some regions, lowering RES and CCS WACC while increasing those of fossils and nuclear can lead

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to lower prices; this is true for Africa (-3%), Mexico (-2%), Australia (-1%), Central and South America (-1%), and India (-0.5%); providing subsidies with WACC remaining constant slightly decreases prices everywhere, except for Australia (0.13%).

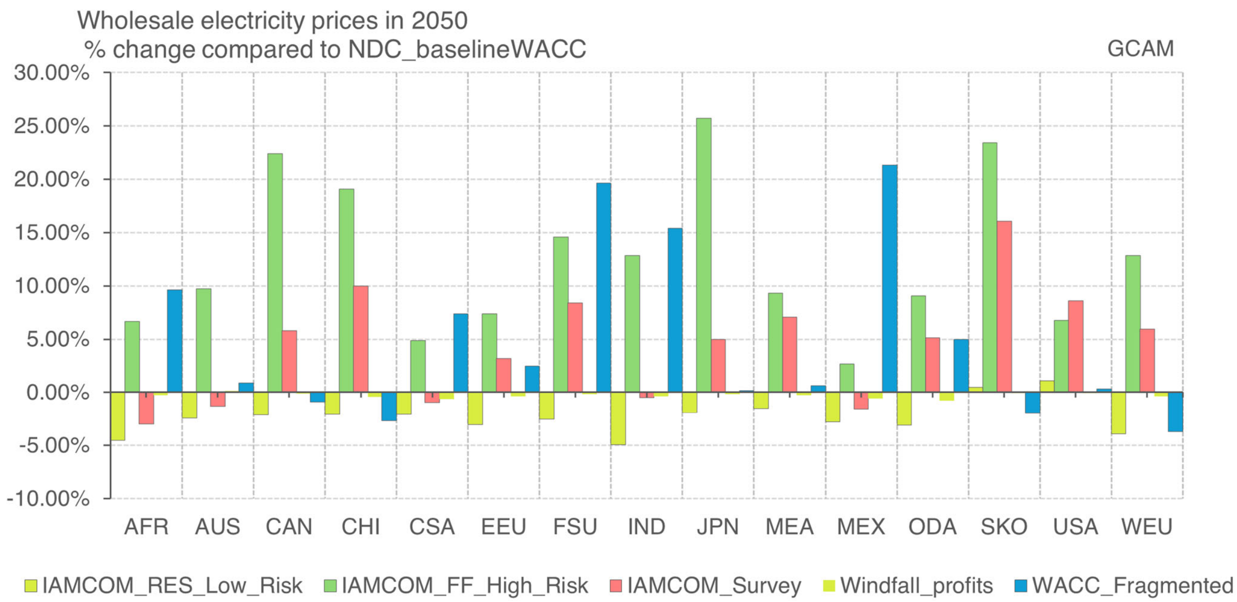

Figure 4-6: Wholesale electricity price in 2050 - % change compared to NDC_baseline_WACC in GCAM by region and scenario.

<u>Investments in electricity generation</u>

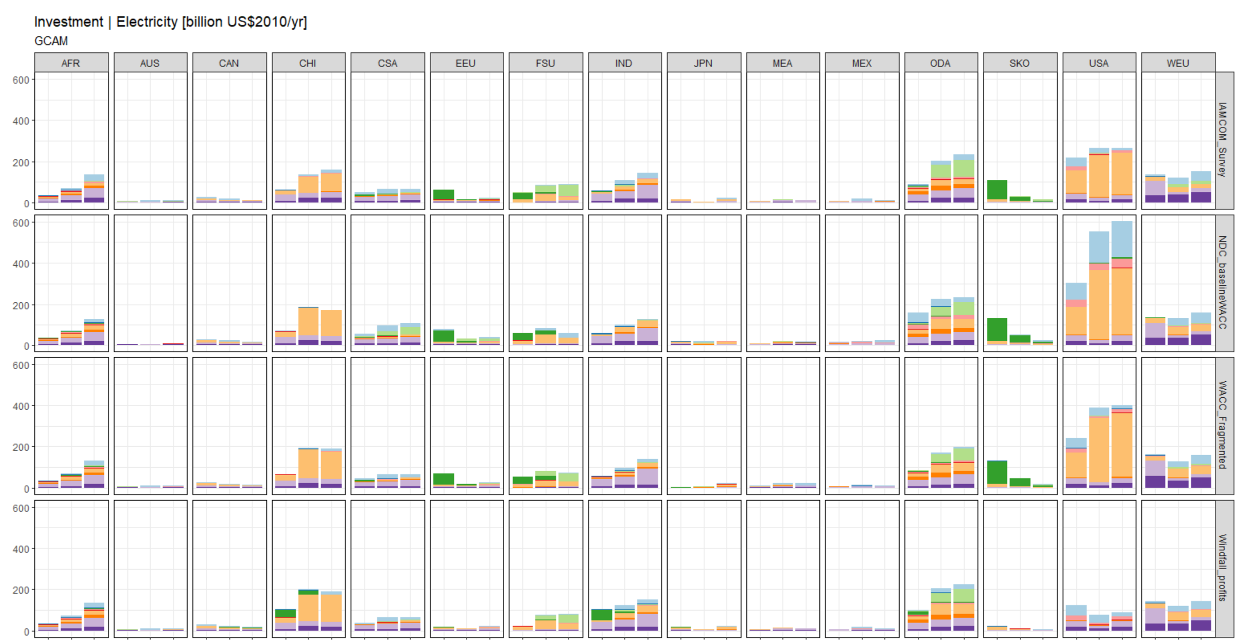

Figure 4-7: Investment by region and technology in GCAM for all scenarios.

In GCAM's NDC_baselineWACC scenario, most investments occur in China, India, EU-15, USA, and Middle East. Introducing technology and region-specific investment risks increases investment in China, FSU, Japan, South Korea, Africa, and South Asia compared to baseline in biomass, solar, and wind. Coal with CCS also increases, predominantly in China and India. A world with diverging investment risks among high and medium-low-income

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countries generally leads to increased investment in solar and coal, and decrease in gas, wind, nuclear, and biomass; it would also lead to a decrease in fossil fuels in some very high-risk regions (as they converge to the 75th percentile of the income category), and thus increase investments towards them (in Africa, and ODA). Finally, in the Windfall_profits scenario, regions not receiving subsidies are mostly not affected in terms of investments; the highest increases are seen in coal in Africa, FSU, SKO, and CSA, which indicates that subsidies alone did not drive clean energy investments when risks remain high.

4.4.2 Greek power sector impacts

We present modelling results from OSeMOSYS-GR in terms of short- and long-term impacts related to CO_2 emissions, power generation mix, capacities, and investments.

Electricity capacity

The results show that a fully renewable-based power sector in Greece will require significant capacity additions of renewable energy and storage technologies (Figure 4-8). Specifically, variable renewable energy (VRE) technologies, i.e., solar and wind, will cover more than 70 GW of the total electricity capacity in 2050 across all the scenarios, peaking at 74 GW in the "**Windfall_allocation**" scenario. In this scenario, solar PV and onshore wind installations take place at a much slower pace from 2024 to 2050, owing to the steep capacity growth in 2023 caused by the utilisation of the energy crisis' windfall profits for the development of new renewable energy projects. The higher VRE capacity in the "**Windfall_allocation**" scenario leads to further electricity storage requirements, i.e., pumped hydro and batteries, namely a total of 36.6 GW, 6.3 GW more than the "**NDC_baselineWACC**" scenario. This increase in electricity storage coincides with the decrease in the total geothermal capacity (2 GW less than in the baseline scenario) in 2050, since the increased storage capacity will enable a larger VRE electricity generation.

In addition, the electrolyser capacity increases by more than 14.2 GW until 2050 across all the scenarios under study, considering that green hydrogen will provide additional flexibility to the future power sector and energy system. Modelling results also suggest that a complete phaseout of the lignite-fired power plants post 2028, and of the natural gas-fired plants post 2037, is feasible from an energy planning standpoint, if the necessary investments in the green energy projects, indeed, materialise.

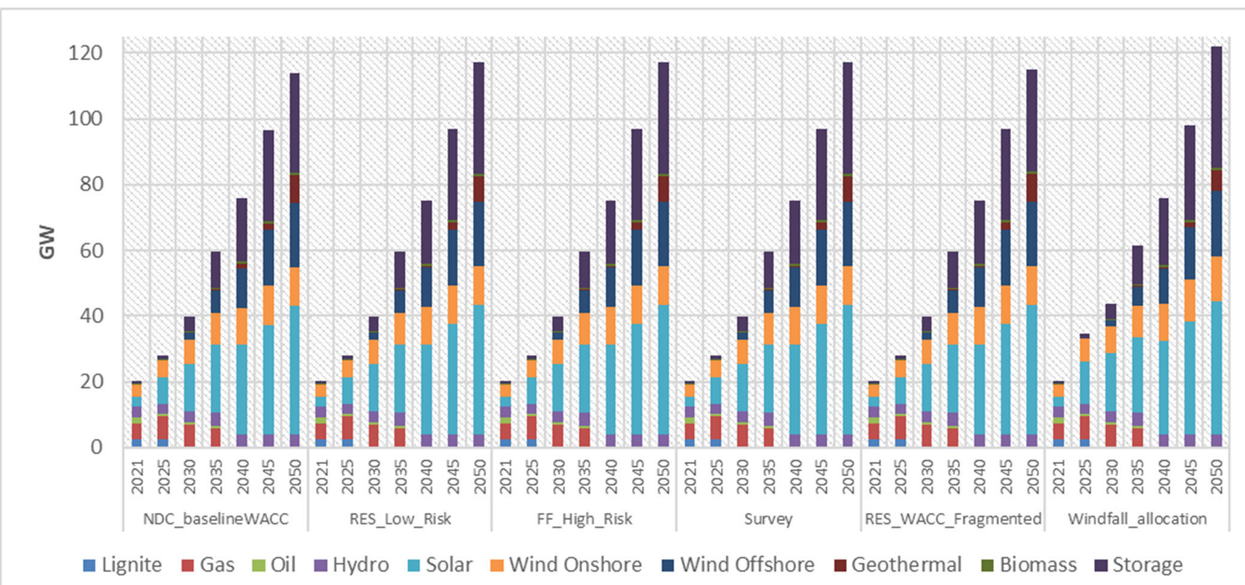

Figure 4-8: Electricity capacity in the Greek power sector by 2050, for the "NDC_baselineWACC", "RES_Low_Risk", "FF_High_Risk", "Survey", "WACC_Fragmented", and "Windfall_allocation" scenarios.

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Investments in electricity supply

As expected, the changes in the average annual investment per technology match with the trends assumed in the WACC scenarios, i.e., decreasing investment rates towards 2050 make technologies less capital intensive and vice versa (Figure 4-9). The results of the "**Windfall_allocation**" scenario reveal lower solar PV and onshore wind investments caused by the capital provision from the windfall profits. On the other hand, this scenario requires additional investments in electricity storage capacities to balance the increased electricity from the VRE technologies, subsequently lowering the investment needs for geothermal energy, which has the highest capital cost across all the technologies under study. This leads to this scenario being the second lowest in terms of the required capital investments. The scenario with the least required investments is the "**WACC_Fragmented**" scenario in which most of the examined technologies' WACC decreases by 2050, apart from electricity storage and geothermal which are assumed to have a fixed WACC across all scenarios. On the contrary, the "**FF_High_Risk**" scenario will require the most investments (slightly above the "**NDC_baselineWACC**" scenario) not only because the WACC of fossil-fuel technologies will increase, but also because the WACC of the VRE technologies will remain stable until 2050.

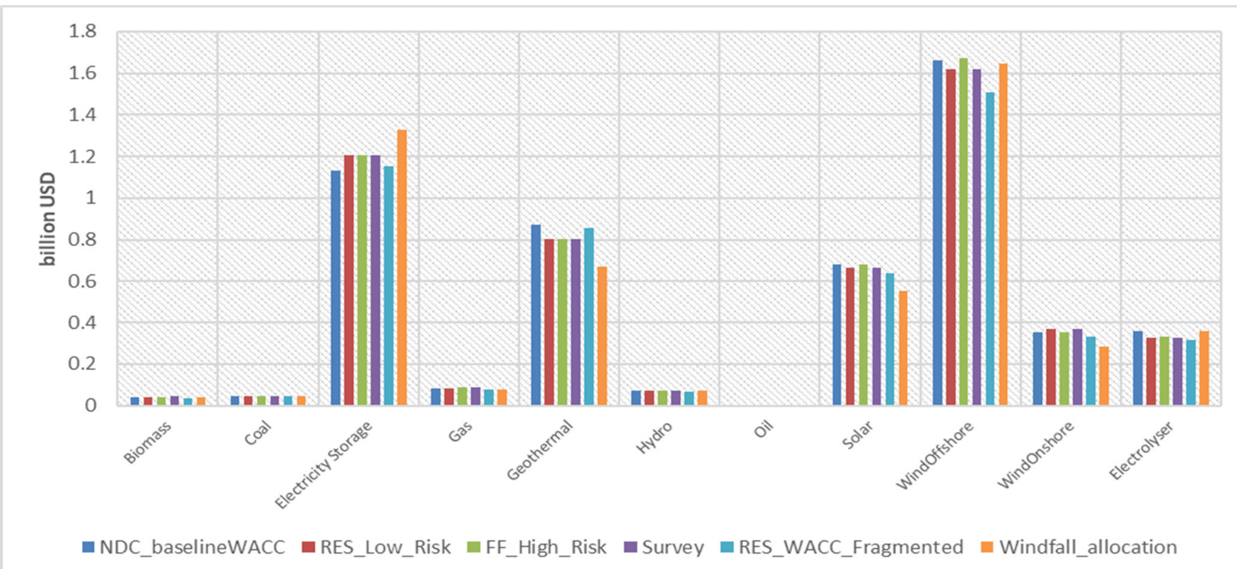

Figure 4-9: Average annual investment per technology in the Greek power sector by 2050, for the "NDC_baselineWACC", "RES_Low_Risk", "FF_High_Risk", "Survey", "WACC_Fragmented", and "Windfall_allocation" scenarios.

Power generation mix

Considering that all the scenarios assume a fully renewable-based electricity mix until 2040, electricity from biomass, lignite, gas, and oil is reduced by 100% until that time. The power generation mixes of the first five (5) scenarios are almost identical until 2050, while the electricity mix of the "**Windfall_allocation**" scenario presents some differences in 2025, 2030, and 2050 (Figure 4-10). These differences are mainly owing to the increased electricity generation from the VRE technologies, which, in 2025, along with the increased electricity from lignite offset the share of the natural gas-fired power plants to the electricity mix by a minimum of 24% in the "**RES_Low_Risk**", "**FF_High_Risk**", and "**WACC_Fragmented**" scenarios, and by a maximum of 39% in the "**Windfall_allocation**" scenario compared to the "**NDC_baselineWACC**" scenario.

Interestingly, in all the scenarios except for "**NDC_baselineWACC**", the electricity generation from lignite in 2025 increases by 53-73% considering that the 2025 carbon emission penalties used in these scenarios were lower than the one used in the baseline due to the derived shadow carbon prices. After the lignite phaseout in 2028, natural gas bounces back reaching very close to (in the "**RES_Low_Risk**", "**FF_High_Risk**", "**Survey**", and "**WACC_Fragmented**" scenarios), or even surpassing (in the "**Windfall_allocation**" scenario) the

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electricity generation levels of the "**NDC_baselineWACC**" scenario in 2030. In 2030, the combined increase in natural gas and VRE electricity generation, and, in 2050, the additional VRE investments (especially in onshore wind) make the "**Windfall_allocation**" scenario the one with the highest electricity generation.

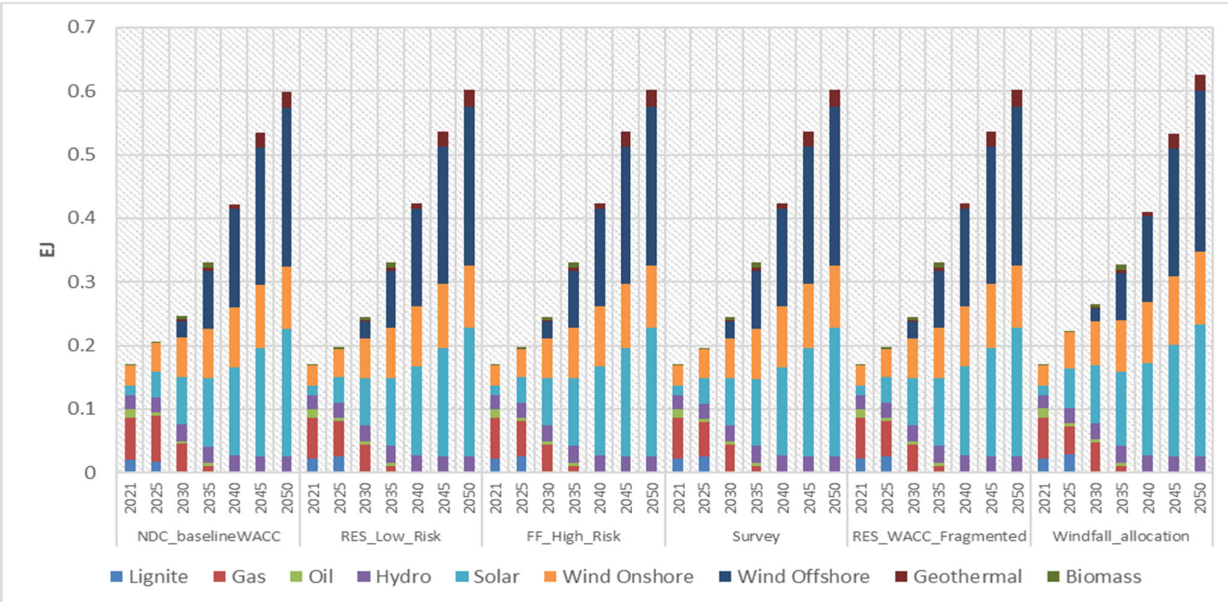

Figure 4-10: Least-cost annual power generation mixes in the Greek power sector by 2050, for the "NDC_baselineWACC", "RES_Low_Risk", "FF_High_Risk", "Survey", "WACC_Fragmented", and "Windfall_allocation" scenarios.

CO_2 emissions

Modelling results on the CO_2 emissions show that the lower -in the short-term- carbon emission penalties used in all the scenarios (except for "**NDC_baselineWACC**") do not force the model to decarbonise the system further than the exogenous emissions' limit (Figure 4-11). This is particularly evident in the short-term when there is more potential for lowering the CO_2 emissions, i.e., more fossil-fuel technologies with higher shares contributing to the electricity mix. In this regard, there are increased CO_2 emissions from lignite, which displace the reduced CO_2 emissions from natural gas in 2025 across all the scenarios (except for "**NDC_baselineWACC**"), while in 2030, there are increased CO_2 emissions from natural gas in the "**Windfall_allocation**" scenario compared to the baseline. This explains why there is no significant short-term CO_2 emissions reduction from the increased VRE electricity generation in the "**Windfall_allocation**" scenario and calls for a combination of tailored carbon tax policies and VRE policy instruments for the attainment of the Greek power sector's decarbonisation.

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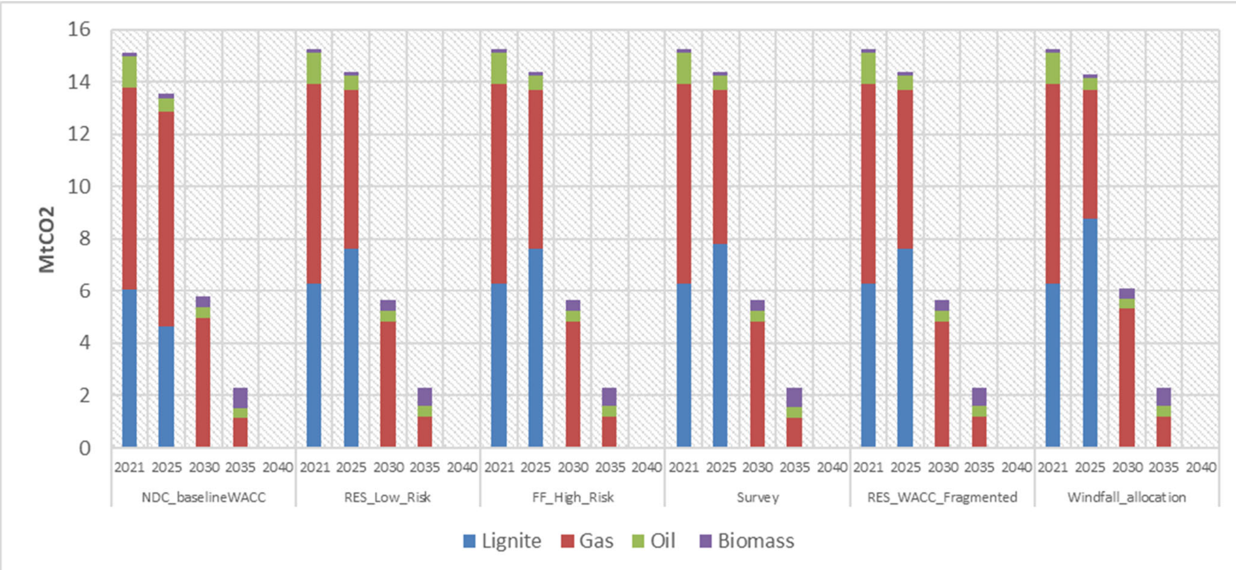

Figure 4-11: CO_2 emissions per power generation technology in the Greek power sector by 2050, for the "NDC_baselineWACC", "RES_Low_Risk", "RES_FF_High_Risk", "Survey", "WACC_Fragmented", and "Windfall_allocation" scenarios.

The results show that the WACC of the different power generation technologies will have direct impacts on the capital investments required to decarbonise the power sector in Greece. Much higher amounts of capital should be directed towards VRE investments, and thus their WACC will play a more significant role with regards to financing the power sector's decarbonisation compared to the ones of the fossil-fuel technologies. Given that the cost structure of the VRE technologies is composed mostly by capital costs, these investments are very susceptible to fluctuations in the interest rates.

At a global level, this is witnessed in the context of the current macroeconomic environment, which poses challenges to the renewable capacity expansion, due to **(i).** inflation that increases equipment cost and **(ii).** the higher interest rates that increase the financing cost of the VRE technologies, resulting in the halting of new VRE projects (IEA, 2023). Taking into account the uncertainty regarding the future trend evolution of the interest rates, and that unilaterally lowering the interest rates is not a reasonable approach for any country, as these are established by markets' expectations of growth, risk, inflation, and the competition for capital spending, governments should make targeted policy improvements to de-risk investments in renewable energy technologies. In particular, the Greek government ought to contemplate the following: **(a).** standardising the power purchase agreements and providing government guarantees to them to mitigate financial risks for off-takers, and **(b).** adjusting auction structures to align with the future macroeconomic conditions by indexing contract prices to a range of renewable technology-specific macroeconomic indicators (commodity prices, inflation, interest rates for distinct technologies, etc.).

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5 The impact of investors' expectations and climate risk assessment on mitigation scenarios

Study lead: *Alaa Al Khourdajie [Imperial]*

This Section will submitted to a peer-reviewed journal.

5.1 Introduction

Investors' expectations about the impact of climate risks, and of climate policies on economic activities is likely to play a key role in the reallocation of capital into the low-carbon economy (Kreibiehl et al., 2022). If investors have climate sentiments, i.e. form expectations about how firms' performance will be affected by different climate mitigation scenarios, depending on the firms' climate risk exposure, they can decide to revise their financial risk assessment, and thus the cost of capital that affects investment decisions (Dunz et al. 2021). For instance, in the EU, banks have to use climate scenarios provided by the Network for Greening the Financial System (NGFS) in their climate stress-test exercises (ECB, 2022). Thus, a bank that has knowledge of the climate scenarios, including those assessed by the Intergovernmental Panel on Climate Change (IPCC, 2022) or published by the International Energy Agency (IEA, 2022) for instance, could expect a worsening of the performance of fossil fuel extractive firms (e.g. coal), and decide to increase their probability of default and downgrade their risk profile. This, in turn, would influence the decisions of the bank to lend to these firms in the future, either by increasing the cost of capital to reflect the higher risk profile, or to stop lending for new extractive activities. The opposite would hold true for renewable energy firms, whose output and performance tend to increase in all climate mitigation scenarios (IPCC, 2022). Thus, by integrating climate considerations into their financial risk assessment, investors can influence firms' investment decisions and foster the structural change in the economy which is needed to achieve ambitious climate mitigation goals. However, if investors do not revise their risk assessment, they could maintain or increase the exposure to climate risks, thus delaying the transition and creating new potential sources of financial risk. Furthermore, such feedback loop between investors' expectations and scenarios can lead to multiple equilibria (Battiston et al., 2021) and in particular to situations where investments in renewables are largely insufficient to sustain what is required to support the low-carbon transition. Therefore, the finance sector (i.e. investors) could either hamper or enable the energy system low-carbon transition depending on its perception of future risks.

In this study, we operationalise the framework of Battiston et al. (2021) by linking process-based Integrated Assessment Models (IAMs) to a climate financial risk (CFR) model (Battiston et al., 2017) through an application of the MESSAGEix-GLOBIOM (Krey et al., 2020; Fricko et al., 2017) modelling framework across a wide range of energy supply technologies and climate scenarios[7], and the CFR model. The CFR model translates the impacts of climate scenarios on adjustment in firms' risk credit risk and financial valuation, considering shifts in market expectations about the impact of the transition from a baseline scenario (absence of climate policy) to a given climate policy scenario on firm's performance, based on the firm's technology and business model. This shift can modify the likelihood of a firm's default. For instance, for a firm whose assets are primarily fossil fuel-based, the introduction of a high carbon tax could mean the premature retirement of some of its assets and operations, thereby increasing the firm's default risk. Consequently, the costs of capital for the firm would increase to reflect

[7] We used mitigation scenarios generated by MESSAGEix-GLOBIOM based on the ENGAGE project methodology (Riahi et al., 2021). While the Network for Greening the Financial System (NGFS) scenarios are commonly used in the finance sector, we do not use NGFS scenarios here as they have very specific assumptions about net-zero and other long-term targets.

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the higher risk considering anticipated losses, leading to a higher yield to maturity (YTM)[8], which determines the required interest rates.

5.2 Methods

For the purpose of our analysis, we have identified three distinct narratives. They are designed to reflect the interplay between investors' expectations and the dual risk of: climate impacts, and climate policies. These narratives are:

1) Enabling – Long-term Policies and Goals with Immediate Action: under this narrative the finance sector (i.e. investors) thoroughly revises its risk assessment to reflect its perception of short and long term risks. This revision results in the realignment of interest rates for both high- and low-carbon firms with trajectories of long-term targets, announced policies and pledges (e.g. Nationally Determined Contributions (NDCs), Net Zero pledges). These trajectories also emphasise immediate action to achieve the Paris Agreement goals.
2) Enabling – Short term Announced Policies: investors exhibit a mild perception of climate-related risks. Accordingly, they align interest rates only with trajectories of short term commitments outlined under the 2030 NDCs pledges. Actions under such trajectories are insufficient for the 1.5°C temperature goal, given that post-2030 climate actions are minimal.
3) Hampering – Implemented Policies: investors do not align their expectations with climate risks. Therefore, interest rates remain based on prevailing market trends and current policies, irrespective of short term pledges or long-term policies and targets.

We map the revision in interest rates as a result of investors' expectations from the three narratives into a wider set of scenarios with various carbon budgets (e.g. carbon budget of 1000GtCO_2 for a 2°C scenario; or 2500GtCO_2 for >2.5°C) in order to reflect the three narratives.

5.3 Results and Discussion

Temperature change

[8] The yield to maturity is the discount rate that equates the value of an asset unit to the expected discounted value of a loan or bond at the time of issuance.

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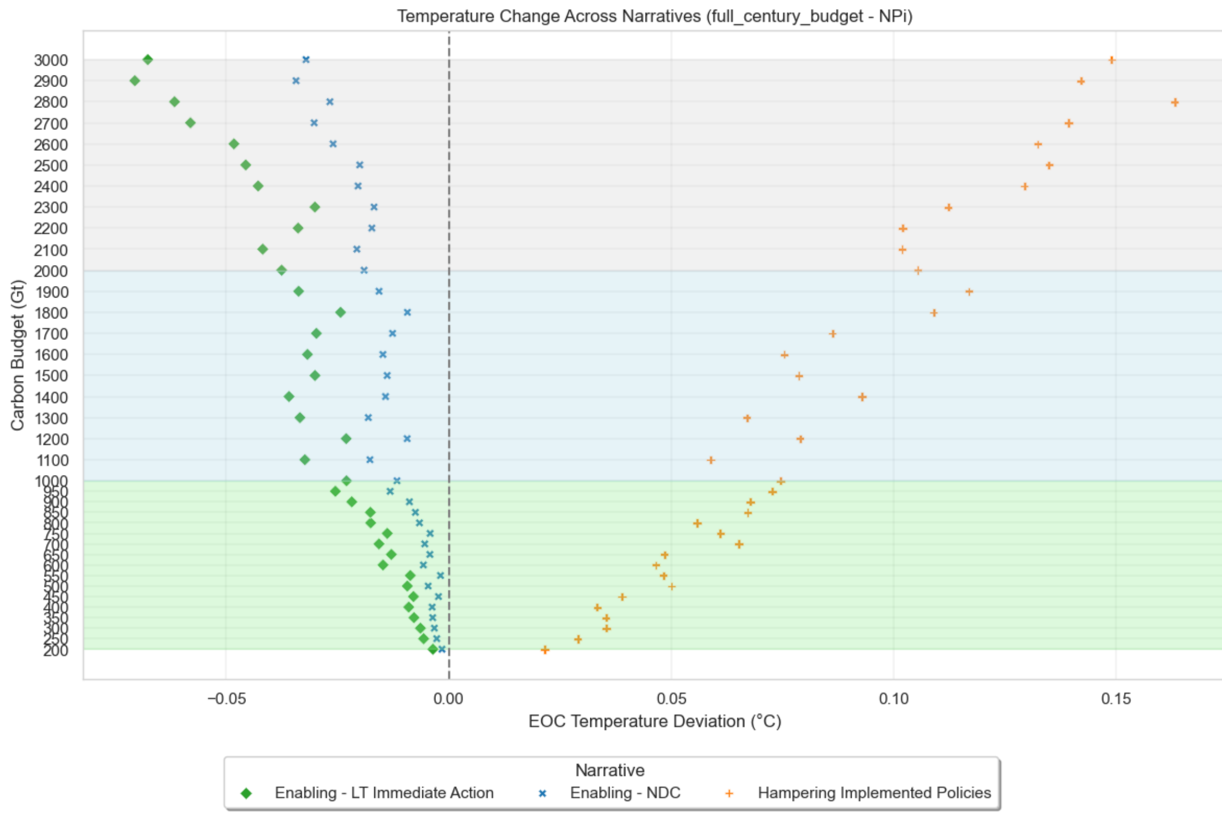

Figure 5-1: Visualises the association between the carbon budget (y-axis) and the absolute temperature change across different financial narratives concerning climate change mitigation (x-axis). Three distinct narratives are depicted: 'Enabling – LT Immediate Action' in green, 'Enabling - NDC' in blue, and 'Hampering Implemented Policies' in orange. These are compared to the original scenario runs, indicated by the vertical dashed line for x=0.

In the enabling narratives ('Enabling – LT Immediate Action' and 'Enabling – NDCs'), the clustering of points on the left of the dashed line suggests that when the finance sector revises risk assessments aligning with short-term and long-term targets, such as 1.5°C scenarios, it could potentially lower end of the century temprature than without the finance sector intervention in interest rates. Conversely, the 'Hampering' narrative, show points shifted to the right, indicating an increase in absolute temperature change for a given carbon budget. This shift suggests that when investors align their expectations with short-term policies or current market trends rather than long-term climate goals, it results in increased temperature change, reflecting a less effective mitigation outcome. The data implies that the financial sector's alignment with ambitious climate policies, or lack thereof, can have a tangible impact on the effectiveness of climate change mitigation, as reflected in the resultant temperature changes and carbon budgets.

Carbon Budgets (CB)

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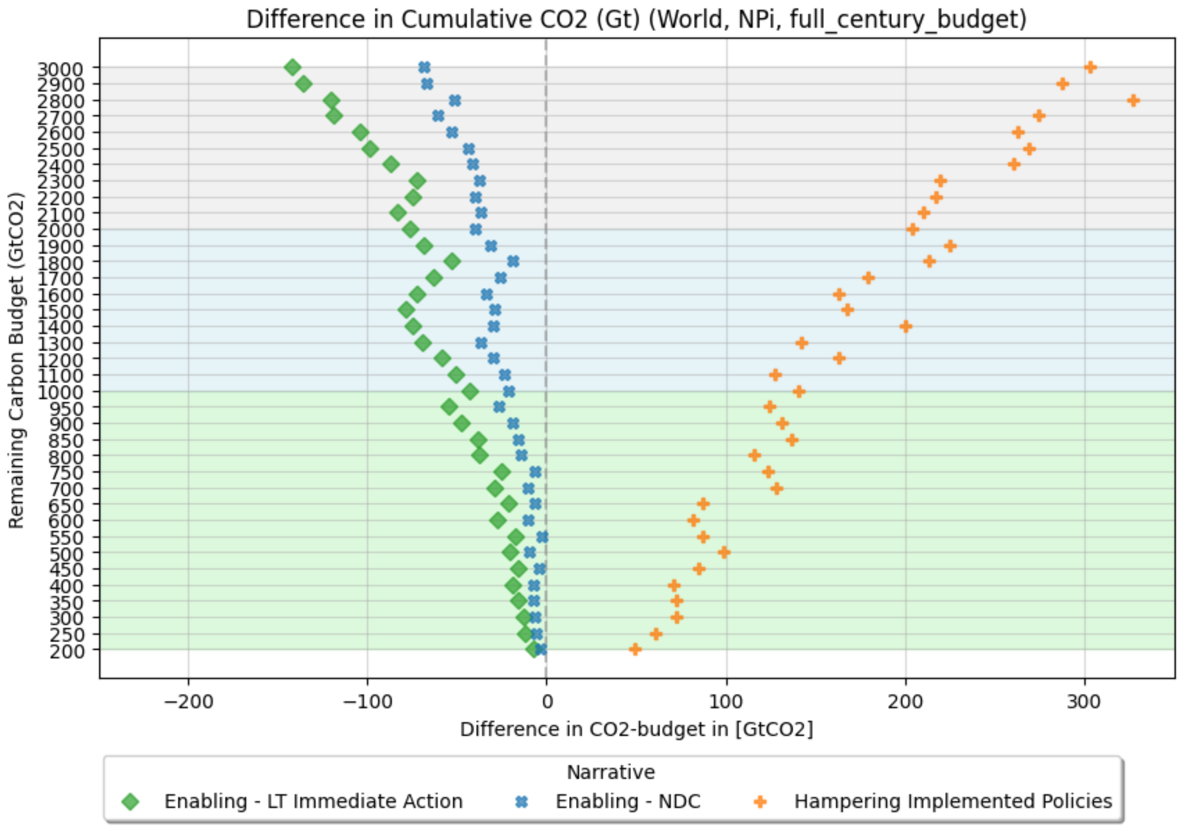

Figure 5-2: the figure provides a comparison of cumulative CO2 emissions across different finance narratives relative to an 'Original' scenario runs, which is represented by vertical dashed line at x=0. Three distinct narratives are depicted: 'Enabling – LT Immediate Action' in green, 'Enabling - NDC' in blue, and 'Hampering Implemented Policies' in orange. The y-axis corresponds to the carbon budgets of the scenarios assessed.

In the enabling narratives ('Enabling – LT Immediate Action' and 'Enabling – NDCs'), most scenarios are positioned to the left of the vertical dashed line, indicating a decrease in cumulative CO_2 emissions compared to the original scenario. This suggests that when the finance sector aligns interest rates with ambitious climate goals and starts immediate action, or with NDCs, there is an increase in the allowable CO_2 budget without deviating from climate targets. On the other hand, the 'Hampering Implemented Policies' narrative shows a increase in the cumulative CO_2 emissions compared to the original scenario runs, suggesting that adhering to current market trends without updating interest rates to reflect long-term climate risks results in a lower CO_2 budget.

CO_2 Net Zero Year (NZ)

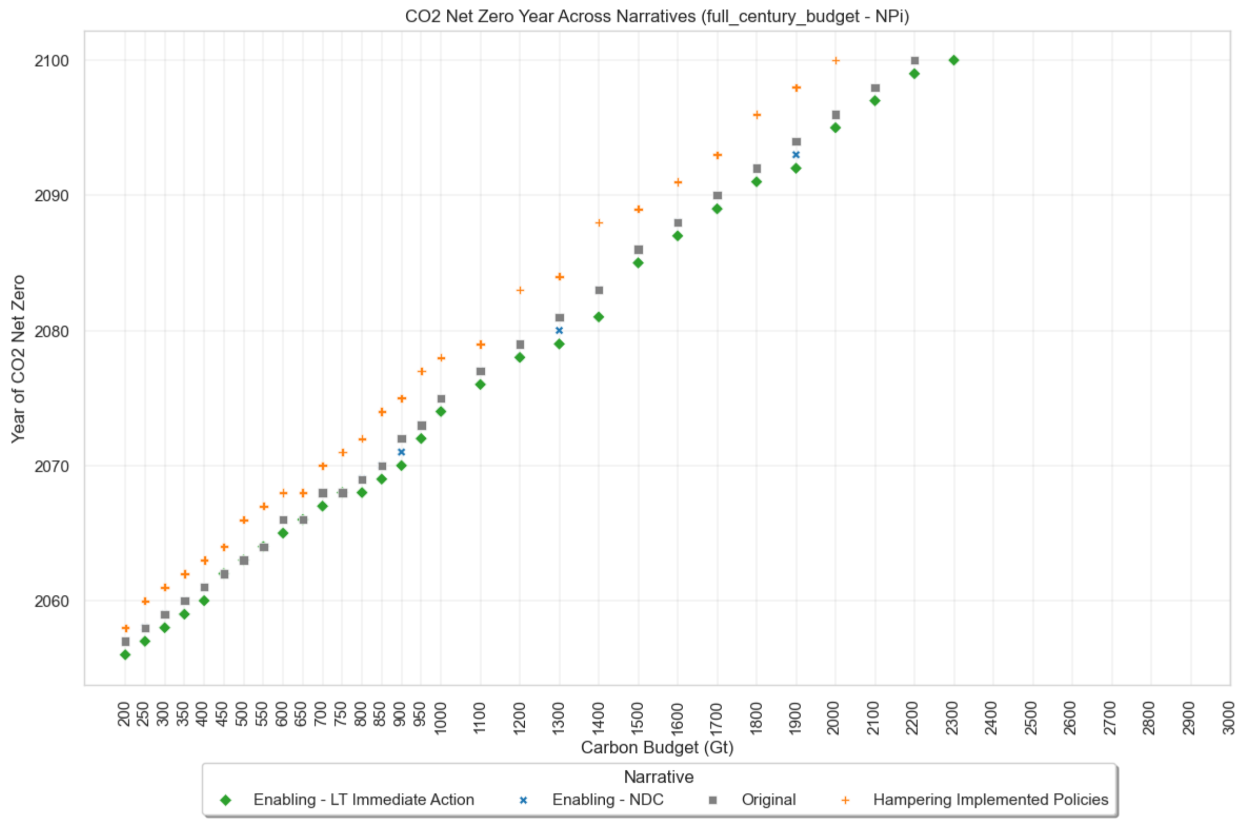

Figure 5-3: illustrate how the year in which net zero CO2 emissions are achieved varies across different finance narratives and carbon budgets. The y-axis represents the CO2 net zero year, while the x-axis indicates the carbon budget of the analysed scenario in gigatonnes (Gt).

In the enabling narratives ('Enabling – LT Immediate Action' and 'Enabling – NDCs'), have data points that generally correspond to earlier CO2 net zero years (below the grey rectangles) for a given carbon budget, suggesting that when investors adjust interest rates immediately in line with NDCs or long-term policies and goals, the transition to net zero can be achieved more quickly. The 'Hampering Implemented Policies' narrative case results in later net zero years, especially for larger carbon budgets. This narrative reflects scenarios where the finance sector's perception of climate risks is lower, and interest rates are set accordingly, leading to a slower transition to net zero. This emphasises that investors' expectations and the resulting adjustments in interest rates can significantly influence the timing of reaching net zero CO_2 emissions, with larger carbon budgets allowing more flexibility in the net zero year across narratives.

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6 Behavioural changes for climate policy: shifting focus from policy costs/effectiveness onto economic impacts (Study 7)

Authors: Mohamed Lifi, Jaime Nieto, Iñigo Capellán-Pérez, Gonzalo Parrado-Hernando, David Alvarez-Antelo, Juan Pérez-Marcos [UVa]; Dirk-Jan van de Ven, Clàudia Rodés-Bachs, Russell Horowitz [BC3]; Adrián Mateo, Noelia Ferreras [CARTIF].

6.1 Introduction

6.1.1 Brief recap of the research objectives of Study 7 and the methodology used

Study 7 endeavours to comprehend the economic ramifications arising from shifts in behaviour and social innovation, situated within the context of the energy transition as conceptualised in Task 5.5. This study emphasises the relevance of behavioural change as an added social value resulting from a policy, rather than focusing solely on evaluating its cost or effectiveness. Addressing the research questions that were generated within the Policy Response Mechanism, namely, “What are the economic impacts (rather than the cost or effectiveness of policy implementation) of a given behavioural change?” and 'How do heterogeneous discount rates across consumer categories affect the adoption rates of clean technologies?', Study 7 investigates the economic implications of considering the adoption rates of clean technologies in the context of heterogeneous discount rates across consumer categories. In other words, the general objective is to explore the potential of behavioural change and social innovation in climate action, with specific goals including the creation of common storylines, quantification of policies, modelling with the Consortium’s models, and assessing the implications of multi-modelled scenarios on climate action.

The study's focus includes a detailed analysis at the EU level, initially concentrating on the topic of transport. The proposed outcomes encompass assessing the effects of behavioural change on GDP, GHG emissions, required investments, employment, and the possibility of regional uniformity in behavioural change impacts. In summary, Section 6, as part of Task 5.5, contributes to a comprehensive exploration of the economic dimensions of behavioural change and social innovation in the transition towards a sustainable climate action.

6.1.2 Brief literature review on behavioural change

The terms "behavioural change" and "lifestyle" carry diverse meanings depending on the context and discipline, leading to potential misunderstandings. It is essential to establish a common ground in shared concepts (van den Berg et al., 2019). As defined by Akengi & Chen (Akengi & Chen, 2016), a sustainable lifestyle encompasses habits and behaviour patterns within a society, guided by institutions, norms, and infrastructures, with the objectives of minimising the natural resource use and waste generation while promoting fairness and prosperity. The IPCC emphasises that behavioural change is a demand-side strategy for sustainable development (Shukla et al., 2022). It involves individuals' preferences and actions, ranging from simple actions to transformative changes disrupting existing developmental trends. The categorization of behavioural change decisions is challenging due to various frameworks. The ASI framework by the IPCC classifies strategies as Avoid, Shift, or Improve, reflecting resource-use reduction, alternative service provision, and efficiency enhancement, respectively. The motivation for behavioural change varies with the socio-cultural shifts, influencing into “Avoid” measures, infrastructure affecting “Shift” options, and technology closely tied to “Improve” actions. However, such decisions may face psychological barriers and societal costs. Other classifications, such as efficiency, consistency, and sufficiency, provide additional perspectives. Definitions often overlap, highlighting the complexity of categorising behavioural changes.

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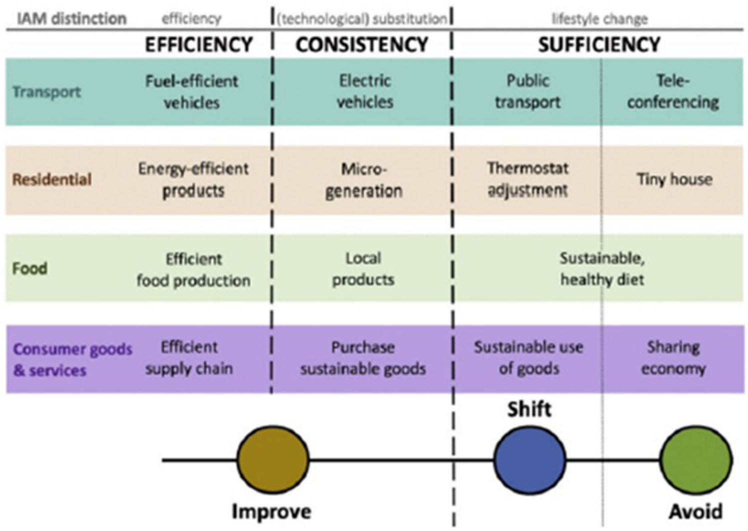

Figure 6-1: Different behavioural change decisions categorised in the different frameworks. Source: (van den Berg et al., 2019)

As illustrated in Figure 6-1, different behavioural change decisions are categorised in various frameworks (van den Berg et al., 2019). This figure provides a visual representation of the relationships between different behavioural change domains.

Despite the extensive research on promoting environmentally friendly behaviour, the potential benefits are underrepresented in Integrated Assessment Models (IAMs). Drivers and barriers influencing climate-related behavioural changes are multifaceted, including socio-demographic, economic, and psychological factors. The individual motivation, along with capacity and infrastructure, is crucial for an effective change. The IPCC calls for more research in understanding the causal mechanisms, narratives associated with technologies, the impact of social media, the effects of social movements, the dynamic feasibility of low-carbon transitions, as well as the effects of shocks and disasters on willingness and capacity to change. In summary, the representation of behavioural change in IAMs can contribute to increase the social awareness and, ultimately, enable behavioural change, addressing challenges in low-carbon transition feasibility and governance (Goldberg et al., 2020; Shukla et al., 2022).

6.2 Methodology, typology, and classification of models

6.2.1 Methodology

To achieve the objectives of Study 7, a comprehensive methodology has been proposed and followed, outlined as follows:

- **Step 1:** Fill Information Table
  - Models participating.
  - Behavioural change dials (Transport, Diets, Buildings, Goods/Services).
  - Parameters/Variables (Modal shift, Diet shift, Retrofitting, Consumption reduction).
  - Regional levels for behavioural change scenarios.
- **Step 2:** Simulate Baseline scenario
  - Use harmonization input data.
  - Apply to all models participating (WILIAM and GCAM).
- **Step 3:** Agree on Behavioural Change Scenario
- **Step 4:** Transport Simulation in WILIAM model
  - Use agreed scenario and endogenous GDP.
  - Obtain endogenous GDP results.
- **Step 5:** Apply GDP Results to Other Models (GCAM)

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- Include all behavioural change scenario dials.
- Models run on exogenous GDP assumptions.

➢ **Step 6:** Run Scenarios in All Modelling Teams
- Exogenous GDP prospects.
- Include agreed-upon behavioural change scenario dials.

➢ **Step 7:** Results Collection, Discussion, Decisions.

6.2.2 Description of model typologies and how that affects to modelling

During our study, a methodologically robust approach has been adopted by employing a diverse set of models, each characterised by distinct assumptions, sectoral and geographical disaggregation, and the treatment of key variables as either endogenous or exogenous factors. The inclusion of models with varying assumptions and structures allows for a more nuanced exploration of the potential range of outcomes, fostering a holistic understanding of the dynamics governing the subject matter. However, the utilization of diverse models, while enriching the analytical depth, introduces challenges related to model integration and comparability. Transparency holds paramount importance in this context as it fosters trust, reproducibility, and robustness in our study. Considering that, in the following sections we describe the main assumptions underlying the models involved in the study, with particular focus on those features related to behaviour.

6.2.2.1 GCAM model

The Global Change Analysis Model (GCAM) is a consolidated IAM aimed at exploring the human-Earth system dynamics of alternative long-term scenarios within a single computational platform at both global and regional scales (Calvin, Patel, Clarke, Asrar, Bond-Lamberty, Cui, et al., 2019b). The model runs in five-year time steps until the end of the century and is designed to analyse the interdependencies between the (1) energy, (2) agriculture, forestry, and other land use (AFOLU), (3) water, (4) socio-economic, and (5) climate systems. GCAM has been largely applied in different national and global studies including the scenarios by the Intergovernmental Panel on Climate Change (IPCC, 2022a), the development of the Shared Socioeconomic Pathways (Horowitz et al., 2022), or the U.S long-term strategy (Horowitz et al., 2022). Moreover, it is a community model, which can be downloaded from an open-source repository (https://github.com/JGCRI/gcam-core), and includes a complete documentation GitHub site, that gathers all the details of the different systems within the model, including input assumptions, parameters, equations, or solving algorithms (https://github.com/JGCRI/gcam-doc).

In GCAM, three behavioural change categories are modelled: transport, buildings, and food.

➢ **For transport:** GCAM transport dynamics relay on service demand of the available modes, size classes, and technologies (Kyle & Kim, 2011b; Mishra et al., 2013). Different fuels are accounted (e.g., liquids, electricity, hydrogen, gas), and different sectors are considered: international aviation, international shipping, passenger transport (walk, cycle, domestic aviation, train, bus, 2/3 wheelers, and 4 wheelers), and freight transport (domestic ship, rail, and light, medium and heavy trucks). For this exercise, overall transport demand (both passenger and freight), modal preferences (passenger only), and average car occupation have been modified in line with the LED scenario reported by Grübler et al. (Clarke et al., 2018).

➢ **For buildings:** GCAM disaggregates the building sector into residential and commercial sectors and models three aggregated services: heating, cooling, and other services. Several heating and cooling fuels are considered (e.g., biomass, coal, gas, liquids, electricity), and the floorspace can be exogenously specified or endogenously computed (Grubler et al., 2018a). For this exercise, the floor space, the thermal efficiency, and the level of building service demand have been modified in line with the LED scenario reported by Grübler et al. (Grubler et al., 2018a).

➢ **For food:** GCAM relies on the *ambrosia* package (Kanishka et al., 2021) to compute the food demand. It is based on the theory of Edmonds et al. (Ferreras et al., 2023), which divides the food consumption into two categories: staples, which represents basic foodstuffs, and non-staples, which represents higher-quality foods. Demand for staples increases at low income, but eventually peaks and begins to decline with higher income. Demand for non-staples increases with income over all income ranges; however, total (staple + non-staple) demand saturates asymptotically at high income. GCAM consider 21 food items (e.g., beef, corn, dairy, fruits, oil crops, fiber crops, nuts and seed), that can be aggregated into sectors

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and sub-sectors (e.g., protein-animal, protein-plant). For this exercise, consumer preferences for animal products have been exogenously modified in line with the LED scenario reported by Grübler et al. (Grubler et al., 2018a).

6.2.2.2 WILIAM model

The WILIAM model (Within Limits Integrated Assessment Model) is a new tool developed in the H2020-LOCOMOTION project, based on system dynamics, which has been designed thereupon MEDEAS models to address limitations in the field. System dynamics allows us to capture complex feedback loops and non-linear relationships between social, economic and environmental variables. WILIAM is made up of 8 modules: (1) demographics, (2) society, (3) economics, (4) finance, (5) energy, (6) materials, (7) land and water, and (8) climate. WILIAM aims to explore the social, economic and environmental implications of long-term socio-ecological transition pathways at both global and regional scales, considering planetary boundaries as well as socio-economic constraints.

In the current WILIAM 1.2. BETA version, two behavioural change categories are captured: transport and food.

- **For transport**: a comprehensive list of all the types of transport behavioural changes identified during the literature review:
  - AVOID (number of trips, trip distance):
    - Reduce vehicle usage.
    - Avoid medium and long-haul flights.
    - Closer holidays.
    - Teleworking.
    - Carsharing.
  - SHIFT (from unsustainable to sustainable modes), implies a transport mode change:
    - Shift from private vehicle (cars and 2-wheeled vehicles) to public transport (bus, train, airplane).
    - Shift from private vehicle (cars and 2-wheeled vehicles) to urban cycling/walking.
    - Shift from airplane to train.
  - IMPROVE (environmental performance through technological improvements), no mode change:
    - Switch to a more fuel-efficient vehicle.
    - Eco driving.
    - Carpooling.
    - Switch to low carbon vehicles (traditional ICE to electric, hybrid, biofuels, hydrogen…).
- **For food**: the land products demanded for food in WILIAM model are calculated based on diets driven by GDP and by policies of diet change. The Diet demanded is calculated for 9 regions and 14 food categories based on the combination of the Diet according to GDP, and the Diet according to policies. The Diet according to GDP is calculated using the historical patterns of food consumption vs gross domestic product per capita and extrapolating them into the future based on the GDP per capita calculated by the economic module of WILIAM model. The Diet according to policies is the desired sustainable diet to be obtained when policies of diet change are applied. Options are Flexitarian, Willet, Baseline, 100% Plant based, and 50% Plant based. The dynamic interaction between Diet according to GDP and Diet according to policies is driven by a stock Change to policy diets, that starts with 0 when the diet is only driven by GDP and reaches 1 when the full change to policy diet is achieved.
  - AVOID:
    - Sustainable and healthy diets.
  - SHIFT:
    - Diet addressed by the local food production.
  - IMPROVE:
    - Reduction of waste food.

6.2.3 Representation of behaviour-related policies in IAM COMPACT (Task 4.1)

In the Deliverable 4.1 "From Policy Needs to Scenario Frameworks", a comprehensive review of modelling capabilities of the IAM COMPACT models was conducted. This analysis covered both which policy measures (or,

in the case of behavioural changes, which social trends) could be represented by IAMs and the mechanisms used to achieve these changes (policy instruments).
While the review was a holistic approach to the policy representation, including several sectors such as buildings, energy or agriculture, the social factors were also very relevant, considering different categories like behaviour, education, labour, and governance. Focusing on what is pertinent for this deliverable, the modelling of eight behavioural trend shifts was tracked:

- Travelling less: Reducing the distance and/or frequency of trips. It could be enhanced by changing work patterns or by promoting local tourism.
- Modal shift: Changes in the mode of transportation, using public transport, bicycles or shared cars instead of individual private cars.
- Less energy service demand: This reduction can be achieved by increasing the energy efficiency or applying innovative technologies, but also by modifying lifestyles towards less energy consumption in everyday activities.
- Lower material consumption: Decreasing the quantity of materials used to manufacture goods or even if services, either by choosing sustainable, durable and less resource-intensive products or by following circular economy guidelines.
- Less product demand: Changes in the behaviour of consumers towards a less materialistic lifestyle, influenced by economic factors and/or social awareness.
- Change of diet: It encompasses changes in food consumption, moving from current food options to a plant-based diet with organic and locally produced products.
- Less food waste: It includes a better food management, addressing environmental impact of food waste and changes in consumer behaviour towards less but smarter purchasing.
- Change of values: This trend covers shifts in people's beliefs and ideals towards building up a society with a greater environmental, social and ethical consciousness.

Regarding policy instruments, almost all of them can be employed to generate a certain change, from taxing meat and oil to establish renewable energy obligations. As such, those instruments closer to behavioural changes could be the "soft" ones. This group includes the provision of information, professional training and qualification and the use of performance labels and advertisements. Although policy measures and instruments have been mapped for all the models, this has been done separately, i.e. it has not been pointed out which mechanism is used to implement each measure. This task could be one of the key challenges to address in future deliverables. Table 6-1, Table 6-2, and Table 6-3 show the information extracted from D4.1 about the behavioural Change Policy Measures/Trends represented by each IAM COMPACT model (see Table 36 from Deliverable 4.1 (Ferreras et al., 2023) for further information).

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Table 6-1: A. Behavioural Change Policy Measures/Trends represented by each IAM COMPACT model. Yes, if representable; M, if representable with some modification or proxy; Blank, if not representable.

		Policy measure/trend	CHANCE	IMACLIM-China	BLUES	GCAM	GCAM-USA	MUSE	SLIM-India	TIAM
SOCIAL/ BEHAVIOURAL	Behavioural/ Consumption	Travelling less	Yes			Yes		M	M	M
		Modal shift	Yes			Yes		M	M	M
		Less energy service demand	Yes	Yes		Yes		M	M	M
		Lower material consumption						M	M	M
		Less product demand	Yes	Yes		Yes		M	M	M
		Change of diet	M			Yes		M		
		Less food waste				Yes		M		
		Change of values						M		

Table 6-2: B. Behavioural Change Policy Measures/Trends represented by each IAM COMPACT model. Yes, if representable; M, if representable with some modification or proxy; Blank, if not representable.

		Policy measure/trend	CLEWs	DyNERIO	MEDEAS	WILIAM	Calliope	China-MAPLE	EnergyPLAN	EXPANSE
SOCIAL/ BEHAVIOURAL	Behavioural/ Consumption	Travelling less	M		M	Yes				
		Modal shift	Yes			Yes		Yes		
		Less energy service demand	M		M	M		Yes		
		Lower material consumption	M		M	M				
		Less product demand	M			M		Yes		
		Change of diet	M			Yes				
		Less food waste				Yes				
		Change of values								

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Table 6-3: C. Behavioural Change Policy Measures/Trends represented by each IAM COMPACT model. Yes, if representable; M, if representable with some modification or proxy; Blank, if not representable.

		Policy measure/trend	MENA-EDS	OSeMOSYS	PROMETHEUS	DREEM (TEEM)	ATOM (TEEM)	WISEE-EDM Industry EU	WISEE-EDM global steel	WTMBT
SOCIAL/ BEHAVIOURAL	Behavioural/ Consumption	Travelling less	Yes		Yes					M
		Modal shift	Yes		Yes					M
		Less energy service demand	Yes		Yes	Yes				M
		Lower material consumption	Yes		Yes	M				
		Less product demand	Yes		Yes	M				
		Change of diet				M				
		Less food waste				M				M
		Change of values				M	Yes			

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As reflected in the tables above, some of the IAMs are capable of directly representing (without any modification) most of the proposed behavioural changes. Thus, the models with the highest social capacity are (in descending order): GCAM, MENA-EDS, PROMETHEUS, WILIAM and CHANCE. On the other hand, other models such as MUSE, CLEWs o DREEM could model many of the above-mentioned trends, but in an indirect or modified way.
Focusing on the behavioural trends themselves, the reduction of energy demand can be represented by 14 IAMs (7 directly and 7 with some modifications), followed by less production demand by 12 (6 and 6, respectively). In contrast, the changes in values and reducing food waste are slightly modelled.

6.2.4 Typologies, behaviour-related policies, and commonalities between models

Considering the use of a diverse set of models, coordination is a paramount necessity in a study such as this one. This entails looking at typologies, policy representation and model linking, as described in Deliverable 3.4 (D3.4), and in scenarios harmonisation, explained in Deliverable 4.3. Considering the D3.4.'s framework, whereas most of the differences among models involved in this study are not relevant in practical terms, others are. Particularly, features regarding approach and methodology, as well as sectoral and spatial granularity. The models used in this study rely on different approaches, from partial equilibrium (GCAM) and disequilibrium (WILIAM) IAMs, to energy and electricity system models (PROMETHEUS, OSeMOSYS and TEEM). Moreover, while WILIAM is a simulation model, the others are based on different optimisation methods. The most challenging issue is related to the consideration of some key variables either endogenous or exogenous. Sectoral and geographical disaggregation also played an important role in designing the scenarios acknowledging for the model's capabilities.

Additionally, policy representation in the models involved is different from each other, adding another layer of complexity to the scenarios' definition. Particularly, Deliverable 4.1. identifies a set of policies represented in the IAM COMPACT models registered as "Social/behaviour". Taking that classification as a starting point, behaviour-related policy representation has been collected in Table 6-4. In this Table, it is identified the common topics/sectors that are addressed, as well as the key policies, variables and regional levels that can be analysed. For the topical/sectoral disaggregation, it has been taken into consideration the framework identified by (van den Berg et al., 2019), selecting "Buildings", "Diets", "Transport" and "Other" (normally related to goods and services consumption) as the key topics for behavioural change in IAMs. The models' capabilities to represent behaviour-related policies effectively constrain the scenarios design in this 1st modelling cycle. Thus, the results obtained within the Policy Response Mechanism have been linked with the models' capabilities described in this section. The next section describes this process.

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Table 6-4: Behaviour-related policy representation in IAM COMPACT models

MODEL	TOPIC	POLICY/SCENARIO	VARIABLE/PARAMETER	REGIONAL LEVEL 1	REGIONAL LEVEL 2	REGIONAL LEVEL 3	REGIONAL LEVEL 4
GCAM	Buildings	Lifestyle change	Heating/cooling demand	World	Europe		
		Energy efficiency	Renovation rate *(exogenously)*	World	Europe		
		Preference towards green technologies	Adoption rate (e.g., heat pumps)	World	Europe		
DREEM	Buildings	RES & energy efficiency (in coal & carbon intensive regions)	Renovation rate and adoption rate of heat pumps			National	Sub-National
		PV self-consumption & storage. Cost-benefit analysis for consumers.	Adoption rate of PV & storage			National	Sub-National
ATOM	Buildings	Small-scale PV & storage adoption	PV & storage cost/ Change of values towards investing in PV & storage			National	
GCAM	Diets	Dietary shift	Type of diet, % population using certain diet	World	Europe		
		Trade and production	Domestic production vs imports	World	Europe		
WILIAM	Diets	-Policies of diet change to several standardised diets (Flexitarian, Willett, Baseline, 100% Plant-based, and 50% Plant-based, Vegetarian, and Vegan diets). -Percentage of the population expected to adopt the new dietary policy.	Diet according to policies and share of change to policy diet	World	Europe	National	
OSeMOSYS-GR	Other	Impact of sociopolitical movements on the energy mix	Capacity constraints to specific technologies			National	
GCAM	Transport	Policies of reduction	Use of polluting transport (cars, flights etc.)	World	Europe		
		Modal shift	Transport modal share	World	Europe		
		Reduced activity	Reduced p-km,tn-km or cars	World	Europe		
WILIAM	Transport	Modal shift	Number of passengers per private vehicle	World	Europe	National	

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		Modal shift	Modal share matrix	World	Europe	National	
		Policies of reduction	Use of polluting transport (cars, flights etc.)	World	Europe	National	

6.3 Stakeholders' input, Data flow, and scenario protocol

6.3.1 Stakeholders' input

The "Behavioural Change workshop", organised within the framework of IAM COMPACT, aimed to foster collaboration between the IAM COMPACT modelling team and key stakeholders, including policymakers, industry associations, and civil society representatives.

During this workshop, valuable insights were sought on the research agenda, realistic scenario design, and potential applications of the analysis. By engaging with senior energy and climate policymakers, the workshop directly contributed to IAM COMPACT's study 7 about "What are the economic impacts (rather than the cost or effectiveness of policy implementation) of a given behavioural change?". The topics that were discussed are as follows:

- Most anticipated behavioural changes.
- Potential barriers to adoption of cleantech and/or sustainable lifestyles.
- Beyond raising awareness: potential structural change requirements to enable behavioural change.

And here is the list of stakeholder inputs from the IAM COMPACT workshop:

1. **Anticipated Behavioural Changes for Decarbonization:**
   a. **Transport Sector:** Stakeholders prioritised modal shifts, advocating for shifts from air to rail transport and private cars to public modes, including biking. They also highlighted the importance of reducing overall transport through urban planning and car-sharing.
   b. **Dietary Changes:** Stakeholders emphasised reducing meat and dairy consumption, promoting local food production, and decreasing ruminants' intensity.
   c. **Buildings:** Renovation, heat pumps, and district heating were identified as essential for decarbonizing the building sector.
   d. **General Consumption:** Stakeholders stressed a need for reducing overall consumption of goods and services, emphasizing a shift from individual to systemic behavioural changes.
2. **Barriers to Adoption of Clean Tech and Sustainable Lifestyles:**
   a. **Cultural Barriers:** The challenge of transitioning from comfortable lifestyles, particularly in the Global North, was acknowledged.
   b. **Advertising Influence:** Stakeholders cited advertising's role in promoting unsustainable consumption patterns, such as cheap flights and SUV purchases.
   c. **Information Gap:** Lack of timely information to consumers and time constraints for informed decisions were recognised as barriers.
   d. **Infrastructure Issues:** Inadequate and unsafe infrastructure, especially for cycling, was highlighted as a barrier.
3. **Structural Changes Needed for Behavioural Change:**
   a. **Supply Side Changes:** Stakeholders proposed grey/brown energy taxes, information on carbon intensity, "time of use" tariffs, and smart city transformations.
   b. **Drivers of Change:** Well-informed policy making, urban and system planning, sharing success cases, and clarifying competencies in public administration were seen as critical.
   c. **Public Sector's Role:** The public sector was identified as key in discouraging building demolition, incentivizing renovation, and influencing the financial sector toward behavioural change.

6.3.2 Link with models' capabilities and gaps

Following the collaborative workshop between the IAM COMPACT modelling team and stakeholders, all outcomes and ideas put forth by the stakeholders have been meticulously collected. Subsequently, we have initiated the process of translating these proposed concepts into the modelling stage. This involves a comprehensive evaluation to determine the capability of our models in effectively representing and simulating the suggested behavioural changes and structural modifications presented by the stakeholders. Through this iterative approach, we aim to validate the alignment between stakeholder insights and the modelling framework, ensuring that our integrated assessment models robustly capture the intricacies of the proposed scenarios and contribute meaningfully to the ongoing study. Table 6-5 reports the stakeholders' propositions corresponding to their respective questions, and outlines whether the IAM COMPACT models can currently address the stakeholders' propositions directly or if they can be represented using proxies.

Table 6-5: Stakeholders' propositions and IAM COMPACT models' capacity to respond to them.

Stakeholders' Questions	Stakeholders' Propositions	Topic	Elements of qualitative discussion	Models can currently answer to the stakeholders' proposition	Models can represent with proxys?
Q1: Which behavioural changes are the most anticipated and necessary to decarbonise?	Change in diets to less meat intensive	Diets		WILIAM & GCAM	
	Change in diets to less ruminant intensive			WILIAM & GCAM	
	Dairy production (milk)			GCAM	
	Boosting local production of food (seasonal, organic)			GCAM	
	Private transport vs. Public transport	Transport		WILIAM/GCAM/PROMETHEUS	
	Impacts of freight transport of goods around the globe			WILIAM/GCAM/PROMETHEUS	
	Alternatives to short-haul flights: rail infrastructure			WILIAM/GCAM/PROMETHEUS	
	Reduce car activities: car sharing, bike sharing			WILIAM/GCAM/PROMETHEUS	
	15-minute city		X		Policies of reduction of transport
	Modal shift to cycling (also rural)			WILIAM/GCAM/PROMETHEUS	
	Home delivery (electricity all urban transport)			WILIAM/GCAM/PROMETHEUS	
	Heat pump or wait for district heating	Heating / Buildings		DREEM/PROMETHEUS	
	Home renovations (energy efficiency improvements)			DREEM/ATOM/PROMETHEUS	
	Urban density			WILIAM	
	Paying for grey/brown energy	Supply Side			
	Information about carbon intensity of the grid		X		
	Time of use tariffs for electricity		X		
	Choice of electricity suppliers for different appliances		X		
	Transform cities into smart cities		X		
	I-frame vs. S-frame solutions	General	X		
	Changes within system vs. changes to the system		X		
	Collaborative consumption (e.g. car sharing, co-homing)			WILIAM/GCAM/PROMETHEUS	
	Represent s-frame system changes in IAMs		X		
	Policy choices focused on global north context		X		
	General consumption Reduction			WILIAM/GCAM/PROMETHEUS	
Q2: Which potential barriers affect the adoption of clean tech	Limitations to consumer choices	General		WILIAM/GCAM/PROMETHEUS	
	Adherence to comfortable /luxury lifestyles				Changes in consumption patterns
	Friction with sustainable choices (e.g. train vs flying)			WILIAM/GCAM/PROMETHEUS	

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and/or sustainable lifestyles?	Safety infrastructure to enable modal shift (e.g. bike lanes, night lighting)			GCAM/PROMETHEUS	
	Smart meters needed for smart electricity consumption (responsive to system)				
	Commercial offers of time of use tariffs		X		
	Time/resources to learn new consumption habits (e.g. electricity)				
	Market opportunities for smart electricity use (ancillary services etc)		X		
	Lack of knowledge/information/awareness about behavioural impacts		X		
	Advertising pushing SUV uptake, cheap flights, etc			GCAM/PROMETHEUS	
	Food environments (layout of supermarkets / marketing / promotions)		X		
	Fear of losing agency over consumption		X		
	Lack of agency (e.g. energy poverty)		X		
Q3: Beyond raising awareness: which potential structural changes are needed to enable behavioural change?	Policymaking decisions	General	X		
	Categorise behavioural changes (food, transport, etc)		X		
	Urban planning and sharing of best practice (towns /cities)				
	System planning		X		
	Clear definition of competencies (European, National, Municipal)		X		
	Financing to scale technological solutions		X		
	Restructure finance system and allow investors to support truly green companies				
	Reform financial offers such that discount rates are aligned to transition needs (EVs and heat pumps)				
	Reframe energy system to serve consumers (secure power, heat)		X		
	Renovate buildings rather than demolish			GCAM/DREEM/PROMETHEUS	

6.3.3 Scenarios protocol' outline and topics

6.3.3.1 Scenario protocol

In Study 7, four scenarios, "NDC_LTT", "NDC_LTT_Trans", "NDC_LTT_LED", and "NDC_LTT_LIFE", have been defined and proposed for use in the IAM COMPACT models. For this first modelling cycle, three models, namely WILIAM and GCAM, are employed to generate results for selected outcomes, including GDP, sectorial emissions, employment, and total investment in the energy sector. Further details about the four scenarios and their narratives can be found in Table 6-6.

Table 6-6: Scenario protocol used in study 7.

Scenario name	Narrative	Current polices till 2030	Model used to apply the scenario
NDC_LTT	-Benchmark scenario	Current Policies	All
NDC_LTT_Trans	-Preference for the public transportation like bus and railways for short and medium distance -Preference for electrified 2W and 3W	Current Policies	WILIAM
NDC_LTT_LED	-Behavioural mitigation measures in transport sector as mentioned in scenario 2 -Floor space converges downwards to a similar level as trends towards suburban single-family dwellings revert to urban living in cleaner, less congested, more amenable cities. -Reduction in final energy demand due to retrofitting	Current Policies	GCAM
NDC_LTT_LIFE	-Behavioural mitigation measures in transport and building sector as mentioned in scenario 3 -Change in dietary Preference: vegetable-based diet and less meat consumption	Current Policies	GCAM

6.3.3.2 Technical description of the four chosen scenarios

6.3.3.2.1 "NDC_LTT" scenario

The NDC_LTT scenario follows the same scenario protocol as the NDC_LTT scenario developed in Study 1 of the PRM-1 (see Deliverable D4.5 "National, regional, global mitigation pathways"). It describes a world in which all countries implement all the current climate policies and achieve the GHG emissions reduction targets aimed at in their respective NDCs up to 2030. After 2030 the long-term targets (LTT) of countries, including net-zero strategies of major economies are included as a linear pathway from the 2030 NDC target. The scenario leads to a temperature increase of 1.7-1.8 °C above pre-industrial levels in 2100, as assessed in Van de ven et al. (2023). With regards to steel trade, the scenario does not put any constraints on EU steel trade. Both carbon leakage as well as the renewables pull effects may lead to offshoring of steel production to other world regions.

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6.3.3.2.2 "NDC_LTT_TRANS" scenario

In order to show the impact of behavioural change in transport, the Low Energy Demand (LED) scenario for passenger transport from Grubler et al. (Grubler et al., 2018a) has been implemented on the top of the NDC_LTT scenario for the EU27 countries. The model used to simulate it has been WILIAM 1.2 BETA. Note that since this version is BETA and results may not be fully reliable. All the parameters are shown and described in ANNEX A.
The alternative pathway of behavioural change in the transport sector (NDC_LTT_TRANS onwards) assumes a reduction of 14.5% in the demand due to the awareness of population and constraints in the oil price facing scarcities from 2025 to 2050 (Grubler et al., 2018a). The load factor increases 25% in this period (see Table A. 5). The modal share (see Table A. 6) has been modified to achieve the target indicated in the LED scenario by 2050.
Nevertheless, Grubler et al. (Grubler et al., 2018a) did not provide detailed input parameters, so it was necessary to assume our own estimations. These were modelled taking as reference the region R2_North:

- Target transport activity levels (passenger • km) until 2050.
- Increase of 25% of load factors.
- Modal shares were estimated in this study with the aim of harmonization.

6.3.3.2.3 "NDC_LTT_LED" scenario

In order to show the impact of behavioural change in buildings, the Low Energy Demand (LED) scenario for buildings from Grubler et al. (Grubler et al., 2018a) has been implemented on the top of the NDC_LTT_TRANSPORT scenario for the EU27 countries. The model used to simulate has been GCAM7.0. All the parameters are shown and described in ANNEX .

In this alternative scenario, it is assumed that the residential per capita floor space will remain constant until half century, whereas the commercial per capita floor space will increase 43%. Nevertheless, since GCAM projected a constant commercial floor space for the NDC_LTT scenario, we assumed it too for the NDC_LTT_LED scenario.

The useful energy demand will be reduced by 75% for both commercial and residential buildings. Finally, the energy service used for end-use consumer goods, will decrease by 30%.

6.3.3.2.4 "NDC_LTT_LIFE" scenario

To illustrate the influence of behavioural changes in diets, we have incorporated the Low Energy Demand (LED) scenario proposed by Grubler et al. (Grubler et al., 2018a) onto the NDC_LTT_LED scenario for the EU27 countries. The model used to simulate has been GCAM7.0. All the parameters are shown and described in ANNEX C.

This alternative scenario assumes a 10% reduction of ruminant meat and a 2% increase of total meat consumption. It assumes further increases for crops and livestock that are not implemented in this study.

6.3.3.3 Study 7 data flow

The data flow between the three chosen models (WILIAM and GCAM) is structured as shown in Figure 6-2. The workflow involves a sequential interaction between the WILIAM and GCAM models, each contributing to a comprehensive analysis of different scenarios. Initially, the WILIAM model applies the scenario "NDC_LTT_Trans" to generate GDP values for the EU region. Alongside GDP values, various outcomes such as sectorial emissions, employment, and total investment in the energy sector are also produced. Subsequently, the GDP values generated by WILIAM through the "NDC_LTT_Trans" scenario are transmitted to GCAM model. In this phase, GCAM model applies distinct scenarios, namely "NDC_LTT_LED" and "NDC_LTT_LIFE", respectively. Within the GCAM model, behavioural change-related inputs are incorporated, including modal share change in the transport sector, change in floor space in the LED scenario, and adjustments to the preference parameter reflecting a reduction in meat consumption. GCAM then provides a comprehensive set of outputs, encompassing GDP values, sectorial emissions, employment, total investment in the energy sector, food demand (crop and livestock), food prices, carbon prices, and energy system costs. This structured data flow and collaborative scenario analysis between WILIAM and GCAM models ensure a thorough evaluation of multiple dimensions, providing valuable insights into the economic, environmental, and social implications of the specified scenarios for the EU region.

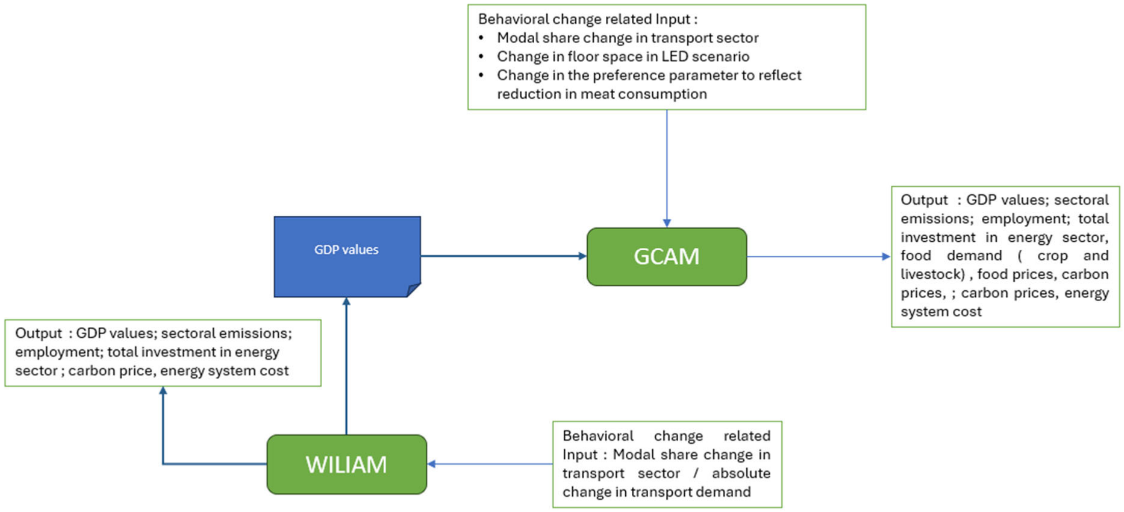

Figure 6-2: Study 7 data flow between models.

6.4 Results

This section presents results of the three scenarios. First, behavioural change in the transport sector. Second, changes by low-carbon technologies in buildings. Third, application of diet change in Europe.

6.4.1 Outcomes derived from implementing the "NDC_LTT_TRANS"

WILIAM runs under ordinary differential equations to deliver a continuous behaviour of the system. Consequently, we first show the results generated with WILIAM by applying the "NDC_LTT_Trans" scenario. Later, the comparison with GCAM is shown and discussed.

The first part has been split into 2 sections: first, the results focusing on the submodule of passenger transport will be shown, allowing to validate the implementation of the LED scenario in WILIAM; second, more general impacts over the model will be tracked in macroeconomic, social and global environmental indicators.
To facilitate interpretation, all results are shown for the "NDC_LTT" and "NDC_LTT_Trans" scenarios.
The activity in terms of pass*km starts increasing at a relative fast rate, however around 2035-

2045 there are some oscillations in the model which are the combined effect of the introduced policies with the trend in increasing oil prices. In 2050 the target of pass*km is approximately reached. These levels are slightly lower (-10%) than what the model estimates as reference (NDC_LTT). Figure 6-3 shows the split by country; no heterogeneities are observed which seems logical as all the EU countries have been parametrised the same.

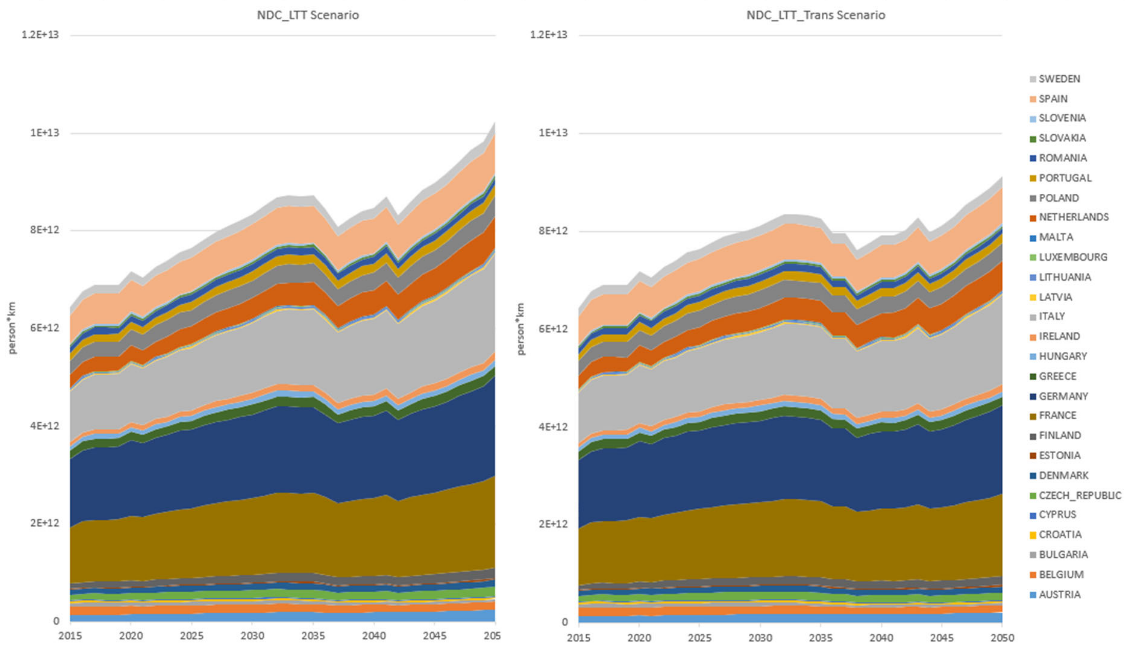

Figure 6-3: Total passenger transport demand for each scenario.

In terms of energy consumption by type of mode, it is observed in Figure 6-4 a reduction in the total energy consumption in the "NDC_LTT_Trans" scenario of around 15%, with a lower contribution of aviation and LDV and an increase in bus and rail.

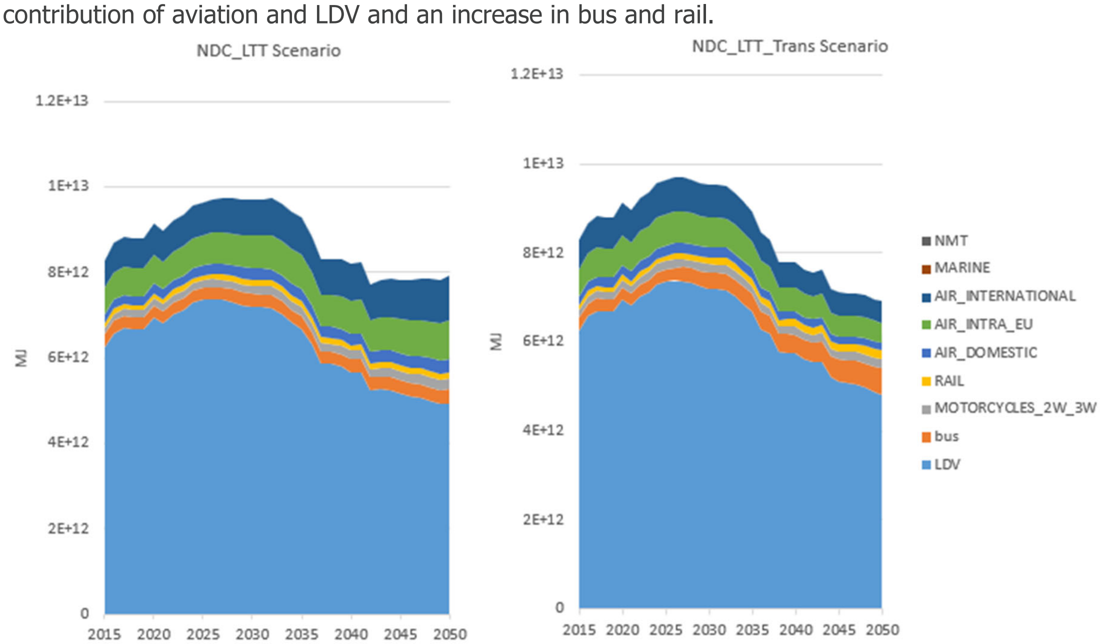

Figure 6-4: Energy consumption by model passenger transport for each scenario.

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In terms of final energy, and as shown in Figure 6-5, it is clearly visible the electrification trend which is enhanced in the "NDC_LTT_Trans" with relation to the "NDC_LTT" scenario.

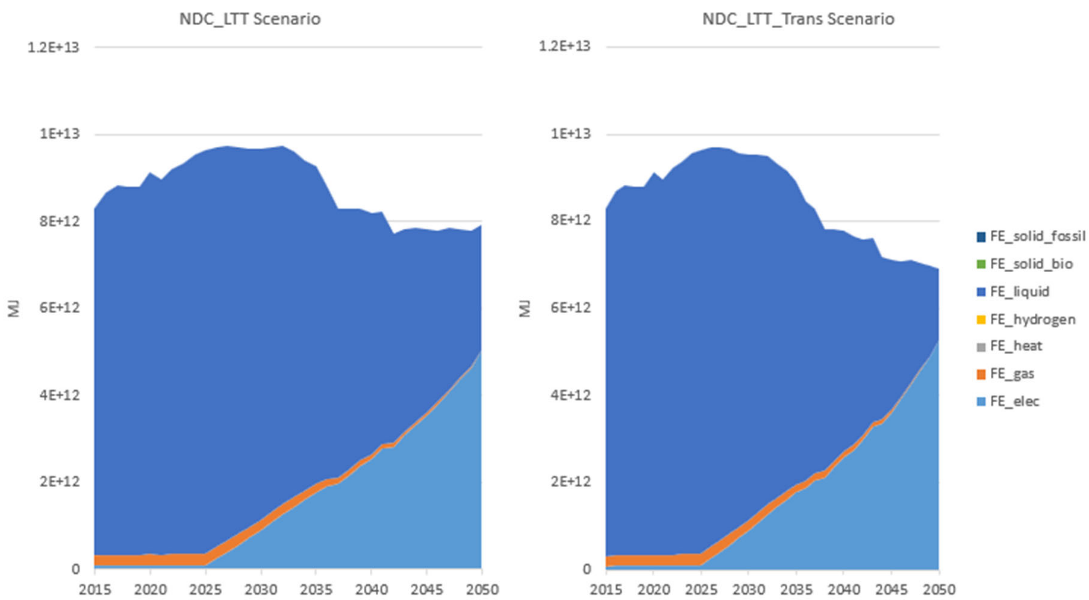

Figure 6-5: Energy consumption by final energy passenger transport for each scenario.

This reduction in the activity levels, in combination with an electrification with higher penetration of RES causes the GHG emissions to reduce faster than in the "NDC_LTT" scenario, reaching a reduction of around 75% with relation to current levels as shown in Figure 6-6.

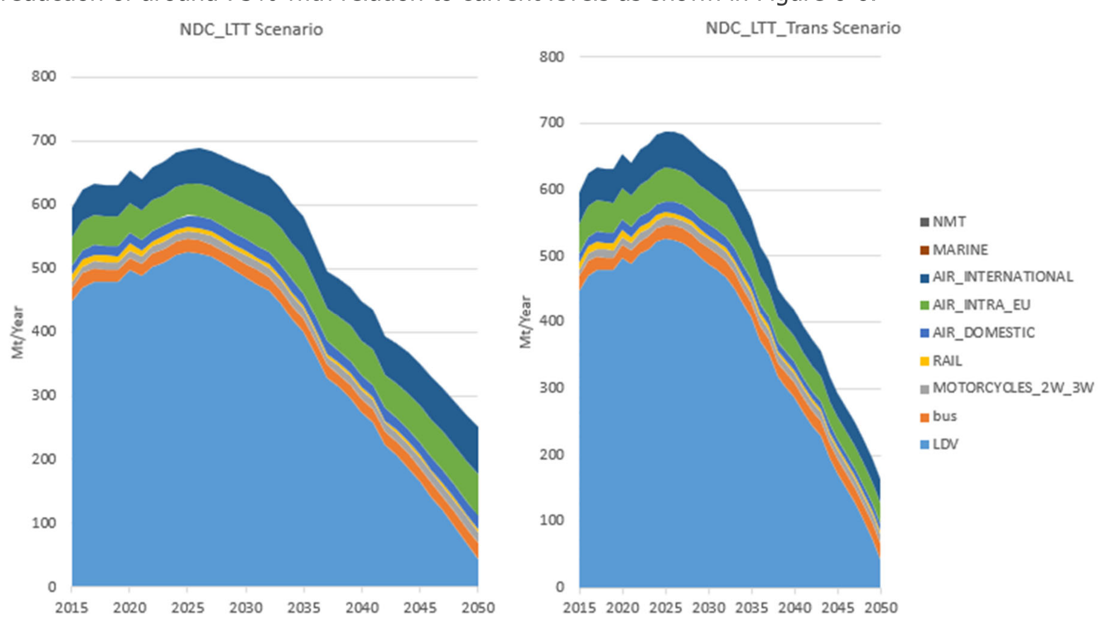

Figure 6-6: GHG emissions passenger transport by mode for each scenario.

This electrification boosts the demand for minerals in both cases (see Figure 6-7), especially for aluminium and copper.

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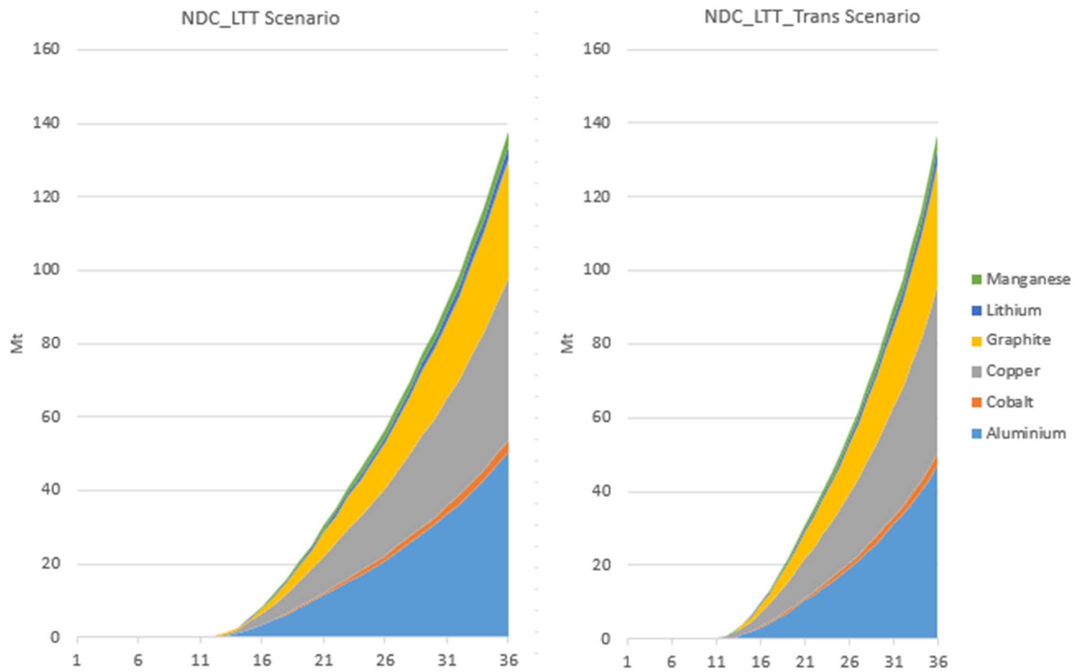

Figure 6-7: Cumulated total extracted materials transport electrification for each scenario.

Results are presented for GDP (Figure 6-8), unemployment (Figure 6-9), investment in the energy sector (Figure 6-10), CO_2 emissions by sector (Figure 6-11), and CO_2 tax rates for all sectors (Figure 6-12). It is important to note that CO_2 taxes are treated as exogenous policy variables in WILIAM. For the first four indicators, very minor differences are observed between the "NDC_LTT" and "NDC_LTT_Trans" scenarios. This is attributed to the immaturity of the current WILIAM, where several critical links between the energy and the economy module are still missing.

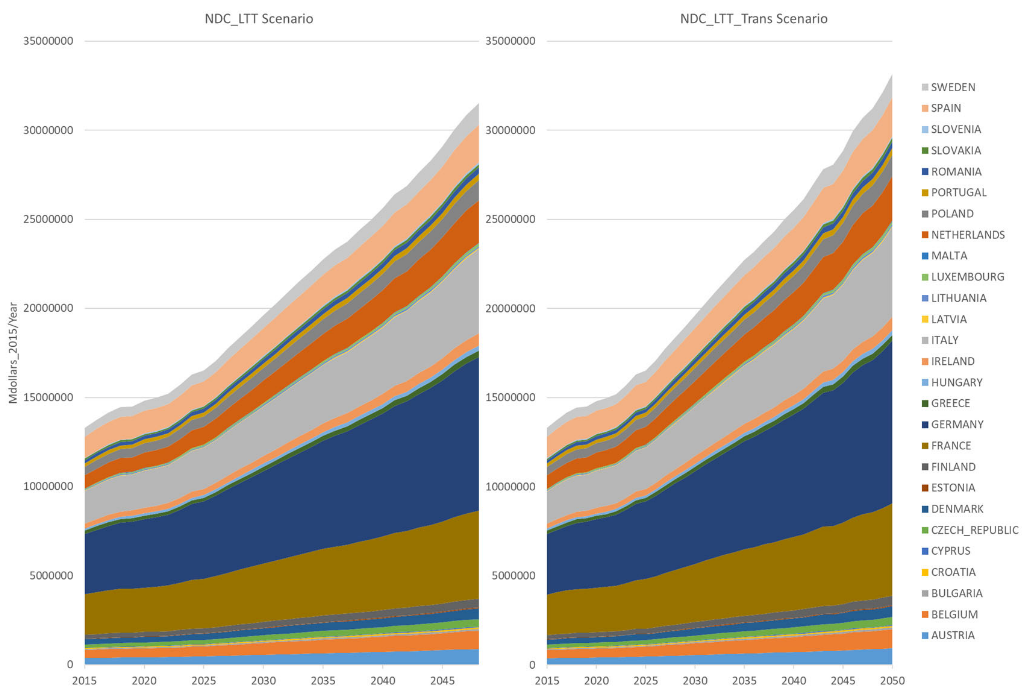

Figure 6-8: GDP for each scenario.

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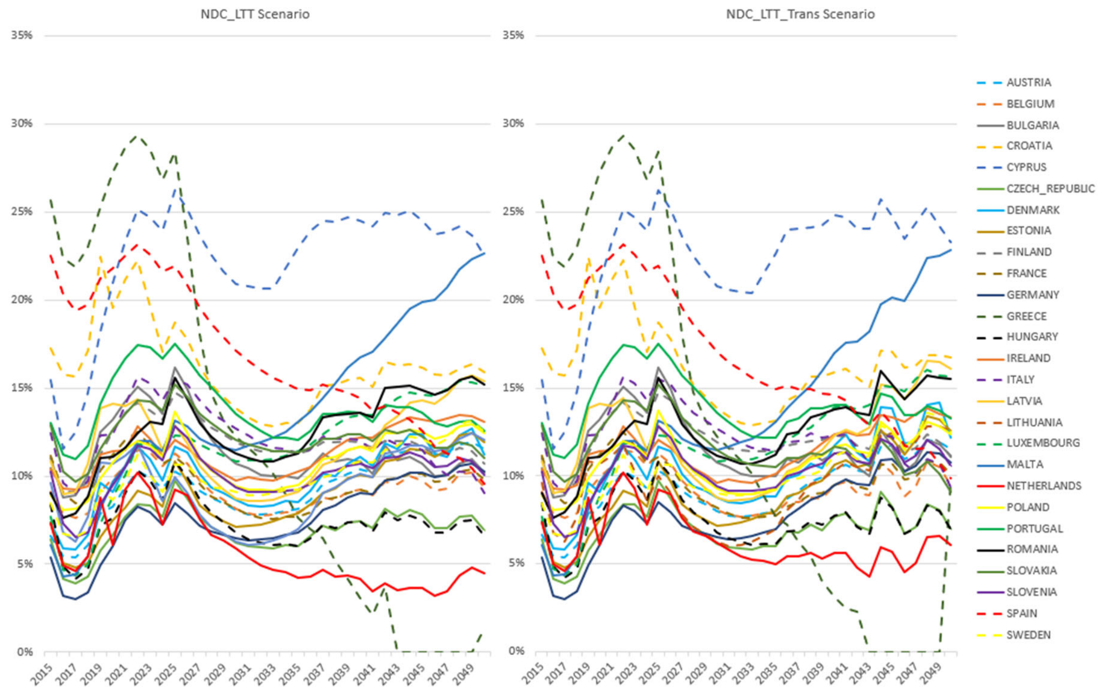

Figure 6-9: Unemployment rate for each scenario.

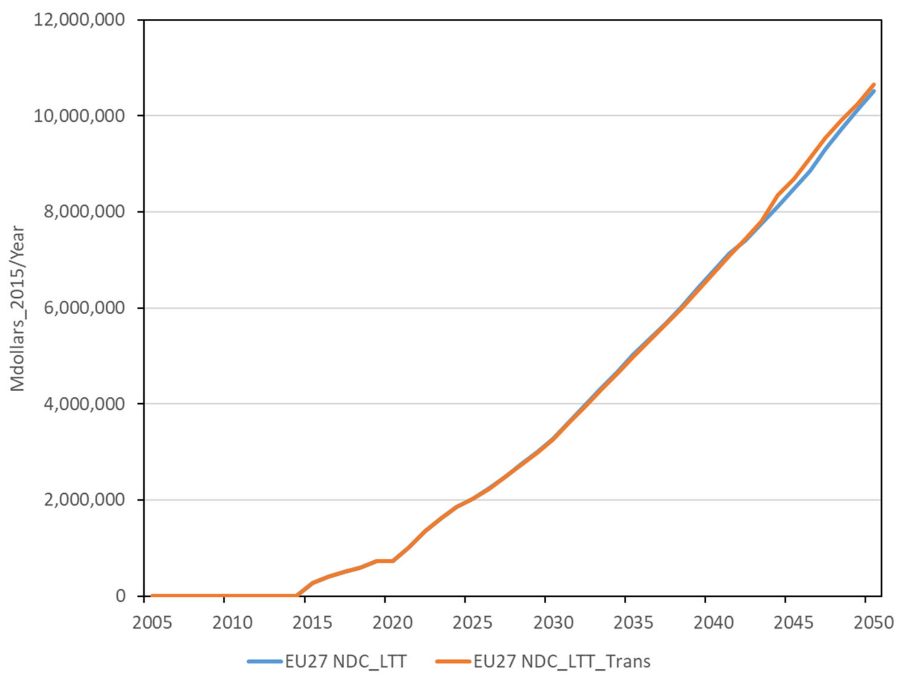

Figure 6-10: Cumulative total investment in energy infrastructure for each scenario.

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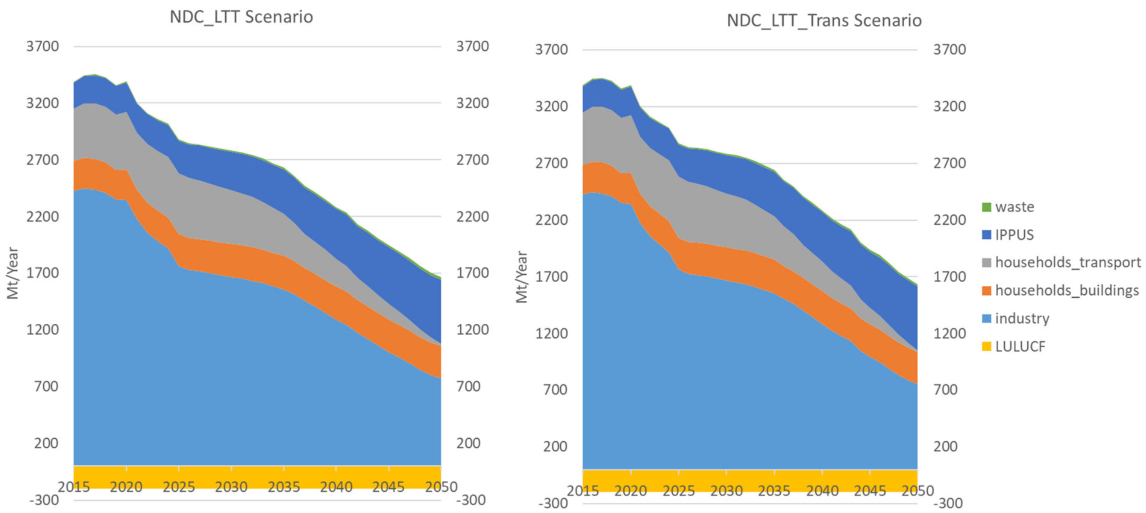

Figure 6-11: CO2 emissions by sector for each scenario.

CO2 total emissions are further reduced in transportation a 20% in "NDC_LTT_Trans" scenario with relation to "NDC_LTT" scenario, which transfer into a -2% in total CO2 emissions.

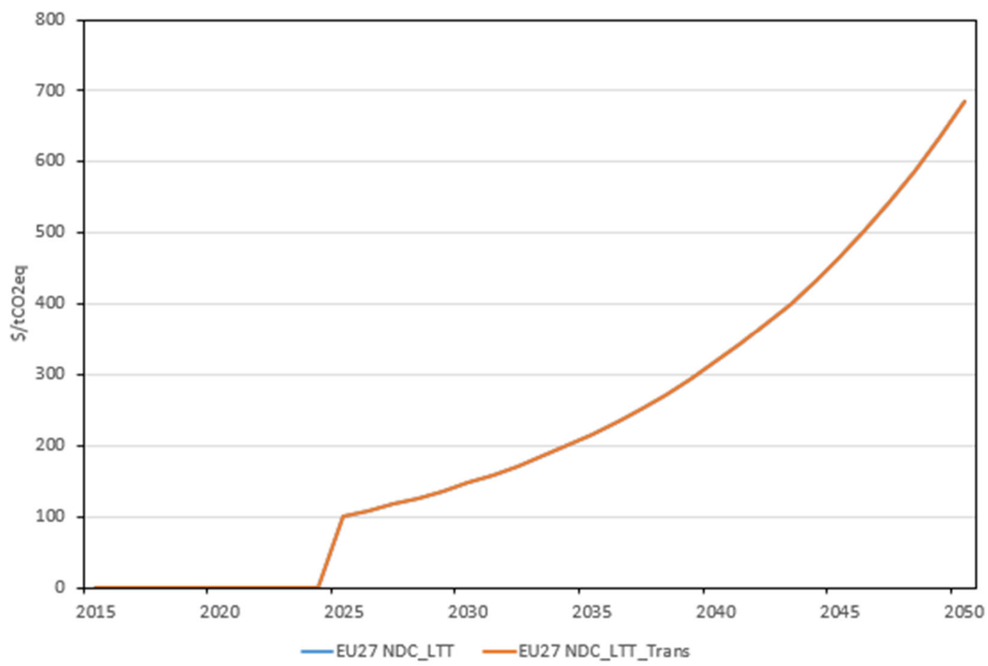

Figure 6-12: CO2 tax rate sectors for each scenario.

On the other hand, the results of the TRANS scenario distinguished by passenger and freight transport are shown for the GCAM model (Figure 6-13). The whole efficiency is increases over time for freight transport since the demand (billion pkm/year) increases 13% from 2015 to 2050, and the final energy falls down to less than 4 EJ (47% of transport consumption) in 2050.

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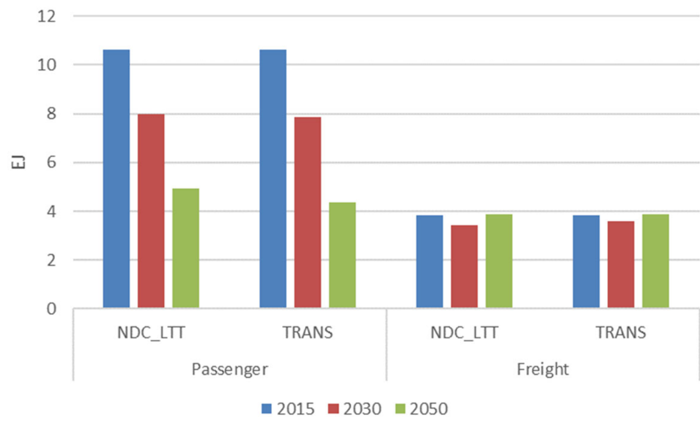
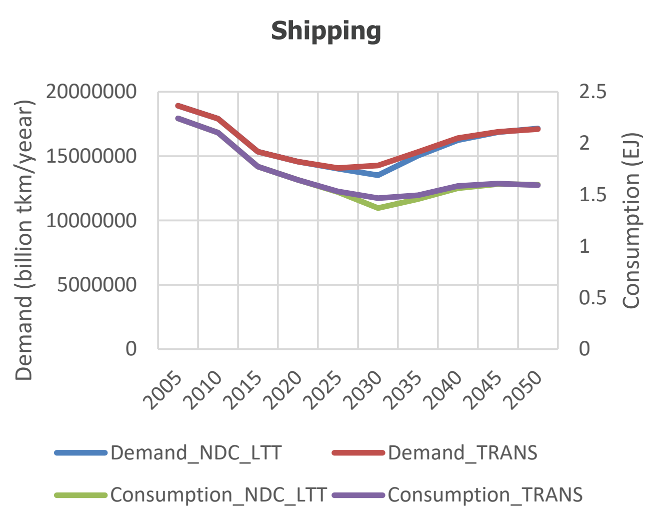


Figure 6-13: Evolution of transport by type (passenger or freight) in GCAM 7.0.

This evolution is different by mode (Figure 6-14). Specifically, in the case of freight transport, in 2015, shipping covered most of the demand (85%), followed by road (10%) and road (3%). TRANS scenario assumes a decrease of maritime freight transport to 2030, and then an increase to similar levels than historical values. Rail, however, experiences a sinusoidal trend with a peak around 2025. Finally, goods transported by road increases over time. As we can see in figures, the consumption of energy is linked to the demand, following a similar temporal behaviour.



Rail

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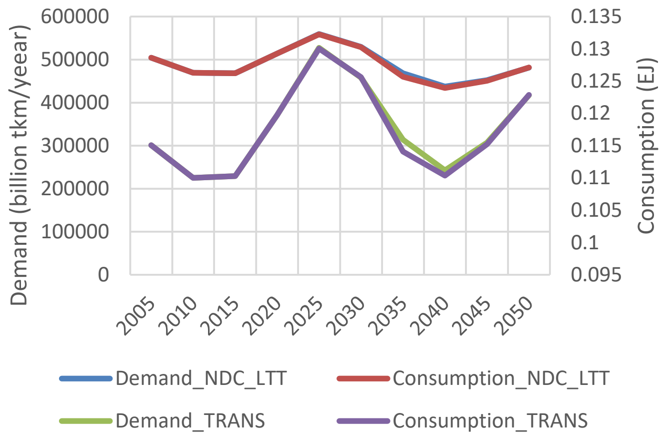

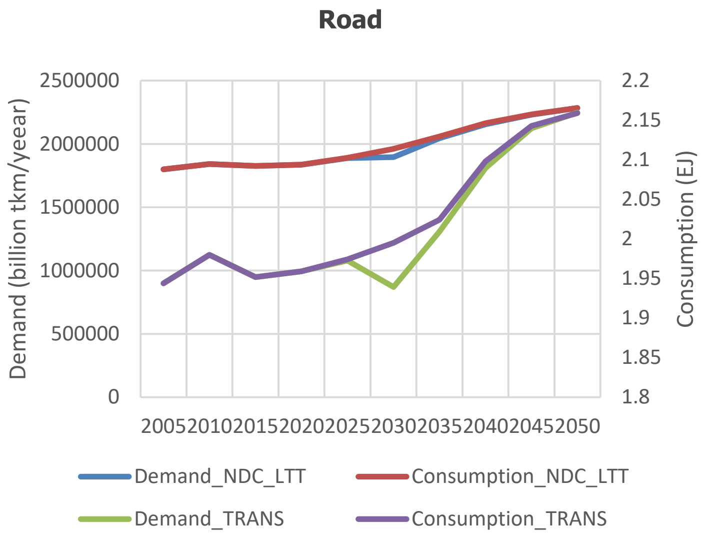

Figure 6-14: Demand and consumption of freight transport by mode in the scenarios simulated by GCAM 7.0.

Figure 6-15 shows the share of fuel consumed by freight transport. Liquids (oil products) is dominant in this sector for all the years of the TRANS scenario, highlighting the actual technological barrier of decarbonizing heavy transportation by road and shipping.

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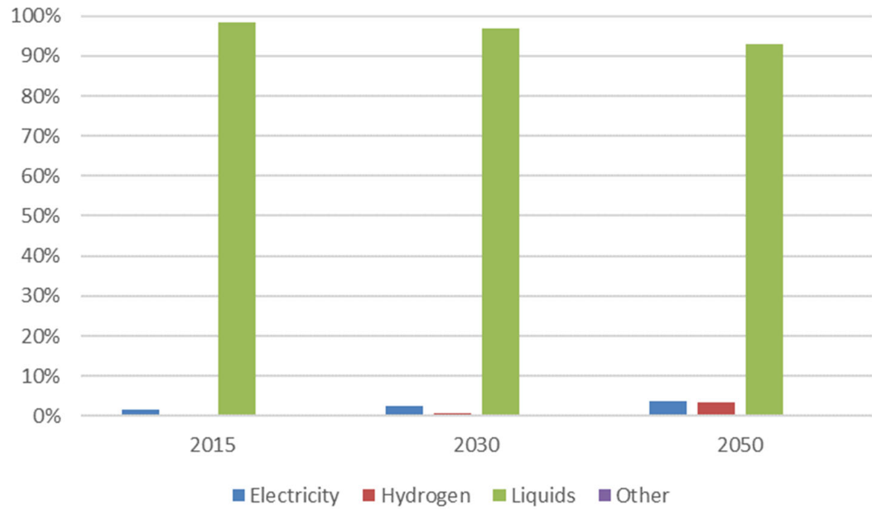

Figure 6-15: Shares of fuel in freight transport in TRANS scenario, simulated by GCAM 7.0.

The impact of the TRANS scenario is different between GCAM and WILIAM. Globally, the "NDC_LTT" scenario already considers decarbonization policies in the transport sector. So, the additional efforts assumed in TRANS scenario would have a low impact into the emissions indicators. For example, GCAM shows an increase of just 0.01% in the carbon concentration in atmosphere by 2050, related to the "NDC_LTT" scenario (Figure 6-16). The impact is higher in WILIAM, which value increases 0.4% at the end of the simulation.

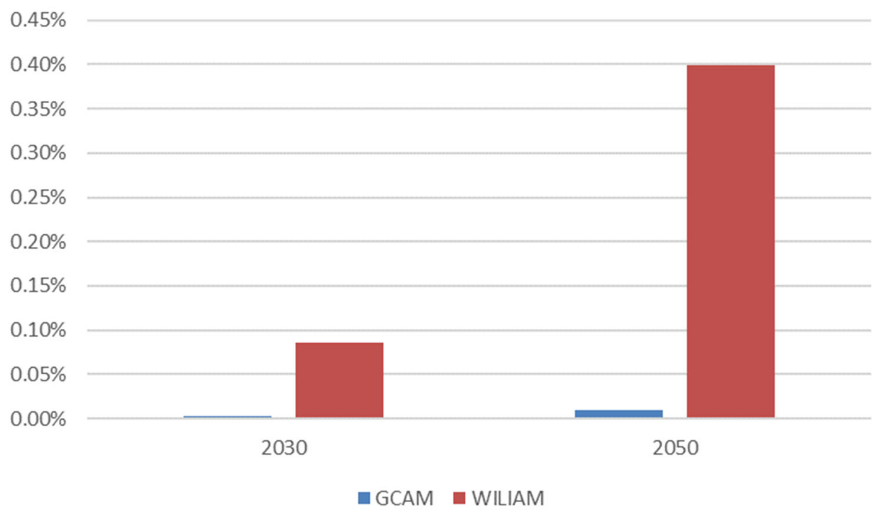

Figure 6-16. Variation of carbon concentration in atmosphere from NDC_LTT to TRANS scenario in 2030 and 2050.

A noticeable impact of TRANS' policies is highlighted in Figure 6-17. In 2030, the emissions of private transport in GCAM are already lower than the "NDC_LTT" scenario, while there is a small increase in the case of WILIAM given that passenger demand increases faster than fuel substitution and efficiency measures before 2030. However, the figure drastically changes from

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2030 to 2050, when the alternative policies assume close to 5% and 20% of reduction in GCAM and WILIAM, respectively. Policies affect more to WILIAM, which emissions in private transport are close to 14 Mt/year in Europe, in comparison to the 459 Mt in 2015.

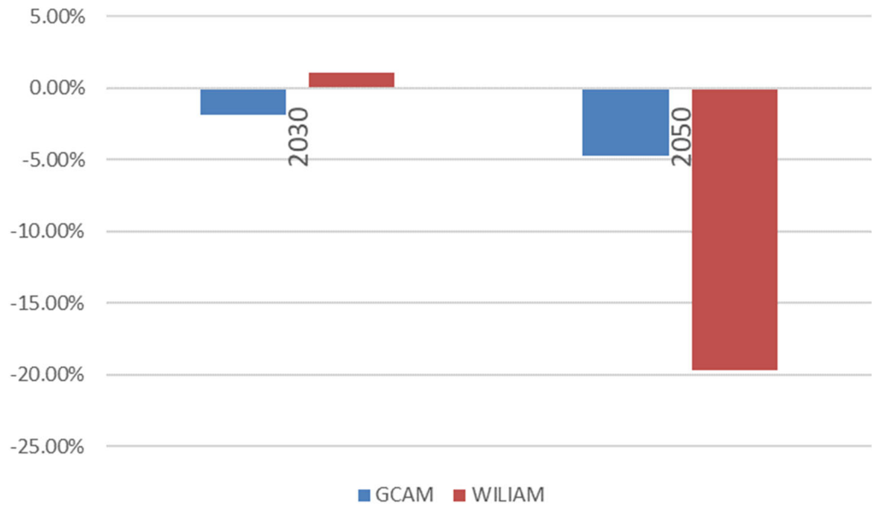

Figure 6-17. Variation of European (EU-27) carbon emissions by transport of passengers from NDC_LTT to TRANS scenario in 2030 and 2050.

Final energy consumption by transport decreases over time in both models. GCAM does it from 10.6 EJ/year in 2015 to 4.4 EJ/year in 2050, while WILIAM does it from 8.3 EJ/year to 6.9 EJ/year. Discrepancy of the historical datum in 2015 is due to differences in the definition of transport modes. In general, both models report similar trends and conclusions.

The passengers' modal share is quite similar in both models in 2015 (Figure 6-18), 76% covered by four-wheeled vehicles, followed by aviation and buses. However, aviation is roughly kept constant in GCAM (0.2 EJ less from 2015 to 2050) and WILIAM (0.4 EJ less for the same period), but the substitution of four-wheel motorised drive is more intensive in GCAM than WILIAM, going from 8.0 (6.3) to 2.2 (4.8) EJ/year, respectively.

Regarding fuel preferences, Figure 6-19 shows the evolution of behavioural change in transport from 2015 to 2050. Liquids are dominant in history due to the high energy density of oil products such as gasoline (13 kWh/kg) and diesel (10 kWh/kg), while energy density of batteries is much lower, in the range of 0.1-0.27 kWh/kg. Although the energy density of hydrogen gas is much higher than the other fuels, the management of the smallest element of the periodic table is dangerous (the lower flammability limit of hydrogen in air is 4% mole fraction) and energetically expensive if we consider, e.g., the pressure to store hydrogen (39.6 kWh/kg at 700 bars pressure). So, gasoline covers in between 96%-98% in 2015, while the rest was mainly gases (e.g., liquified gas petrol). Results reveal a different strategy for the scenario. On the one hand, GCAM states for using hydrogen, whose share increases from 0% to 2% by 2030, and 18% by 2050. On the other hand, WILIAM states for an electrification process, covering 10% by 2030, and 76% by 2050.

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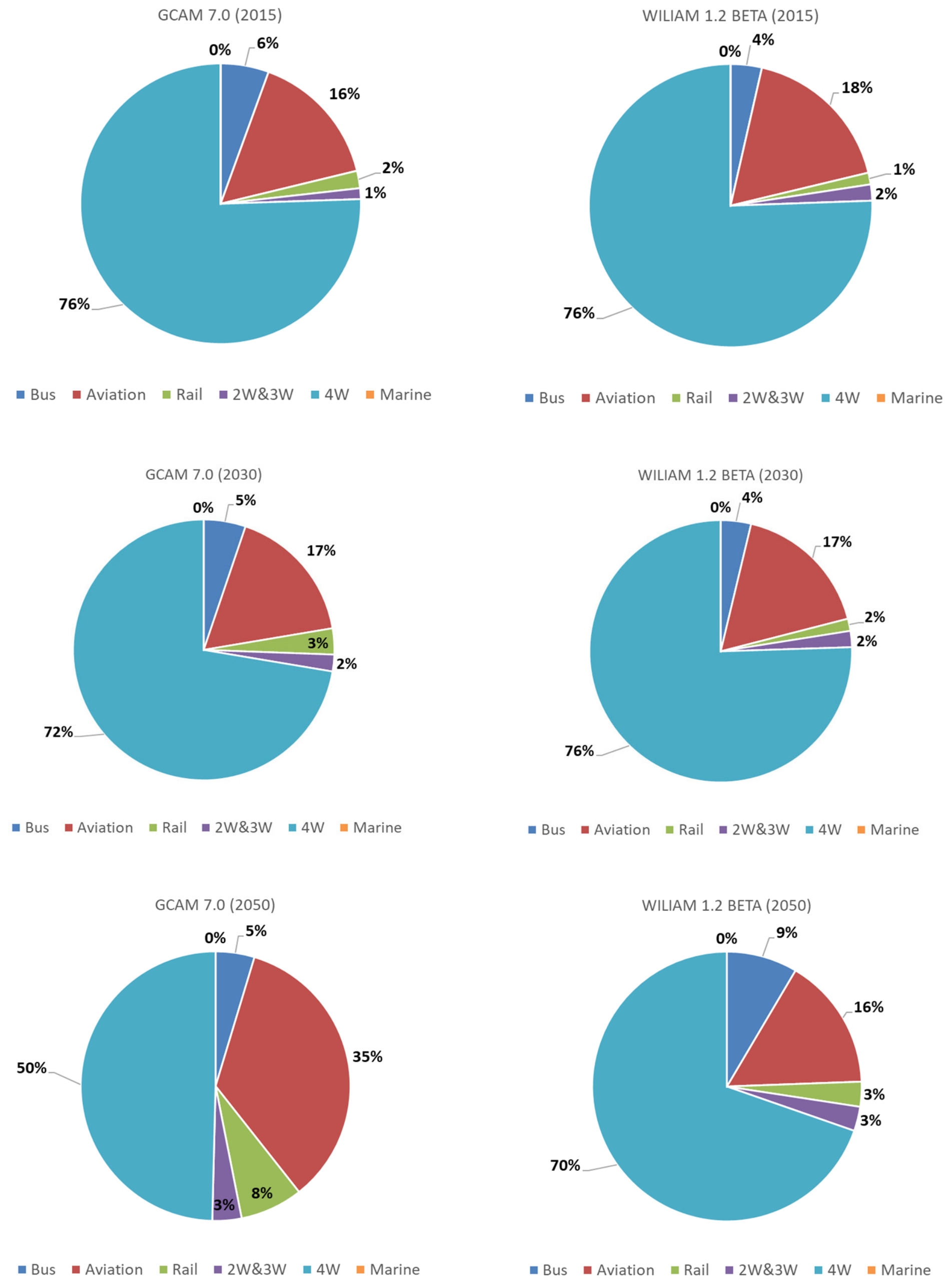

Figure 6-18: Share of final energy consumption by transport mode of passengers in WILIAM and GCAM. Years: 2015 (historical), 2030, and 2050. 2W&3W means two-and-three wheeled motorised vehicles (e.g. motorcycle).

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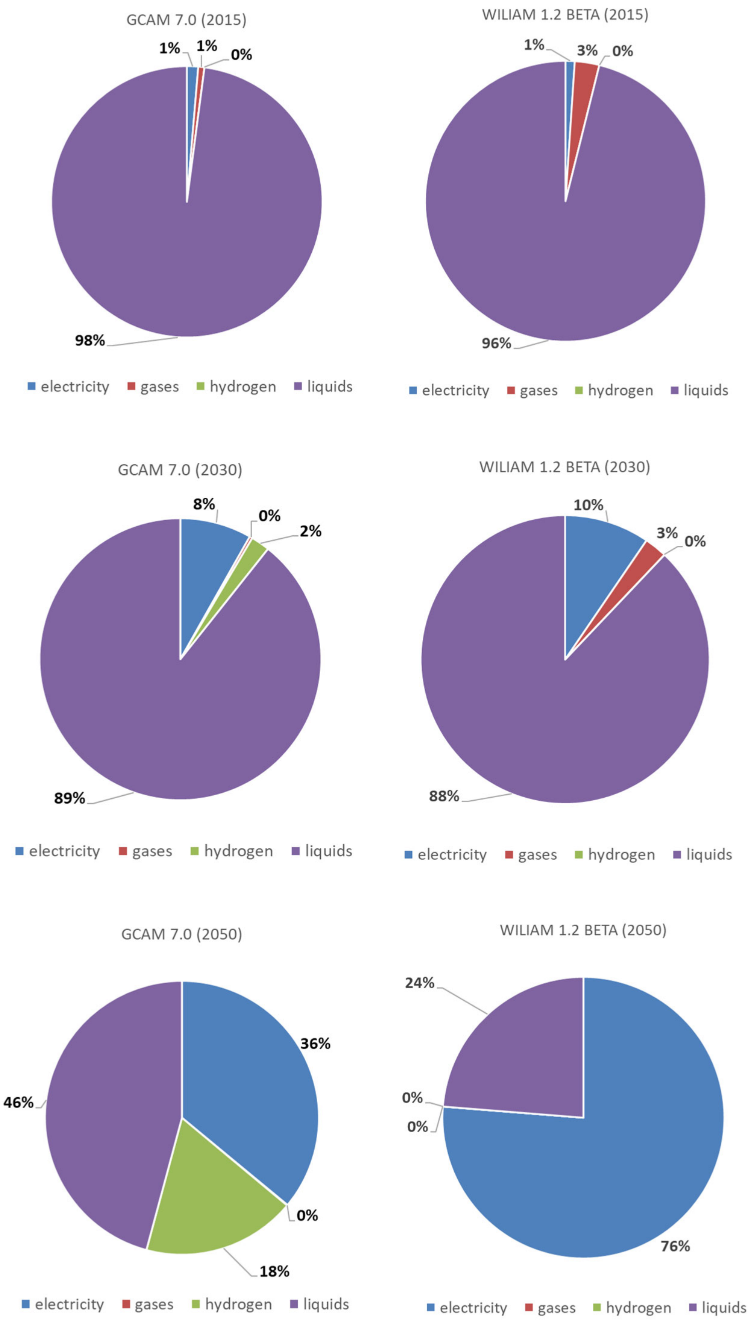

Figure 6-19: Share of final energy consumption by fuel in transport of passengers (GCAM and WILIAM models). Years: 2015 (historical), 2030, and 2050.

6.4.2 Outcomes derived from implementing the "NDC_LTT_LED" scenario

Within this section, the findings pertaining to the "NDC_LTT_LED" scenario are reported, focusing on the EU 27 region. The analysis spans from 2015 to 2050, utilizing the population and GDP values established in the "NDC_LTT" scenario as a point of reference.

A comparison has been made between the "NDC_LTT_LED" and "NDC_LTT" scenarios for each output. This analysis utilises the *MAD* parameter to provide a clear analysis and interpretation of

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the output behaviour when transitioning from one scenario to another, as expressed below:

$$MAD = 100 \cdot \frac{(X_{NDC\_LTT} - X_{NDC\_LTT\_LED})}{X_{NDC\_LTT\_LED}}$$

Where X represents the output presented, which could be, for example, final energy, emissions, global mean temperature, CO_2 concentration, etc.

The presentation of results is organised into three distinct sections. The initial section focuses on energy outputs, delving into factors such as final energy and energy service. Following this, the second section explores economy outputs, encompassing the carbon tax related to buildings demand. Lastly, the third section is dedicated to climate outputs, providing insights into emissions, global mean temperature, and CO_2 concentration.

- **Energy outputs:**

Figure 6-20 and Figure 6-21 illustrate the final energy consumption categorised by end-use in both the "NDC_LTT" and "NDC_LTT_LED" scenarios. It can be observed from Figure 6-20 that in the "NDC_LTT" scenario, there are some significant changes from 2015 to 2050, particularly in three end-uses: electricity, liquids, and gases. In 2015, the percentages of electricity, liquids, and gases were 10%, 20%, and 10%, respectively. However, by 2050, we observe an increase in the percentage of electricity to 25%, while the percentages of liquids and gases have decreased to 11% and 4%, respectively. Additionally, there is a slight variation in the rest of the end-uses between the two years. For the "NDC_LTT_LED" scenario, as depicted in Figure 6-21, there is a significant increase in the final energy dedicated to electricity, rising from 10% in 2015 to 26% in 2050. Concurrently, there is also a decrease in the use of liquids and gases, with the percentage dropping from 20% and 10% in 2015 to 11% and 3% in 2050, respectively. These significant fluctuations can be attributed to behavioural changes implemented in buildings, such as the floor space increase and a significant improvement in the useful energy demand.

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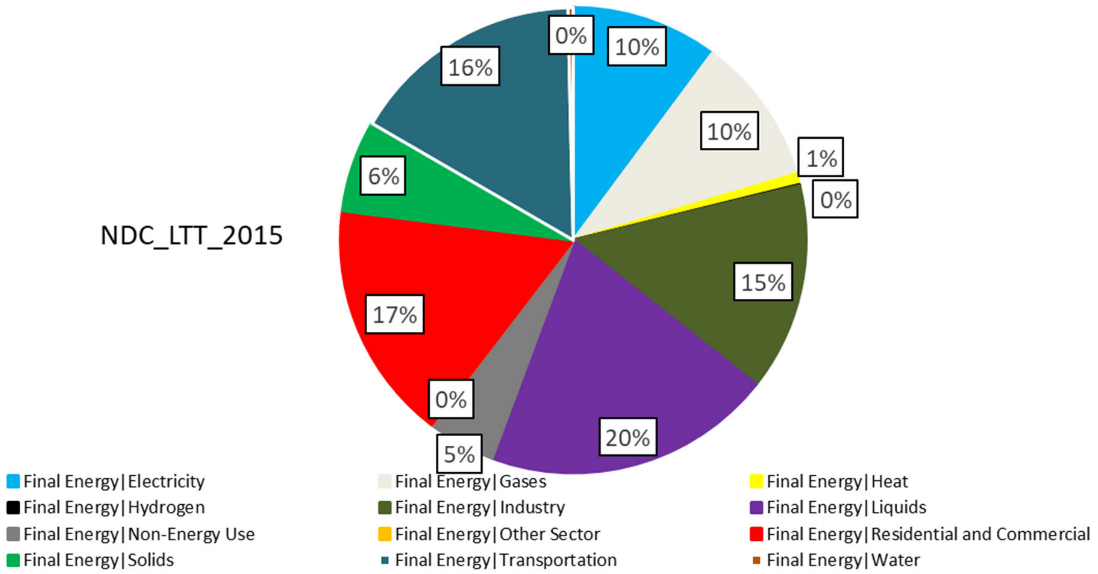

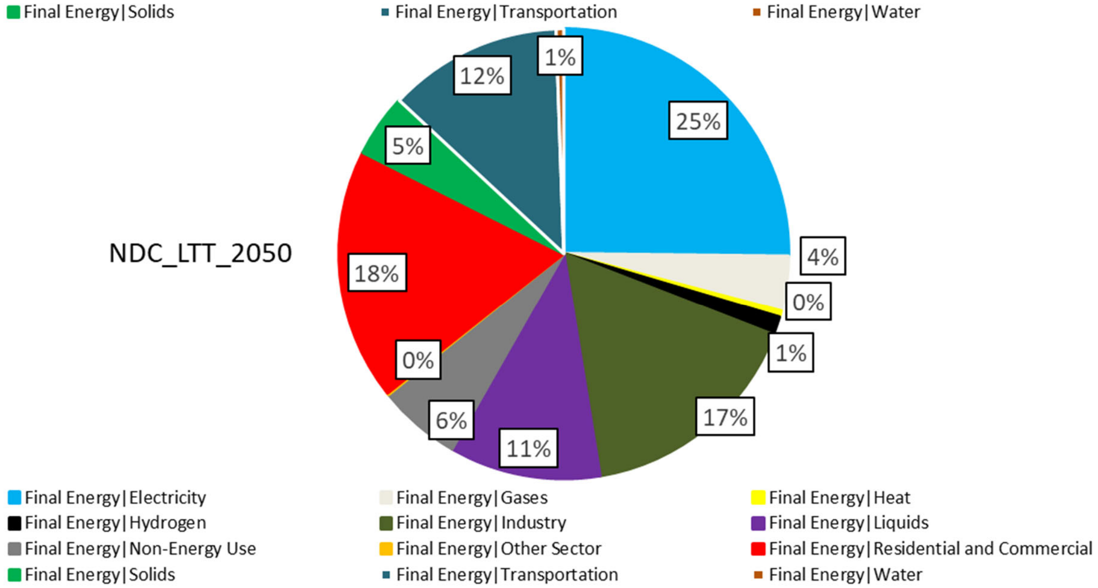

Figure 6-20: Final energy consumption categorised by end-use in the "NDC_LTT" scenario.

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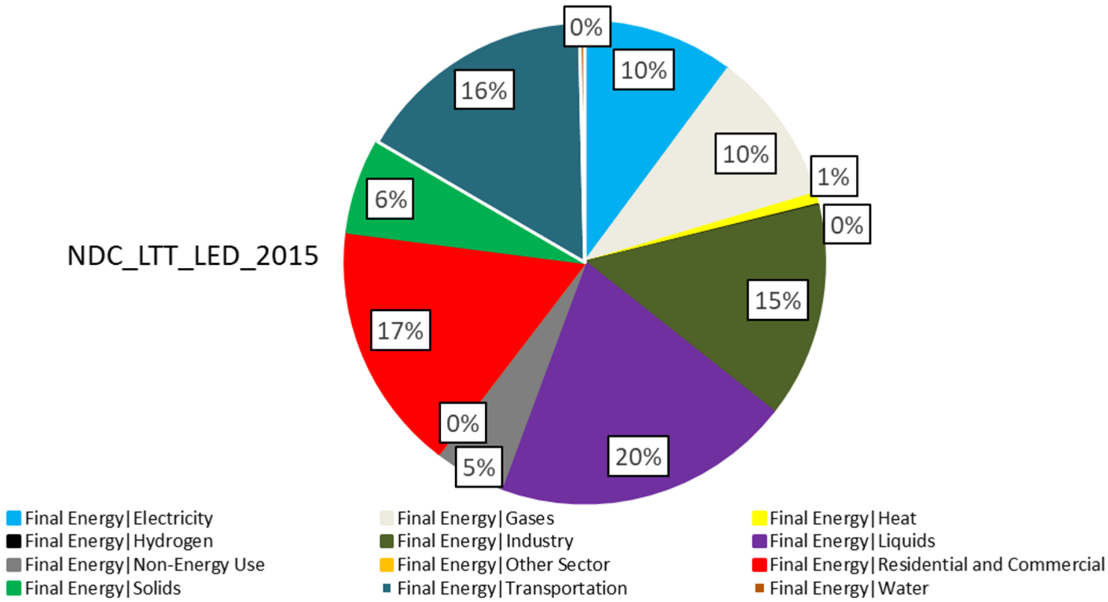

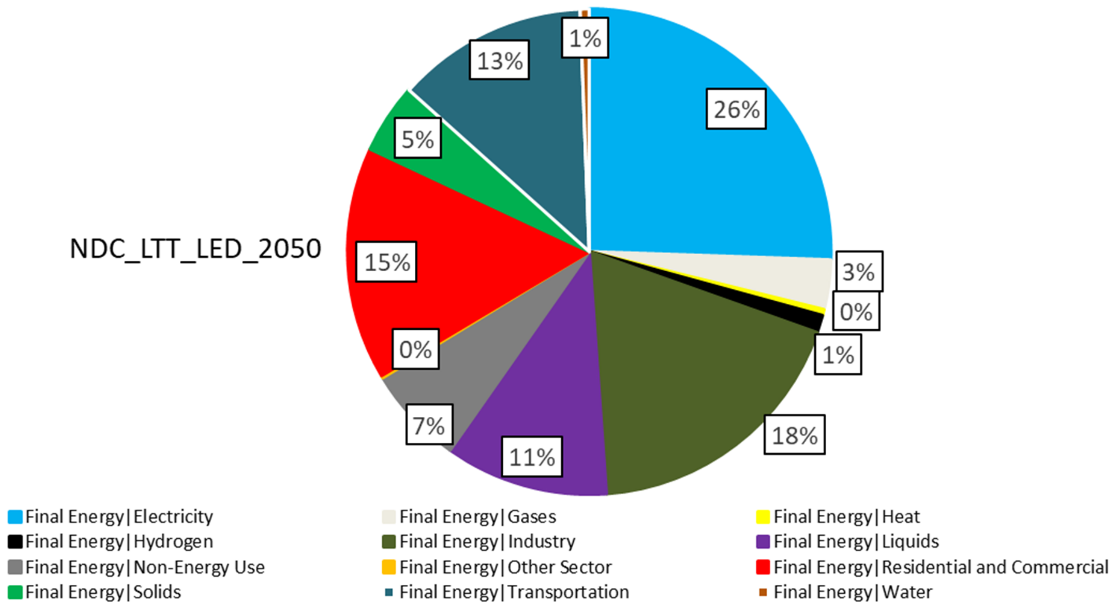

Figure 6-21: Final energy consumption categorised by end-use in the "NDC_LTT_LED" scenario.

➢ **Climate outputs:**

The climate-related outcomes, including GHG emissions, CO_2 concentration, global mean temperature, are depicted in Figure 6-22, Figure 6-24, and Figure 6-25, respectively.

As shown in Figure 6-22, there were high values of Kyoto gases and CO_2 emissions in the year 2015. The Kyoto gases emissions had a value of 529.28 Mt CO_2eq/year, and the CO2 emissions had a value of 432.04 Mt CO_2/year. From 2015 to 2050, a noticeable decrease in these emissions occurred, with the value of Kyoto gases emissions becoming 95.70 Mt CO_2eq/year, and for CO_2 emissions, it became 72.20 Mt CO_2/year. For the rest of the GHG emissions, the values remained very small from 2015 and approached zero by the year 2050. All these variations in GHG emissions, especially in Kyoto gases and CO2 emissions, are due to the effect of the buildings efficiency improvement over the "NDC_LTT" policies.

The comparison between "NDC_LTT" and "NDC_LTT_LED" scenarios is conducted by calculating the *MAD* parameter. The results of this comparison are shown in Figure 6-23, and there are high disparities, especially from 2030 to 2050. We notice that most calculated MAD parameter values are positive, representing a significant decrease in GHG emissions in the "NDC_LTT_LED" scenario, and this could be justified by the reduction in residential energy demand.

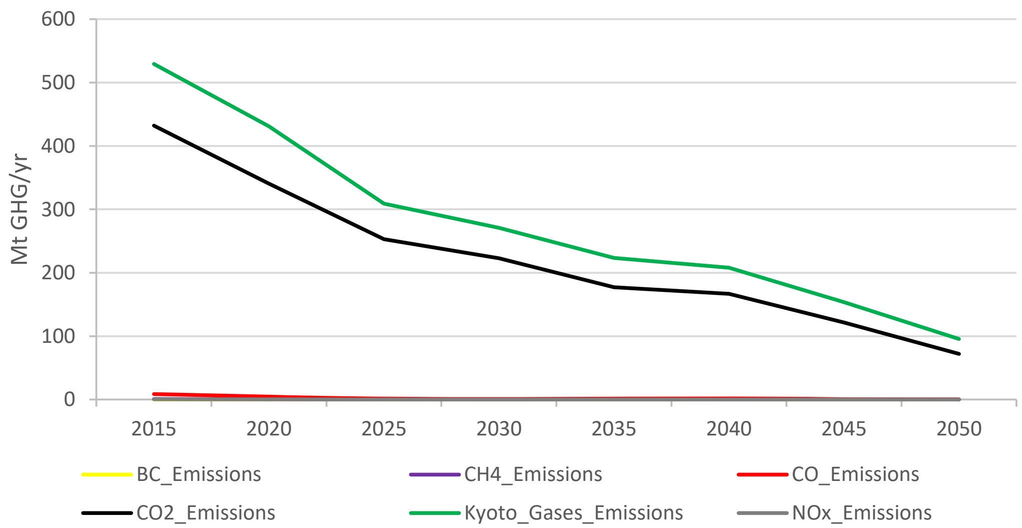

Figure 6-22: GHG emissions in the "NDC_LTT_LED" scenario, measured in Mt (GHG) per year.

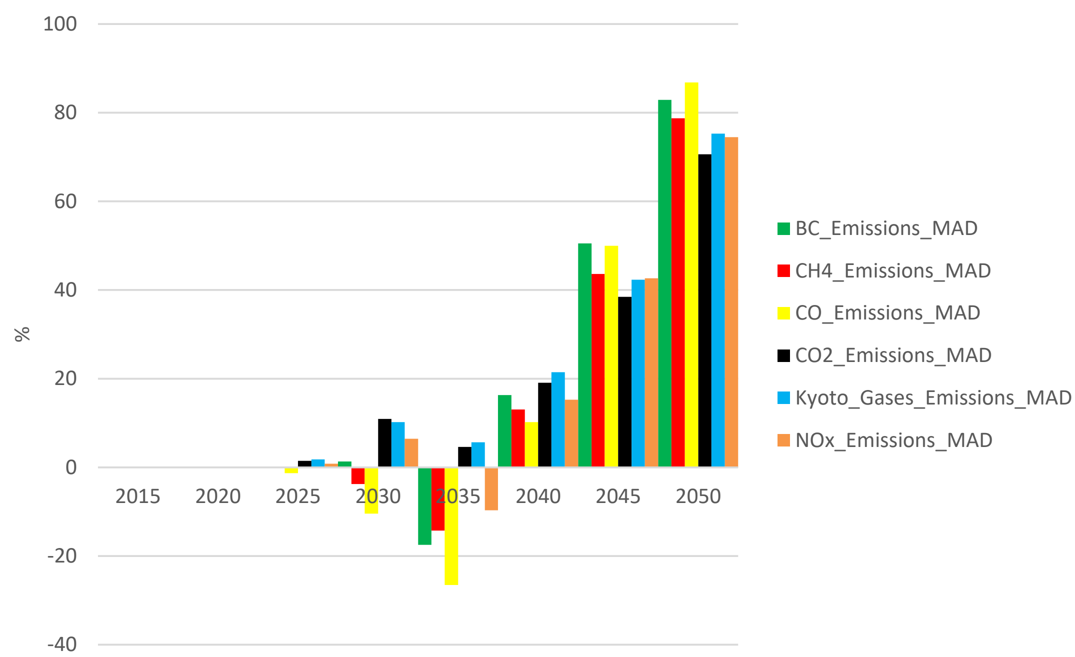

Figure 6-23: Disparities in GHG emissions between the "NDC_LTT" and "NDC_LTT_LED" scenarios.

For the CO_2 concentration and global mean temperature, we observe the same behavior with nearly identical values in the two scenarios, "NDC_LTT" and "NDC_LTT_LED", as shown in Figure

6-24 and Figure 6-25. The MAD is very small, indicating minimal differences between the scenarios.

Figure 6-24: CO_2 concentration evolution in the "NDC_LTT" and "NDC_LTT_LED" scenarios.

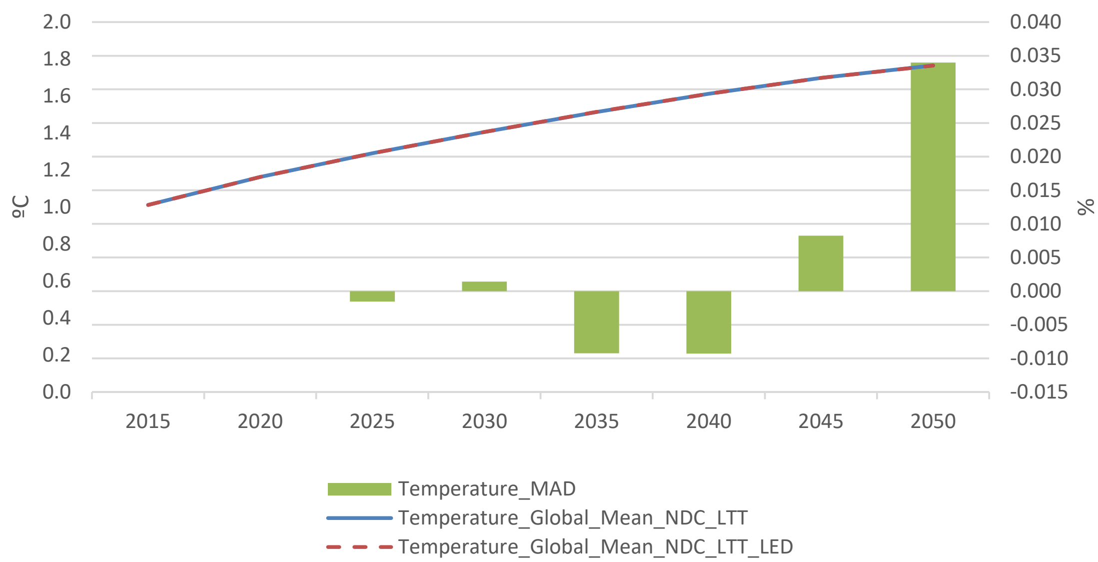

Figure 6-25: Global mean temperature evolution in the "NDC_LTT" and "NDC_LTT_LED" scenarios.

6.4.3 Outcomes derived from implementing the "NDC_LTT_LIFE" scenario

In this section, the results for the "NDC_LTT_LIFE" scenario are presented for the EU 27 region, spanning from 2015 to 2050, using the population and GDP values generated in the "NDC_LTT" scenario as a reference.

A comparative assessment was conducted between the "NDC_LTT_LIFE" and "NDC_LTT" scenarios for each result. The examination employs the *MAD* parameter, as detailed in section 7.4.2, to offer a distinct analysis and understanding of how the output behaves during the transition from the "NDC_LTT" scenario to the "NDC_LTT_LIFE" scenario.

The presentation of results is organised into four distinct sections. The initial section focuses on land outputs, delving into factors such as agricultural demand, production, and land cover. Following this, the second section explores energy outputs, encompassing aspects like final and primary energy, as well as electricity capacity. Moving forward, the third section delves into economic outputs, examining parameters such as the prices of corn, soybean, and wheat, along with the carbon tax. Lastly, the fourth section is dedicated to climate outputs, providing insights into emissions, global mean temperature, and CO2 concentration.

- **Land outputs:**

The first two land outputs, agricultural demand, and production are depicted in Figure 6-26. As observed in the figure, both parameters show an increasing trend from 2015 to 2050 in the two studied scenarios. In the "NDC_LTT_LIFE" scenario, agricultural demand and production are slightly lower than those in the "NDC_LTT" scenario, with a MAD of 1.48% and 0.28% in 2050, respectively. This difference is attributed to the reduction in feed crops used to feed livestock.

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Since in the "NDC_LTT_LIFE" scenario there is a reduction of ruminant meat but also of total meat consumption, fewer feed crops are needed to feed the livestock, which are highly land and water intensive.

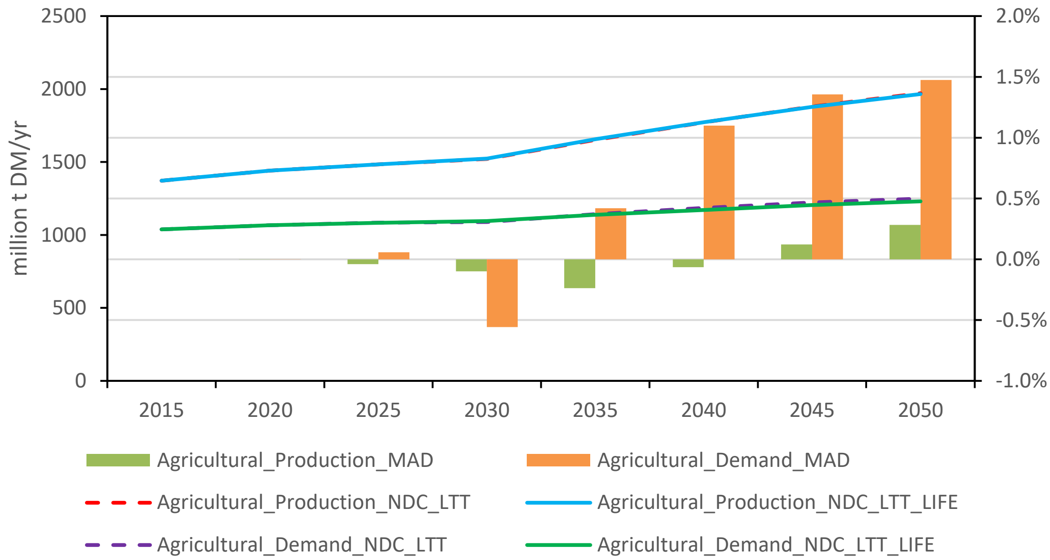

Figure 6-26: Agricultural Demand and Production in the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

Another land output, land cover, is illustrated in Figure 6-27. As depicted, there are changes in land cover from 2015 to 2050. Notably, there is an expansion of cropland, attributed to the shift of feed crops to food crops, and reduction of pasture areas, attributed to the reduction of livestock, in particular ruminant livestock (e.g., cow, sheep, and goat), which require vast pasture areas.

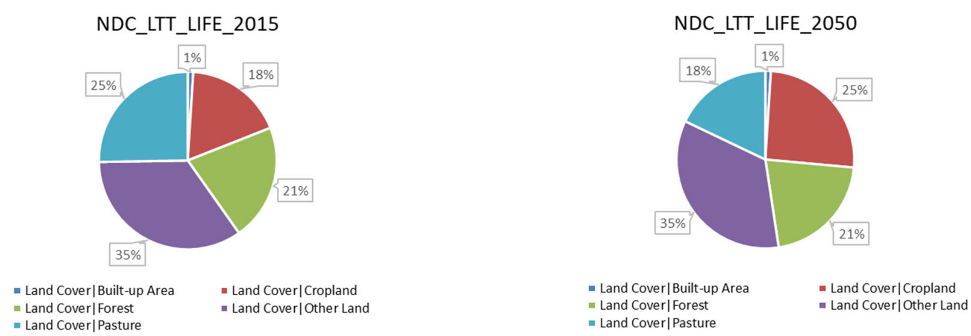

Figure 6-27: Land Cover by land type in the "NDC_LTT_LIFE" Scenario for the years 2020 and 2050.

➢ **Energy outputs:**

To evaluate the impacts of the "NDC_LTT_LIFE" on energy and compare them with those of the "NDC_LTT" scenario, three energy outputs have been selected: final and primary energy, and electricity capacity. These are plotted respectively in Figure 6-28 and Figure 6-29.

As illustrated in Figure 6-28, the trends of final and primary energy exhibit similar behaviour from 2015 to 2050 in both studied scenarios. Notably, in the "NDC_LTT" scenario, final and primary energy values consistently outpace those in the "NDC_LTT" scenario, particularly from 2030 to

2050. This discrepancy is quantified by the MAD, with values reaching 10.13% and 9.78% in 2050 for final and primary energy, respectively. The differences observed in final and primary energy in the "NDC_LTT_LIFE" scenario are driven by strong behaviour-induced reductions in energy for transport and buildings, such as reduced use of private transport, and reduced use of heating, cooling and other services in buildings. Most of those final energy savings are in the form of petroleum products (private transport) or natural gas (heating), hence savings in primary energy almost precisely resemble savings in final energy.

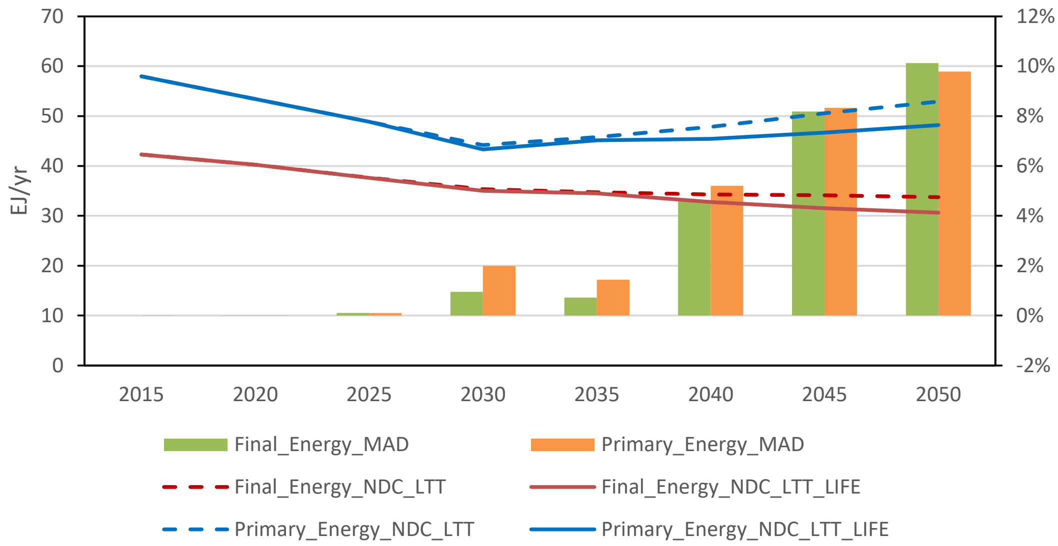

Figure 6-28: Final and Primary Energy in the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

For electricity capacity, as illustrated in Figure 6-29, a similar behavior can be observed in both scenarios, with a slight disparity that can be justified by savings in electricity use resulting from behavioral changes in transportation and buildings.

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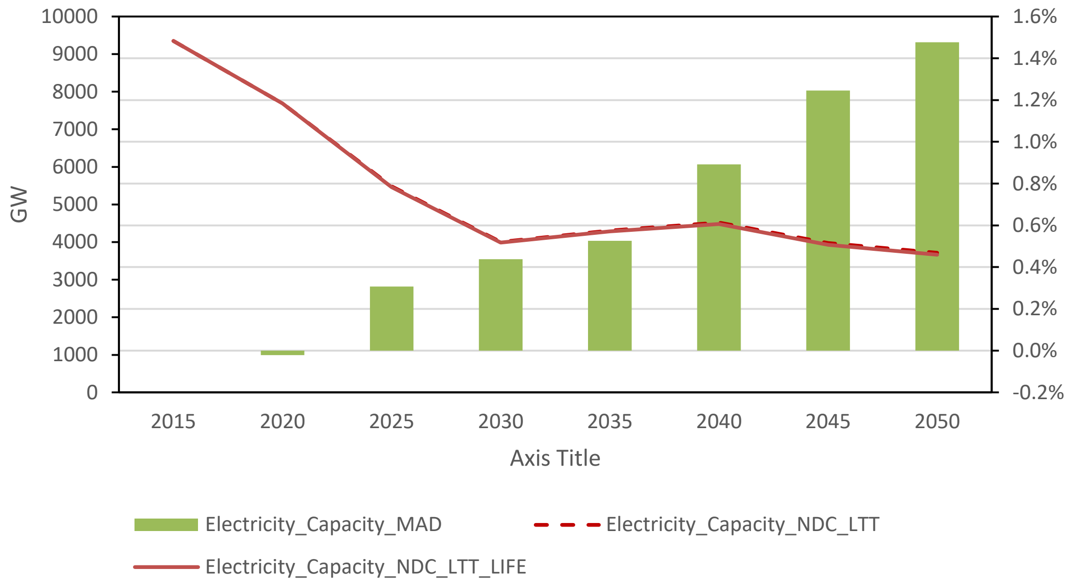

Figure 6-29: Electricity Capacity across the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

- **Economic outputs:**

The economic outputs, including the carbon tax and the prices of corn, soybean, and wheat, are depicted in Figure 6-30 and Figure 6-31, respectively.

Significant variations are observed in the carbon tax (Figure 6-30) during the transition from the "NDC_LTT" scenario to the "NDC_LTT_LIFE" scenario, particularly from 2030 to 2050, with a notable MAD of -38.00% in 2050. The reduction in the carbon price from 2035 onwards for "NDC_LTT_LIFE" can be attributed to a decrease in overall energy and food demand, hence reducing the overall pressure on the EU´s GHG mitigation trajectory.

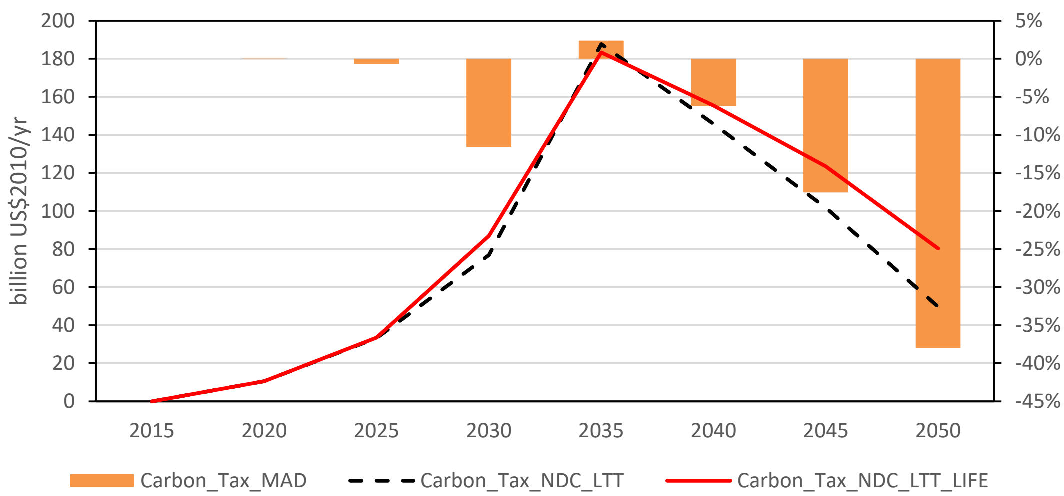

Figure 6-30: Carbon tax evolution in the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

In Figure 6-31, the prices of corn, soybean, and wheat exhibit a relatively consistent behavior, indicating a linear evolution from 2015 to 2050. Notably, the three products demonstrate comparable pricing trends over time. By calculating the MAD, plotted in the same figure, between the prices of the first and second scenarios, slight disparities are observed. These subtle variations can be attributed to slightly reduced demand for feed crops for meat (mostly ruminant meat) on the one hand and biofuels on the other hand.

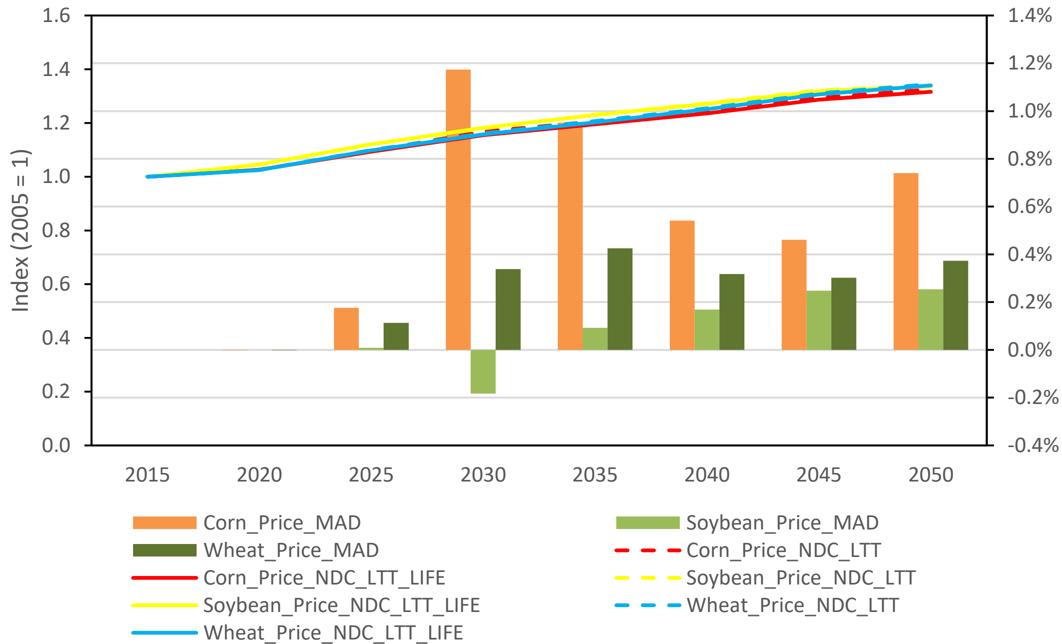

Figure 6-31: Prices of corn, soybeans, and wheat over time in the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

- **Environmental outputs:**

The climate-related outcomes, including AFOLU (Agriculture, Forestry, and Other Land Use) emissions by greenhouse gases (GHG), global mean temperature, and CO_2 concentration are depicted in Figure 6-32, Figure 6-33, and Figure 6-34.

Figure 6-32 illustrates significant disparities in AFOLU emissions between the first and second scenarios. In the "NDC_LTT_LIFE" scenario, AFOLU emissions have decreased for most of the time period, except for the period from 2025 to 2035, during which a maximum *MAD* of -95.77% (indicating more emissions in the "NDC_LTT_LIFE" scenario) is observed in the year 2030. This is specifically noticeable for CO_2 AFOLU emissions, where in the "NDC_LTT" scenario, CO_2 emissions are -2.72 Mt CO_2/year, whereas in the "NDC_LTT_LIFE" scenario, this value has increased to -64.27 Mt CO_2/year. These fluctuations in AFOLU emissions by GHG can be attributed to the impact of pasture area reduction and re-forestation. Moreover, the N_2O reduction can be attributed to the fertiliser's usage reduction driven by the cropland reduction; and the CH_4 reduction is driven by the ruminant's reduction.

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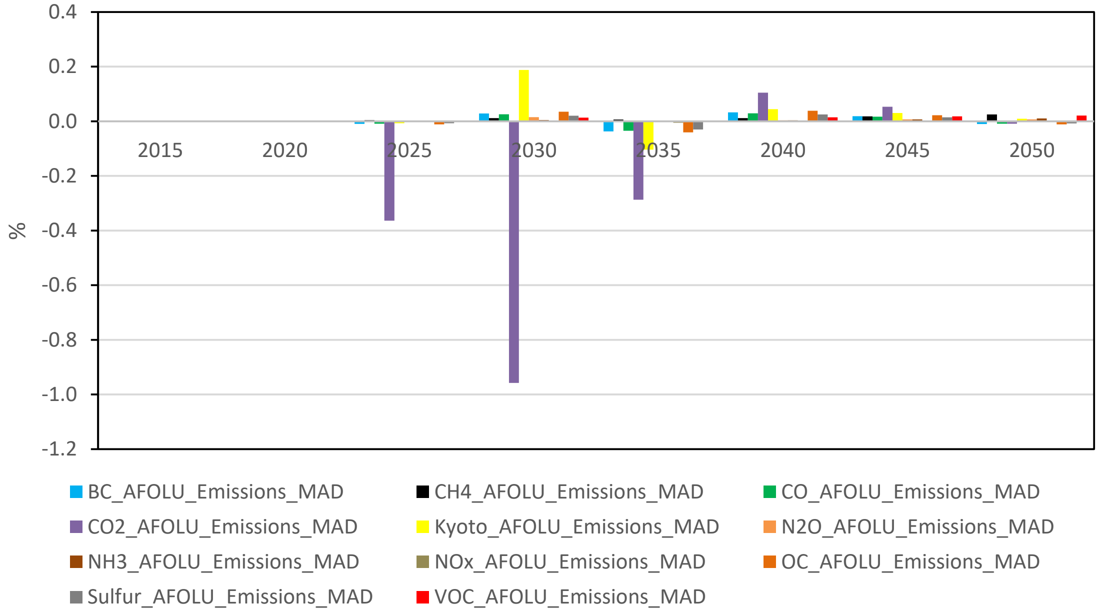

Figure 6-32: Differences in AFOLU emissions by GHG between the the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

For the global mean temperature and CO_2 concentration, we observe the same behavior with nearly identical values in the two scenarios, "NDC_LTT" and "NDC_LTT_LIFE", as shown in Figure 6-33 and Figure 6-34. The MAD is very small, indicating minimal differences between the scenarios.

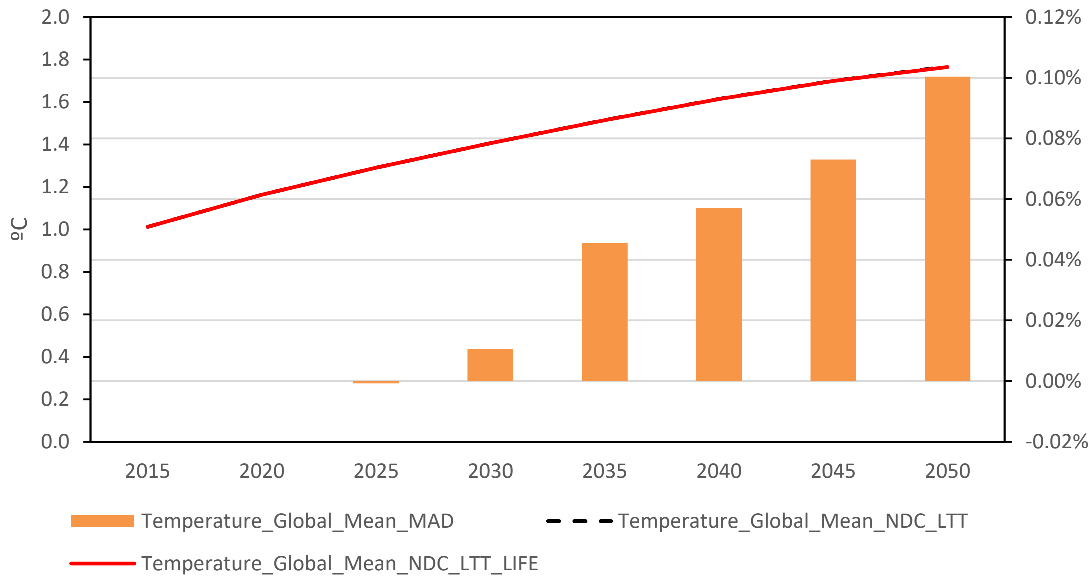

Figure 6-33: Global mean temperature evolution in the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

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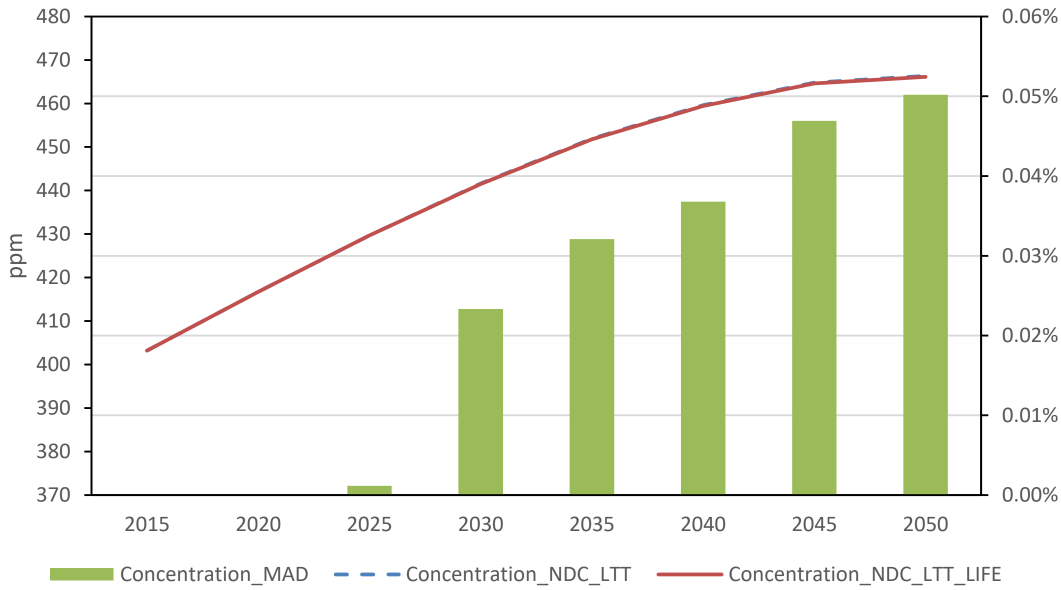

Figure 6-34: CO_2 concentration evolution in the "NDC_LTT" and "NDC_LTT_LIFE" scenarios.

6.5 Conclusion

6.5.1 Summary of key findings and significance of the results

- The inertia of the economic system and the fact that emissions in the EU-27 region account around 8-9% worldwide makes that, although the behavioural change clearly impacts on the three scenarios by 2050, the carbon concentration in the atmosphere is slightly affected (<0.5% in TRANS).
- Nevertheless, results of both models highlight the noticeable potential of mitigation and technological flexibility that transport has facing behavioural changes towards hydrogen-based or electric passenger mobility, even with the general growth of passengers' demand. Consequently, emissions drop while the cumulated extracted materials and investments exponentially increase.
- By examining the results of the "NDC_LTT" scenario and the "NDC_LTT_LED" scenario, significant changes in final energy consumption by end-use are observed in both scenarios. The "NDC_LTT_LED" scenario shows a notable increase in electricity consumption and a decrease in liquids and gases, attributed to behavioural changes in buildings. Additionally, there is a significant decrease in GHG emissions, particularly Kyoto gases and CO2 emissions, in the "NDC_LTT_LED" scenario, with a noticeable reduction from 2030 to 2050. Minimal differences are observed in CO2 concentration and global mean temperature between the two scenarios.
- The comparison between the "NDC_LTT" and "NDC_LTT_LIFE" scenarios shows significant disparities in various land, energy, economy, and climate outputs. Agricultural demand and production exhibit an increasing trend from 2015 to 2050, with the "NDC_LTT_LIFE" scenario displaying slightly lower values attributed to reduced feed crops for livestock. Land cover changes indicate cropland expansion and pasture reduction attributed to the reduction of livestock, in particular ruminant livestock (e.g., cow, sheep, and goat), which require vast pasture areas. Energy outputs reveal higher

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final and primary energy in the “NDC_LTT” scenario, notably from 2030 to 2050. Economic outputs demonstrate significant variations in carbon tax, with a notable reduction in “NDC_LTT_LIFE” from 2030 to 2050. Climate-related outcomes illustrate disparities in AFOLU emissions, particularly in CO2 emissions, attributed to pasture area reduction and reforestation. Global mean temperature and CO2 concentration exhibit minimal differences between the two scenarios.

- Among the four scenarios studied in this work, namely, "NDC_LTT", "NDC_LTT_TRANS", "NDC_LTT_LED", and "NDC_LTT_LIFE", the analysis of the generated results indicates that "NDC_LTT_LIFE" scenario offers significant benefits across various levels, including land, energy, economy, and climate.

6.5.2 Potential improvements for 2nd modelling cycle

For the TRANS we have compared passenger transport from GCAM and WILIAM. A clear improvement would be the integration of freight transport into the analysis. Since GCAM already considers it, the efforts of modelling fall in the hands of WILIAM’s modellers. On the other hand, new data collection for the modes of MARITIM and NMT (Non-Motorised Transport) would help to deliver a broader set of options for people to move.

A set of dietary patterns is already modelled in WILIAM. However, this model would need the missing feedback from the economy of households to the budget for food. This would equal WILIAM to GCAM, since the second has the relationship already implemented.

GCAM and WILIAM have been used to the first case of study (TRANS). However, only GCAM could contribute to the other two scenarios (LIFE & LED). Additional models like PROMETHEUS could enhance the assessment of human behavioural change in mitigation pathways in the second modelling cycle.

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ANNEX A

➢ Transport demand:

Table A. 1. Passenger transport demand evolution in LED scenario.

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Passenger	bn pkm/yr	19,900	21,777	23,475	25,000
			Annual change	dmnl		9.44%	7.8 %	6.49 %

Taking as the annual variation data of the total transport demand for the R2_NORTH region, the same increase has been applied for the transport demand of the EU_27 region to obtain the demand in the year 2050 of around 9000 million pass*km (see Table 5).

Table A. 2. Passenger transport demand in WILIAM model adapted to LED scenario.

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
WILIAM	Baseline	EU27	Passenger	bn pkm/yr	7181	7868	9659	10364
WILIAM	Baseline	EU27	Annual change	dmnl		9.57%	22.75%	7.31%
WILIAM	Trans	EU27	Passenger	bn pkm/yr	7181	7859	8472	9022

Since the GCAM results for the baseline scenario NDC_LTT had lower passenger transport demand increase than the one detailed in Grubler et al. (Grubler et al., 2018a), the NDC_LTT_TRANS scenario kept the same passenger transport demand.

Table A. 3. Passenger transport demand in GCAM model adapted to LED scenario.

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
GCAM	Baseline	EU27	Passenger	bn pkm/yr	7762.32	7952.006	8198.627	8274.221
GCAM	Baseline	EU27	Annual change	dmnl		2.44%	3.10%	0.92%
GCAM	Trans	EU27	Passenger	bn pkm/yr	7762.32	7952.006	8198.627	8274.221

The variable "OBJECTIVE_REDUCTION_PASSENGER_TRANSPORT_DEMAND_SP" has been modified for all Passenger transport modes and power train to achieve a transport demand target for EU27 close to 9000 million pass*km by 2050. For all scenario parameters the same initial and objective year has been used (see Table 6)

Table A. 4. Passenger transport demand policy timeframe.

Variable	Value
YEAR_INITIAL_REDUCTION_PASSENGER_TRANSPORT_DEMAND_SP	2025
YEAR_FINAL_REDUCTION_PASSENGER_TRANSPORT_DEMAND_SP	2050

The objective reduction transport demand used to reach the total transport demand in 2050 is shown in Table 7.

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Table A. 5. Passenger transport demand reduction policy by transport mode and power train.

POWER_TRAIN_I│DMNL	LDV	BUS	2W	RAIL	AIR DOMESTIC	AIR INTRA EU	AIR INTERNAT	MARINE	NMT
ICE_gasoline	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
ICE_diesel	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
ICE_LPG	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
ICE_gas	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
BEV	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
PHEV	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
HEV	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
FCEV	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
EV	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855
HPV	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855	0.855

➢ Load factor:

Table A. 6. Vehicle load factor objective policy by transport mode.

OBJECTIVE_LOAD_FACTOR_MOD_SP	
PRIVATE_TRANSPORT_I│_UNIT	_VALUE
LDV	1.25
MOTORCYCLES_2W_3W	1.25
NMT	1.25

➢ Modal share:

Table A. 7. Literature review for few parameters.

EU27	Passenger transport mode share	
	2020 (from Eurostat)	2050
rail	5%	9%
Light duty vehicles	82%	55%
Bus	7%	22%
ship	0%	0%
air	6%	11%
2W-3W	NA	3%

To this end, the values of the "OBJECTIVE_PASSENGER_TRANSPORT_DEMAND_MODAL_SHARE_SP" matrices for the different types of Passenger transport mode have been modified so that the percentage for each of the 27 EU27 countries is obtained the target modal share for the year 2050 indicated in the table above. Thus, taking the baseline values as a starting point, the percentage of LDV-BEV, BUS-BEV, 2W-HPV, RAIL-EV and AIR has been modified to achieve the indicated values.
Thus:

$$BUS_{BEV} = 0.22 - (BUS_{ICE_{gasoline}} + BUS_{ICE_{diesel}} + BUS_{ICE_{LPG}} + BUS_{ICE_{gas}})$$

$$2W_{HPV} = 0.03 - 2W_{ICE\_gasoline}$$

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$$RAIL_{EV} = 0.09 - RAIL_{ICE\_diesel}$$

$$AIR\_DOMESTIC_{2050} = 0.11 * (AIR\_DOMESTIC_{initial}/(AIR\_DOMESTIC_{initial} + AIR\_INTRA\_EU_{initial} + AIR\_INTERNATIONAL_{initial}))$$

$$AIR\_INTRA\_EU_{2050} = 0.11 * (AIR\_INTRA\_EU_{initial}/(AIR\_DOMESTIC_{initial} + AIR\_INTRA\_EU_{initial} + AIR\_INTERNATIONAL_{initial}))$$

$$AIR\_INTERNATIONAL_{2050} = 0.11 * (AIR\_INTERNATIONAL_{initial}/(AIR\_DOMESTIC_{initial} + AIR\_INTRA\_EU_{initial} + AIR\_INTERNATIONAL_{initial}))$$

Considering the modal shares according to Gurber et al. (Grubler et al., 2018a), the GCAM modal shares were modified gradually from 2025 to 2050 to meet the behavioural change standards.

Table A. 8. GCAM passenger transport modal shares

Model	Scenario	Region	Vehicle	2020	2030	2040	2050
GCAM	NDC_LTT	EU27	LDV	68.615%	69.588%	70.112%	71.132%
GCAM	NDC_LTT	EU27	2W-3W	1.672%	1.600%	1.594%	1.564%
GCAM	NDC_LTT	EU27	Rail	5.655%	5.738%	5.844%	5.912%
GCAM	NDC_LTT	EU27	Bus	12.602%	11.474%	10.931%	10.320%
GCAM	NDC_LTT	EU27	Air	11.453%	11.597%	11.517%	11.069%
GCAM	TRANS	EU27	LDV	68.614%	65.346%	60.763%	57.794%
GCAM	TRANS	EU27	2W-3W	1.672%	3.385%	4.500%	5.264%
GCAM	TRANS	EU27	Rail	5.655%	6.382%	7.028%	7.735974
GCAM	TRANS	EU27	Bus	12.602%	15.023%	16.889%	17.796%
GCAM	TRANS	EU27	Air	9.0481%	9.861%	10.817%	11.408%

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In the case of AUSTRIA, the passenger transport share objective matrix is shown in Table A. 9.

Table A. 9. Passenger transport share objective matrix for Austria.

							11.00%	
		55.00%	22.00%	3.00%	9.00%	0.07%	3.46%	7.47%
REGIONS_I	POWER_TRAIN_I	LDV	BUS	2W	RAIL	AIR_DOMESTIC	AIR_INTRA_EU	AIR_INTERNATIONAL
AUSTRIA	ICE_gasoline	0	0.000	0.013	0	0.001	0.035	0.075
	ICE_diesel	0	0.069	0	0.012	0	0	0
	ICE_LPG	0	0.001	0	0	0	0	0
	ICE_gas	0	0.004	0	0	0	0	0
	BEV	0.550	0.146	0	0	0	0	0
	PHEV	0	0	0	0	0	0	0
	HEV	0	0	0	0	0	0	0
	FCEV	0	0	0	0	0	0	0
	EV	0	0	0	0.078	0	0	0
	HPV	0	0	0.017	0	0	0	0

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ANNEX B

Table B. 1. Per capita floor space evolution according to Grubler et al. (Grubler et al., 2018a)

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Residential	Billion m2	30	30	30	30
			Annual change	dmnl		0 %	0 %	0 %
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Commercial	Billion m2	16	18.33	20.66	23
			Annual change	dmnl		1.13%	1.13%	1.13%

Since the GCAM commercial per capita floor space increase was lower than the scenario suggested by Grubler et al. (Grubler et al., 2018a), only the residential floor space per capita was modified.

Table B. 2. GCAM per capita floor space evolution for the (NDC_LTT and/or TRANS) and LED scenario.

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
GCAM	NDC_LTT	EU27	Residential	Billion m2	29.26	29.16	29.32	29.68
			Annual change	dmnl		-0.34%	0.54%	1.22%
GCAM	NDC_LTT	EU27	Commercial	Billion m2	14.95	14.90	14.98	15.17
			Annual change	dmnl		-0.32%	0.52%	1.25%
GCAM	LED	EU27	Residential	Billion m2	29.26	29.26	29.26	29.26
			Annual change	dmnl		0 %	0 %	0 %
GCAM	LED	EU27	Commercial	Billion m2	14.95	14.90	14.98	15.17
			Annual change	dmnl		-0.32%	0.52%	1.25%

The useful thermal energy demand was modified in Grubler et al. (Grubler et al., 2018a) as indicated in Table B. 3

Table B. 3. Useful energy demand according to Grubler et al. (Grubler et al., 2018a)

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Residential	MJ/m2	634	475.33	316.66	158
			Annual change	dmnl		74.97%	66.62%	49.89%
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Commercial	MJ/m2	538	402.66	267.33	132
			Annual change	dmnl		74.97%	66.62%	49.89%

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However, to achieve the 75% reduction suggested by the authors was not feasible in the GCAM model. Thus, the 55% reduction was applied.

Table B. 4. Food consumption in GCAM for the (NDC_LTT/TRANS/LED) and LIFE scenario.

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
GCAM	NDC_LTT	EU27	Residential	MJ/m2	531.70	490.80	531.87	540.19
			Annual change	dmnl		93.30%	108.36%	101.56%
GCAM	NDC_LTT	EU27	Commercial	MJ/m2	674.96	614.20	739.94	830.87
			Annual change	dmnl		90.9%	120.47%	112.28%
GCAM	LIFE	EU27	Residential	MJ/m2	531.70	486.92	446.30	402.97
			Annual change	dmnl		91.54%	91.65%	90.29%
GCAM	LIFE	EU27	Commercial	MJ/m2	674.96	663.45	668.30	708.16
			Annual change	dmnl		98.3%	100.73%	105.96%

In the same line, energy use for non-thermal energy consumption in buildings was modified to meet the reduction suggested by Grubler et al. (Grubler et al., 2018a). The per capita non-thermal energy consumption in EU households in 2050 was changed to 2277 kWh per capita, from 2417 kWh in the NDC_LTT_LED scenario.

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ANNEX C

Both the Ruminant consumption and the Meat consumption were detailed in Grübler et al. (Grubler et al., 2018a) as it can be seen in Table C. 1.

Table C. 1. Per capita food consumption according to Grubler et al. (Grubler et al., 2018a)

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Total meat	g/day	335	339.66	344.33	349
			Annual change	dmnl		101.39%	101.39%	101.35%
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Ruminant meat	g/day	89	87	85	83
			Annual change	dmnl		97.75%	97.70%	97.64%

Which corresponds to the percentages listed in Table C. 2.

Table C. 2. Per capita food consumption according to Grubler et al. (Grubler et al., 2018a)

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Meat / Total consumption	%	14.22	14.32	14.4	14.5
			Annual change	dmnl		100.69%	100.68%	100.68%
MESSAGEix-GLOBIOM 1.3	LowEnergyDemand_1.1	R2_North	Ruminant meat / Total meat consumption	%	26.56	25.64	24.71	23.78
			Annual change	dmnl		96.50%	96.37%	96.24%

GCAM modified the consumption to meet these percentual demands as shown in Table C. 3.

Table C. 3. Food consumption in GCAM for the (NDC_LTT/TRANS/LED) and LIFE scenario

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050
GCAM	NDC_LTT	EU27	Meat / Total consumption	%	9.54	9.64	9.70	9.75
			Annual change	dmnl		100.95%	100.65%	100.51%
GCAM	NDC_LTT	EU27	Ruminant meat / Total meat consumption	%	17.19	17.02	16.95	16.91
			Annual change	dmnl		98.98%	99.62%	99.76%
GCAM	LIFE	EU27	Meat / Total consumption	%	9.54	9.68	9.75	9.74
			Annual change	dmnl		101.37%	100.76%	99.91%
GCAM	LIFE	EU27	Ruminant meat / Total meat consumption	%	17.19	16.45	15.81	15.20
			Annual change	dmnl		95.70%	96.12%	96.06%

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ANNEX D: Section 4 baseline WACC values

Table Annex D 1: Baseline WACC values by country and technology taken from (Calcaterra et al., 2024; IRENA, 2022)

Countries	Year	Coal-fired plant	Gas plants	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Algeria	2018	11.4%	9.2%	11.0%	10.2%	11.4%	11.4%	13.1%	13.4%	13.4%	13.3%
Argentina	2018	15.2%	13.0%	14.8%	14.0%	15.2%	15.2%	15.5%	15.8%	15.8%	15.7%
Australia	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	3.7%	4.8%	6.2%	4.9%
Austria	2018	5.4%	3.2%	5.1%	4.3%	5.4%	5.4%	5.1%	4.3%	6.7%	5.3%
Azerbaijan	2018	7.6%	5.4%	7.3%	6.5%	7.6%	7.6%	8.7%	9.0%	9.0%	8.9%
Bangladesh	2018	8.1%	5.9%	7.8%	7.0%	8.1%	8.1%	8.5%	8.8%	8.8%	8.7%
Belarus	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.6%	11.9%	11.9%	11.8%
Belgium	2018	5.6%	3.4%	5.2%	4.5%	5.6%	5.6%	4.2%	5.4%	5.4%	5.0%
Bolivia	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	10.4%	10.7%	10.7%	10.6%
Bosnia and Herzegovina	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	12.1%	12.4%	12.4%	12.3%
Brazil	2018	7.6%	5.4%	7.3%	6.5%	7.6%	7.6%	8.0%	6.8%	8.3%	7.7%
Bulgaria	2018	6.4%	4.2%	6.1%	5.3%	6.4%	6.4%	6.5%	6.8%	8.2%	7.2%
Burkina Faso	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	7.7%	10.5%	10.5%	9.6%
Canada	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	6.0%	5.0%	6.3%	5.8%
Chile	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	5.2%	5.5%	6.8%	5.8%
China	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	4.4%	4.5%	6.9%	5.3%
Colombia	2018	6.7%	4.5%	6.3%	5.5%	6.7%	6.7%	7.3%	7.6%	7.6%	7.5%
Costa Rica	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	10.1%	7.6%	10.4%	9.4%
Croatia	2018	7.2%	5.0%	6.8%	6.0%	7.2%	7.2%	8.3%	6.1%	8.6%	7.7%
Cuba	2018	12.6%	10.5%	12.3%	11.5%	12.6%	12.6%	13.3%	13.6%	13.6%	13.5%
Cyprus	2018	7.6%	5.4%	7.3%	6.5%	7.6%	7.6%	7.6%	7.9%	9.3%	8.3%
Czech Republic	2018	5.6%	3.4%	5.2%	4.5%	5.6%	5.6%	5.4%	7.0%	7.0%	6.5%
Denmark	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	4.8%	4.1%	4.1%	4.3%
Dominican Republic	2018	8.1%	5.9%	7.8%	7.0%	8.1%	8.1%	7.3%	9.0%	9.0%	8.5%
Ecuador	2018	13.5%	11.3%	13.1%	12.3%	13.5%	13.5%	13.9%	14.2%	14.2%	14.1%
Egypt	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	10.5%	10.8%	10.8%	10.7%

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Countries	Year	Coal-fired plant	Gas plants	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
El Salvador	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	8.2%	11.1%	11.1%	10.1%
Estonia	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	6.8%	4.7%	7.1%	6.2%
Ethiopia	2018	11.4%	9.2%	11.0%	10.2%	11.4%	11.4%	10.1%	7.7%	10.4%	9.4%
Finland	2018	5.4%	3.2%	5.1%	4.3%	5.4%	5.4%	6.5%	4.4%	6.8%	5.9%
France	2018	5.5%	3.3%	5.2%	4.4%	5.5%	5.5%	5.1%	4.3%	6.7%	5.4%
Germany	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	3.6%	3.8%	4.8%	4.1%
Ghana	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Greece	2018	8.1%	5.9%	7.8%	7.0%	8.1%	8.1%	6.4%	6.6%	9.2%	7.4%
Guatemala	2018	7.2%	5.0%	6.8%	6.0%	7.2%	7.2%	8.0%	8.3%	8.3%	8.2%
Honduras	2018	8.9%	6.7%	8.5%	7.7%	8.9%	8.9%	6.5%	7.9%	9.5%	8.0%
Hungary	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	7.1%	8.8%	8.8%	8.2%
India	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	6.2%	6.4%	7.9%	6.8%
Indonesia	2018	6.7%	4.5%	6.3%	5.5%	6.7%	6.7%	7.7%	8.0%	8.0%	7.9%
Iran	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	13.1%	13.4%	13.4%	13.3%
Iraq	2018	11.4%	9.2%	11.0%	10.2%	11.4%	11.4%	11.3%	11.6%	11.6%	11.5%
Ireland	2018	5.8%	3.6%	5.5%	4.7%	5.8%	5.8%	7.2%	5.0%	7.5%	6.6%
Israel	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	5.4%	7.0%	7.0%	6.4%
Italy	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	5.4%	6.7%	8.1%	6.8%
Jamaica	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	8.9%	9.1%	10.7%	9.6%
Japan	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	4.2%	6.7%	6.7%	5.9%
Jordan	2018	8.9%	6.7%	8.5%	7.7%	8.9%	8.9%	7.5%	8.7%	10.2%	8.8%
Kazakhstan	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	8.0%	8.3%	8.3%	8.2%
Kenya	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	10.1%	7.7%	10.4%	9.4%
Korea, Republic of	2018	5.5%	3.3%	5.2%	4.4%	5.5%	5.5%	5.1%	6.8%	6.8%	6.2%
Kuwait	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	7.0%	7.3%	7.3%	7.2%
Latvia	2018	6.1%	3.9%	5.7%	5.0%	6.1%	6.1%	7.2%	7.5%	7.5%	7.4%
Lebanon	2018	22.9%	20.7%	22.5%	21.7%	22.9%	22.9%	22.7%	23.0%	23.0%	22.9%
Lithuania	2018	5.8%	3.6%	5.5%	4.7%	5.8%	5.8%	7.4%	5.2%	7.7%	6.8%
Luxembourg	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	4.8%	5.0%	6.4%	5.4%
Malaysia	2018	6.1%	3.9%	5.7%	5.0%	6.1%	6.1%	7.1%	7.3%	7.3%	7.2%
Malta	2018	5.8%	3.6%	5.5%	4.7%	5.8%	5.8%	4.0%	6.7%	6.7%	5.8%

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Countries	Year	Coal-fired plant	Gas plants	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Mauritius	2018	6.7%	4.5%	6.3%	5.5%	6.7%	6.7%	6.3%	8.0%	8.0%	7.5%
Mexico	2018	6.4%	4.2%	6.1%	5.3%	6.4%	6.4%	7.1%	6.0%	7.4%	6.9%
Mongolia	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	9.7%	8.7%	11.5%	10.0%
Montenegro	2018	8.9%	6.7%	8.5%	7.7%	8.9%	8.9%	10.5%	8.2%	10.8%	9.8%
Morocco	2018	7.2%	5.0%	6.8%	6.0%	7.2%	7.2%	7.8%	5.6%	8.1%	7.1%
Myanmar	2018	15.2%	13.0%	14.8%	14.0%	15.2%	15.2%	11.2%	11.5%	11.5%	11.4%
Namibia	2018	8.1%	5.9%	7.8%	7.0%	8.1%	8.1%	6.1%	8.8%	8.8%	7.9%
Netherlands	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	3.8%	4.0%	6.4%	4.7%
New Zealand	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	6.0%	4.9%	6.3%	5.7%
Nicaragua	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	10.9%	8.3%	11.1%	10.1%
Norway	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	6.2%	6.5%	6.5%	6.4%
Pakistan	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	10.9%	11.2%	11.2%	11.1%
Panama	2018	6.7%	4.5%	6.3%	5.5%	6.7%	6.7%	6.0%	6.2%	7.6%	6.6%
Peru	2018	6.1%	3.9%	5.7%	5.0%	6.1%	6.1%	6.9%	7.1%	7.1%	7.0%
Philippines	2018	6.7%	4.5%	6.3%	5.5%	6.7%	6.7%	7.4%	7.7%	7.7%	7.6%
Poland	2018	5.8%	3.6%	5.5%	4.7%	5.8%	5.8%	6.9%	4.8%	7.2%	6.3%
Portugal	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	8.0%	5.7%	8.3%	7.3%
Romania	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	6.8%	6.0%	8.5%	7.1%
Russian Federation	2018	6.9%	4.7%	6.6%	5.8%	6.9%	6.9%	8.0%	8.3%	8.3%	8.2%
Rwanda	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	7.5%	10.4%	10.4%	9.4%
Saudi Arabia	2018	5.7%	3.5%	5.3%	4.5%	5.7%	5.7%	7.9%	8.2%	8.2%	8.1%
Senegal	2018	8.1%	5.9%	7.8%	7.0%	8.1%	8.1%	6.2%	8.9%	8.9%	8.0%
Singapore	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	6.3%	6.6%	6.6%	6.5%
Slovakia	2018	5.8%	3.6%	5.5%	4.7%	5.8%	5.8%	5.5%	7.2%	7.2%	6.6%
Slovenia	2018	6.1%	3.9%	5.7%	5.0%	6.1%	6.1%	5.9%	7.5%	7.5%	7.0%
South Africa	2018	7.6%	5.4%	7.3%	6.5%	7.6%	7.6%	6.9%	8.6%	8.6%	8.0%
Spain	2018	6.4%	4.2%	6.1%	5.3%	6.4%	6.4%	7.3%	5.1%	7.6%	6.7%
Sri Lanka	2018	11.4%	9.2%	11.0%	10.2%	11.4%	11.4%	12.0%	12.3%	12.3%	12.2%
Sweden	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	6.2%	4.1%	6.5%	5.6%
Switzerland	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	4.1%	6.7%	6.7%	5.8%
Taiwan	2018	5.6%	3.4%	5.2%	4.5%	5.6%	5.6%	5.4%	7.0%	7.0%	6.5%

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Countries	Year	Coal-fired plant	Gas plants	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Thailand	2018	6.4%	4.2%	6.1%	5.3%	6.4%	6.4%	6.2%	7.8%	7.8%	7.3%
Tunisia	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.0%	11.3%	11.3%	11.2%
Turkey	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	9.2%	9.5%	11.0%	9.9%
Uganda	2018	9.7%	7.5%	9.4%	8.6%	9.7%	9.7%	10.1%	10.4%	10.4%	10.3%
Ukraine	2018	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.6%	11.9%	11.9%	11.8%
United Arab Emirates	2018	5.5%	3.3%	5.2%	4.4%	5.5%	5.5%	7.3%	7.6%	7.6%	7.5%
United Kingdom	2018	5.6%	3.4%	5.2%	4.5%	5.6%	5.6%	4.4%	4.6%	4.6%	4.5%
United States of America	2018	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	6.0%	4.9%	6.3%	5.8%
Uruguay	2018	6.7%	4.5%	6.3%	5.5%	6.7%	6.7%	5.9%	5.1%	7.6%	6.2%
Venezuela	2018	22.9%	20.7%	22.5%	21.7%	22.9%	22.9%	20.4%	20.7%	20.7%	20.6%
Viet Nam	2018	8.1%	5.9%	7.8%	7.0%	8.1%	8.1%	9.1%	9.4%	9.4%	9.3%
Yemen	2018	22.9%	20.7%	22.5%	21.7%	22.9%	22.9%	19.1%	22.6%	22.6%	21.4%

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ANNEX E: Section 4 expert elicitation survey results

Table Annex E 1: Experts were asked by how much they believe investment will have changed for each technology in 2050, indicated as % change. Professional capacity is indicated with "R" for research; "EP" for European policy; "NP" for national policy; and "O" for other.

Technology – Income classification	R	R	R	EP	R	R	EP	E	NP	EP	O	Average
Natural Gas - High-income countries	3%	5%	3%	50%	2%	10%	10%	-2%	5%	1%	10%	9%
Natural Gas - Middle-income countries	1%	3%	1%	50%	3%	3%	10%	-2%	2%	2%	12%	8%
Natural Gas - Low-income countries	0%	0%	0%	20%	5%	2%	5%	-2%	0%	3%	12%	4%
Hydro - High-income countries	4%	0%	0%	0%	0%	2%	0%	-3%	-2%	2%	7%	1%
Hydro - Middle-income countries	3%	0%	0%	0%	-2%	2%	0%	-5%	-2%	3%	7%	1%
Hydro - Low-income countries	2%	-2%	0%	0%	-2%	2%	0%	-3%	-4%	5%	7%	0%
Biomass - High-income countries	2%	0%	-1%	10%	0%	-1%	5%	-3%	-25%	35%	6%	3%
Biomass - Middle-income countries	1%	0%	-2%	10%	0%	-1%	5%	-3%	-2%	4%	8%	2%
Biomass - Low-income countries	0%	-2%	-3%	10%	-2%	-1%	5%	3%	-4%	5%	10%	2%
Solar PV - High-income countries	-2%	0%	-1%	0%	-3%	-6%	-10%	-3%	-3%	3%	6%	-2%
Solar PV - Middle-income countries	-1%	-2%	-3%	0%	-4%	-10%	-10%	-3%	-3%	4%	8%	-2%
Solar PV - Low-income countries	-1%	-5%	-5%	0%	-6%	-15%	-10%	-8%	-4%	5%	10%	-4%
Onshore Wind - High-income countries	-1%	0%	-1%	10%	-3%	-1%	-10%	-3%	-2%	3%	6%	0%
Onshore Wind - Middle-income countries	0%	-2%	-3%	5%	-5%	-3%	-10%	-3%	-2%	4%	8%	-1%
Onshore Wind - Low-income countries	0%	-4%	-5%	5%	-6%	-6%	-10%	-5%	-2%	5%	10%	-2%
Offshore Wind - High-income countries	2%	-1%	-2%	5%	-3%	-3%	-10%	-3%	-5%	3%	7%	-1%
Offshore Wind - Middle-income countries	1%	-4%	-3%	5%	-5%	-5%	-10%	-3%	-5%	4%	10%	-1%
Offshore Wind - Low-income countries	0%	-3%	-4%	5%	-6%	-10%	-10%	-5%	-2%	5%	15%	-1%
Coal - High-income countries	3%	4%	2%	50%	2%	10%	15%	3%	5%	1%	15%	10%
Coal - Middle-income countries	2%	4%	1%	50%	3%	3%	10%	2%	3%	4%	15%	9%
Coal - Low-income countries	1%	3%	0%	10%	5%	2%	5%	2%	0%	5%	13%	4%
CCS - High-income countries	10%	0%	0%	5%	-3%	-5%	-15%	-3%	-3%	1%	10%	0%
CCS - Middle-income countries	5%	0%	0%	5%	-3%	-7%	-15%	-5%	-2%	2%	10%	-1%

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CCS - Low-income countries	3%	-2%	0%	5%	0%	-10%	-15%	-5%	-2%	3%	12%	-1%
Green hydrogen - High-income countries	2%	-2%	-1%	0%	-2%	-5%	-10%	-3%	-3%	3%	8%	-1%
Green hydrogen - Middle-income countries	1%	-3%	-2%	0%	-2%	-7%	-10%	-5%	-2%	4%	9%	-2%
Green hydrogen - Low-income countries	0%	-2%	-3%	0%	0%	-10%	-10%	-5%	-2%	5%	11%	-1%
Nuclear - High-income countries	8%	6%	0%	30%	3%	2%	5%	-1%	-1%	2%	5%	5%
Nuclear - Middle-income countries	4%	2%	-1%	30%	3%	-1%	5%	-2%	-1%	3%	5%	4%
Nuclear - Low-income countries	2%	0%	-2%	30%	3%	-4%	5%	-2%	-1%	3%	5%	4%

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ANNEX F: Section 4 survey-based 2050 WACC values

Table Annex F 1: WACC values for 2050 by country and technology according to the IAM COMPACT survey results

Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Algeria	2050	20%	17%	15%	11%	13%	10%	11%	12%	12%	12%
Argentina	2050	24%	21%	19%	15%	17%	14%	13%	15%	14%	14%
Australia	2050	15%	12%	10%	5%	8%	5%	2%	5%	5%	4%
Austria	2050	15%	12%	10%	5%	8%	5%	4%	5%	5%	5%
Azerbaijan	2050	16%	13%	12%	7%	9%	7%	6%	8%	8%	7%
Bangladesh	2050	17%	14%	12%	8%	10%	7%	6%	8%	7%	7%
Belarus	2050	19%	16%	14%	10%	12%	10%	9%	11%	11%	10%
Belgium	2050	16%	12%	11%	5%	8%	5%	6%	7%	7%	6%
Bolivia	2050	19%	15%	14%	9%	12%	9%	8%	10%	9%	9%
Bosnia and Herzegovina	2050	19%	16%	14%	10%	12%	10%	10%	11%	11%	11%
Brazil	2050	16%	13%	12%	7%	9%	7%	6%	6%	7%	6%
Bulgaria	2050	15%	12%	10%	6%	8%	6%	4%	6%	7%	6%
Burkina Faso	2050	14%	12%	13%	9%	12%	9%	4%	9%	9%	8%
Canada	2050	15%	12%	10%	5%	8%	5%	4%	5%	5%	5%
Chile	2050	16%	12%	11%	5%	8%	5%	3%	4%	4%	3%
China	2050	14%	11%	10%	5%	7%	5%	2%	4%	6%	4%
Colombia	2050	16%	12%	11%	6%	9%	6%	5%	7%	6%	6%
Costa Rica	2050	19%	15%	14%	9%	12%	9%	8%	7%	9%	8%
Croatia	2050	17%	14%	12%	7%	9%	7%	5%	6%	8%	6%
Cuba	2050	21%	18%	17%	12%	14%	12%	11%	13%	12%	12%
Cyprus	2050	17%	14%	12%	7%	10%	7%	7%	6%	8%	7%
Czech Republic	2050	16%	12%	11%	5%	8%	5%	2%	5%	5%	4%
Denmark	2050	15%	12%	10%	5%	8%	5%	3%	4%	3%	3%
Dominican Republic	2050	17%	14%	12%	8%	10%	7%	5%	8%	8%	7%
Ecuador	2050	22%	19%	17%	13%	15%	13%	12%	13%	13%	13%
Egypt	2050	19%	15%	14%	9%	12%	9%	8%	10%	9%	9%
El Salvador	2050	19%	16%	14%	10%	12%	10%	6%	10%	10%	9%

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Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Estonia	2050	16%	12%	11%	5%	8%	5%	3%	5%	6%	5%
Ethiopia	2050	16%	13%	15%	11%	13%	10%	7%	6%	9%	8%
Finland	2050	15%	12%	10%	5%	8%	5%	3%	4%	6%	4%
France	2050	15%	12%	10%	5%	8%	5%	5%	4%	6%	5%
Germany	2050	15%	12%	10%	5%	8%	5%	2%	4%	4%	3%
Ghana	2050	19%	16%	14%	10%	12%	10%	9%	10%	10%	10%
Greece	2050	18%	14%	13%	7%	10%	7%	6%	8%	8%	7%
Guatemala	2050	16%	13%	11%	7%	9%	6%	6%	7%	7%	7%
Honduras	2050	18%	14%	13%	8%	11%	8%	4%	7%	8%	6%
Hungary	2050	17%	13%	12%	6%	9%	6%	4%	5%	7%	5%
India	2050	16%	12%	11%	6%	9%	6%	4%	5%	7%	5%
Indonesia	2050	16%	12%	11%	6%	9%	6%	6%	7%	7%	6%
Iran	2050	19%	15%	14%	9%	12%	9%	11%	12%	12%	12%
Iraq	2050	20%	17%	15%	11%	13%	10%	9%	11%	10%	10%
Ireland	2050	16%	12%	11%	5%	8%	5%	6%	8%	7%	7%
Israel	2050	16%	12%	11%	5%	8%	5%	5%	4%	6%	5%
Italy	2050	17%	14%	12%	7%	9%	7%	5%	9%	8%	7%
Jamaica	2050	19%	15%	14%	9%	12%	9%	7%	8%	9%	8%
Japan	2050	16%	12%	11%	5%	8%	5%	4%	7%	6%	5%
Jordan	2050	18%	14%	13%	8%	11%	8%	5%	8%	9%	7%
Kazakhstan	2050	16%	12%	11%	6%	9%	6%	6%	7%	7%	7%
Kenya	2050	19%	15%	14%	9%	12%	9%	8%	7%	9%	8%
Korea, Republic of	2050	16%	12%	11%	5%	8%	5%	3%	7%	6%	5%
Kuwait	2050	16%	12%	11%	5%	8%	5%	2%	7%	6%	5%
Latvia	2050	16%	12%	11%	6%	8%	6%	4%	7%	6%	5%
Lebanon	2050	32%	28%	27%	22%	25%	22%	21%	22%	22%	21%
Lithuania	2050	16%	12%	11%	6%	8%	6%	5%	5%	7%	5%
Luxembourg	2050	15%	12%	10%	5%	8%	5%	3%	5%	5%	4%
Malaysia	2050	15%	12%	10%	6%	8%	5%	5%	6%	6%	6%
Malta	2050	16%	12%	11%	6%	8%	6%	6%	5%	7%	6%

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Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Mauritius	2050	16%	12%	11%	6%	9%	6%	4%	7%	7%	6%
Mexico	2050	15%	12%	10%	6%	8%	6%	5%	5%	6%	5%
Mongolia	2050	19%	16%	14%	10%	12%	10%	7%	8%	10%	8%
Montenegro	2050	18%	14%	13%	8%	11%	8%	8%	7%	9%	8%
Morocco	2050	16%	13%	11%	7%	9%	6%	6%	5%	7%	6%
Myanmar	2050	24%	21%	19%	15%	17%	14%	9%	10%	10%	10%
Namibia	2050	17%	14%	12%	8%	10%	7%	4%	8%	7%	6%
Netherlands	2050	15%	12%	10%	5%	8%	5%	2%	4%	5%	4%
New Zealand	2050	15%	12%	10%	5%	8%	5%	4%	5%	5%	5%
Nicaragua	2050	19%	16%	14%	10%	12%	10%	9%	7%	10%	9%
Norway	2050	15%	12%	10%	5%	8%	5%	4%	6%	6%	5%
Pakistan	2050	19%	16%	14%	10%	12%	10%	9%	10%	10%	10%
Panama	2050	16%	13%	11%	6%	9%	6%	6%	5%	7%	6%
Peru	2050	15%	12%	10%	6%	8%	5%	5%	6%	6%	6%
Philippines	2050	16%	12%	11%	6%	9%	6%	5%	7%	6%	6%
Poland	2050	16%	12%	11%	6%	8%	6%	2%	7%	6%	5%
Portugal	2050	17%	14%	12%	7%	9%	7%	4%	7%	7%	6%
Romania	2050	17%	14%	12%	7%	9%	7%	6%	6%	7%	6%
Russian Federation	2050	16%	12%	11%	6%	9%	6%	6%	7%	7%	7%
Rwanda	2050	14%	12%	13%	9%	12%	9%	4%	9%	9%	8%
Saudi Arabia	2050	16%	12%	11%	5%	8%	5%	5%	7%	6%	6%
Senegal	2050	17%	14%	12%	8%	10%	7%	4%	8%	8%	6%
Singapore	2050	15%	12%	10%	5%	8%	5%	5%	6%	6%	5%
Slovakia	2050	16%	12%	11%	6%	8%	6%	5%	5%	6%	5%
Slovenia	2050	16%	13%	11%	6%	9%	6%	5%	7%	7%	6%
South Africa	2050	16%	13%	12%	7%	9%	7%	5%	8%	7%	6%
Spain	2050	16%	13%	11%	6%	9%	6%	4%	7%	7%	6%
Sri Lanka	2050	20%	17%	15%	11%	13%	10%	10%	11%	11%	11%
Sweden	2050	15%	12%	10%	5%	8%	5%	4%	4%	6%	4%
Switzerland	2050	15%	12%	10%	5%	8%	5%	2%	6%	6%	5%

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Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Taiwan	2050	16%	12%	11%	5%	8%	5%	4%	7%	6%	5%
Thailand	2050	15%	12%	10%	6%	8%	6%	4%	7%	6%	6%
Tunisia	2050	19%	16%	14%	10%	12%	10%	9%	10%	10%	10%
Turkey	2050	19%	15%	14%	9%	12%	9%	7%	8%	10%	8%
Uganda	2050	14%	12%	13%	9%	12%	9%	7%	9%	9%	9%
Ukraine	2050	19%	16%	14%	10%	12%	10%	9%	11%	11%	10%
United Arab Emirates	2050	16%	12%	11%	5%	8%	5%	3%	4%	6%	4%
United Kingdom	2050	16%	12%	11%	5%	8%	5%	4%	7%	6%	5%
United States of America	2050	18%	15%	13%	8%	11%	8%	5%	6%	8%	6%
Uruguay	2050	17%	13%	12%	6%	9%	6%	4%	6%	7%	5%
Venezuela	2050	32%	28%	27%	22%	25%	22%	18%	20%	19%	19%
Viet Nam	2050	17%	14%	12%	8%	10%	7%	7%	8%	8%	8%
Yemen	2050	27%	25%	26%	22%	25%	22%	16%	21%	21%	20%

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ANNEX G: Section 4 diverging 2050 WACC values

Table Annex G 1: Diverging WACC values for 2050 by region and technology. For high-income countries (incl. China), WACC values converge to the 25th percentile of the average baseline WACC per technology. For middle-income & low-income countries, WACC values converge to the 75th percentile of the average baseline WACC per technology.

Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Algeria	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Argentina	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Australia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Austria	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Azerbaijan	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Bangladesh	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Belarus	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Belgium	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Bolivia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Bosnia and Herzegovina	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Brazil	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Bulgaria	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Burkina Faso	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Canada	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Chile	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
China	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Colombia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Costa Rica	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Croatia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Cuba	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Cyprus	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Czech Republic	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Denmark	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Dominican Republic	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Ecuador	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Egypt	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
El Salvador	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%

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Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Estonia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Ethiopia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Finland	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
France	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Germany	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Ghana	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Greece	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Guatemala	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Honduras	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Hungary	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
India	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Indonesia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Iran	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Iraq	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Ireland	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Israel	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Italy	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Jamaica	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Japan	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Jordan	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Kazakhstan	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Kenya	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Korea, Republic of	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Kuwait	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Latvia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Lebanon	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Lithuania	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Luxembourg	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Malaysia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Malta	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Mauritius	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%

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Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Mexico	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Mongolia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Montenegro	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Morocco	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Myanmar	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Namibia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Netherlands	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
New Zealand	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Nicaragua	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Norway	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Pakistan	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Panama	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Peru	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Philippines	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Poland	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Portugal	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Romania	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Russian Federation	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Rwanda	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Saudi Arabia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Senegal	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Singapore	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Slovakia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Slovenia	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
South Africa	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Spain	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Sri Lanka	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Sweden	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Switzerland	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Taiwan	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Thailand	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%

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Countries	Year	Coal-fired plant	Gas plant	Nuclear plant	Hydro	Biomass	CCS	Solar PV	Onshore Wind	Offshore Wind	Green Hydrogen
Tunisia	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Turkey	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Uganda	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Ukraine	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
United Arab Emirates	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
United Kingdom	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
United States of America	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Uruguay	2050	5.1%	2.9%	4.7%	4.0%	5.1%	5.1%	5.1%	4.8%	6.5%	5.7%
Venezuela	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Viet Nam	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%
Yemen	2050	10.5%	8.4%	10.2%	9.4%	10.5%	10.5%	11.2%	11.5%	11.5%	11.4%

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ANNEX H: Section 4 windfall profits tax revenue allocation

Table Annex H 1: Windfall profits tax revenue allocation by country

Region	Country	Subsidy per country | current USD
Europe	Austria	0
Europe	Belarus	9,848,443,917
Europe	Belgium	0
Europe	Bosnia and Herzegovina	10,473,120,451
Europe	Bulgaria	6,735,748,173
Europe	Croatia	6,420,896,178
Europe	Cyprus	5,924,829,005
Europe	Czech Republic	6,282,223,955
Europe	Denmark	0
Europe	Estonia	4,991,178,686
Europe	Finland	0
Europe	France	0
Europe	Germany	0
Europe	Greece	6,887,448,043
Europe	Hungary	7,169,926,317
Europe	Ireland	5,612,522,960
Europe	Italy	13,588,629,747
Europe	Latvia	5,947,941,606
Europe	Lithuania	5,482,645,721
Europe	Luxembourg	0
Europe	Malta	0
Europe	Montenegro	7,914,903,935
Europe	Netherlands	0
Europe	Norway	5,452,241,601
Europe	Poland	9,168,666,845
Europe	Portugal	6,707,305,662
Europe	Romania	7,555,774,455
Europe	Slovakia	5,805,289,274
Europe	Slovenia	5,430,933,962
Europe	Spain	11,343,581,318
Europe	Sweden	0
Europe	Switzerland	0
Europe	Ukraine	12,548,667,029
Europe	United Kingdom	0
Africa	Ethiopia	29,310,030,996
Africa	Egypt	14,260,795,534
Africa	South Africa	10,674,684,710
Africa	Kenya	16,895,184,891
Africa	Uganda	27,250,798,148
Africa	Algeria	13,238,194,540
Africa	Morocco	10,947,847,935
Africa	Ghana	16,362,550,948
Africa	Burkina Faso	29,002,452,743
Africa	Senegal	19,058,174,798

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Region	Country	Subsidy per country | current USD
Africa	Rwanda	29,049,408,952
Africa	Tunisia	11,094,107,489
Africa	Namibia	9,245,795,326
Africa	Mauritius	6,428,510,764
Asia	Lebanon	15,868,176,522
Asia	Yemen	36,580,207,292
Asia	Iran	15,013,995,850
Asia	Sri Lanka	11,364,861,937
Asia	Iraq	12,458,977,903
Asia	Myanmar	17,902,463,005
Asia	Pakistan	19,547,254,965
Asia	Mongolia	9,706,004,129
Asia	Türkiye	15,202,773,953
Asia	Azerbaijan	8,924,916,370
Asia	Bangladesh	16,821,131,456
Asia	Kazakhstan	8,088,937,558
Asia	Russian Federation	19,716,974,181
Asia	Saudi Arabia	11,201,411,307
Asia	Indonesia	19,014,521,118
Asia	Philippines	13,120,620,490
Asia	United Arab Emirates	7,059,544,552
Asia	Malaysia	8,801,779,817
Asia	Kuwait	5,677,798,321
Asia	Singapore	6,013,005,329
Asia	India	41,331,711,039
Asia	Thailand	11,083,512,871
Asia	Taiwan	8,574,117,772
Asia	Israel	5,947,404,432
Asia	Republic of Korea	11,984,523,848
Asia	China	0
Asia	Japan	0
Asia	Vietnam	13,381,612,059
Asia	Jordan	10,291,966,119
North America	USA	0
North America	Mexico	14,795,578,790
North America	Canada	0
Central & South America	Argentina	14,306,154,895
Central & South America	Ecuador	12,708,876,447
Central & South America	Nicaragua	14,419,280,130
Central & South America	Bolivia	11,988,987,852
Central & South America	Costa Rica	8,010,488,905
Central & South America	El Salvador	11,411,885,128
Central & South America	Guatemala	10,988,796,019
Central & South America	Brazil	18,077,181,995
Central & South America	Colombia	9,962,586,124
Central & South America	Peru	9,085,615,195
Central & South America	Honduras	13,398,822,371

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Region	Country	Subsidy per country | current USD
Central & South America	Panama	5,673,486,268
Central & South America	Uruguay	5,845,201,911
Central & South America	Chile	0
Central & South America	Costa Rica	8,010,488,905
Central & South America	Venezuela	17,426,854,455
Central & South America	Jamaica	10,266,087,682
AUS & NZL	New Zealand	0
AUS & NZL	Australia	0

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