Environment International 136 (2020) 105513

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Health co-benefits and mitigation costs as per the Paris Agreement under different technological pathways for energy supply

Jon Sampedro[a,b,*], Steven J. Smith[b,c], Iñaki Arto[a], Mikel González-Eguino[a,d], Anil Markandya[a], Kathleen M. Mulvaney[e], Cristina Pizarro-Irizar[a,d], Rita Van Dingenen[f]

[a] Basque Centre for Climate Change (BC3), Leioa, Spain
[b] Joint Global Change Research Institute, Pacific Northwest National Laboratory, 5825 University Research Court, Suite 3500, College Park, MD 20740, USA
[c] Department of Atmospheric and Oceanic Science, University of Maryland, MD 20742, USA
[d] University of the Basque Country (UPV/EHU), Bilbao, Spain
[e] Department of Environmental Sciences and Engineering, University of North Carolina at Chapel Hill, Chapel Hill, NC, United States
[f] Joint Research Centre, Energy, Transport and Climate Directorate, Via Enrico Fermi 2749, I 21027 Ispra, VA, Italy

ARTICLE INFO

Handling Editor: Xavier Querol

Keywords:
Deep decarbonization
Air pollution
Health
Co-benefits
Integrated assessment

JEL classifications:
Q47
Q48
Q52
Q53

ABSTRACT

This study assesses the reductions in air pollution emissions and subsequent beneficial health effects from different global mitigation pathways consistent with the 2 °C stabilization objective of the Paris Agreement. We use an integrated modelling framework, demonstrating the need for models with an appropriate level of technology detail for an accurate co-benefit assessment. The framework combines an integrated assessment model (GCAM) with an air quality model (TM5-FASST) to obtain estimates of premature mortality and then assesses their economic cost. The results show that significant co-benefits can be found for a range of technological options, such as introducing a limitation on bioenergy, carbon capture and storage (CCS) or nuclear power. Cumulative premature mortality may be reduced by 17–23% by 2020–2050 compared to the baseline, depending on the scenarios. However, the ratio of health co-benefits to mitigation costs varies substantially, ranging from 1.45 when a bioenergy limitation is set to 2.19 when all technologies are available. As for regional disaggregation, some regions, such as India and China, obtain far greater co-benefits than others.

1. Introduction

Air pollution is currently the 5th biggest risk to health, being responsible for about one in every nine deaths annually (Forouzanfar et al., 2016; World Health Organization, 2016). According to World Health Organization (hereinafter WHO), air pollution is the cause of 7.2 million premature mortalities, of which ambient air pollution is responsible for 3–4 million (World Health Organization, 2016). However, recent literature estimates that this amount could be even larger (Lelieveld et al., 2019a). The most harmful pollutants in terms of health impacts are fine particulate matter ($PM_{2.5}$) and Ozone (O_3) (Brauer et al., 2016).

One of the main sources of air pollution is the combustion of fossil fuels, which is also the main source of greenhouse gas (GHG) emissions. This means that climate change and air pollution are two interrelated environmental risks, and many polices aimed at limiting GHG emissions reduce air pollution, generating health co-benefits (Lelieveld et al., 2019b; Scovronick et al., 2019; Thompson et al., 2014). Similarly, policies focusing on reducing air pollutants can also reduce GHG emissions, although GHG emission increases can also occur.

There is a growing interest within the research and policy communities in quantifying the mitigation costs and health co-benefits of climate policy. These depend on many factors such as the global temperature target and associated emissions reduction, the temporal allocation of the carbon budget (when reductions are made), the spatial distribution of the global mitigation effort (who makes the reductions), and the technological pathway associated with the reduction of emissions (how the reductions are made). In this regard, West et al. (2013) examined the global co-benefits of GHG mitigation by comparing a baseline with a decarbonization scenario where radiative forcing is limited to 4.5 W/m^2 by the end of the century ("Representative Concentration Pathway", RCP4.5). They showed that the monetized co-benefit exceeds the mitigation cost, and they locate the largest net benefits in South and East Asia, specifically India and China. Similar

* Corresponding author at: Joint Global Change Research Institute, USA.
E-mail addresses: jon.sampedro@bc3research.org, jon.sampedro@pnnl.gov (J. Sampedro).

https://doi.org/10.1016/j.envint.2020.105513
Received 19 October 2019; Received in revised form 15 December 2019; Accepted 20 January 2020
Available online 29 January 2020

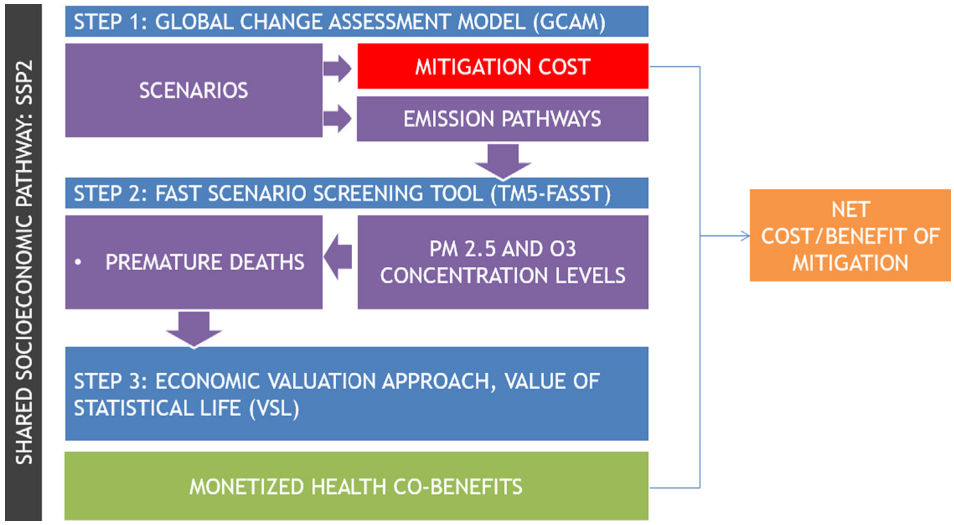

Fig. 1. Summary of the developed integrated modelling framework.

results can be found in Markandya et al., (2018), where the authors demonstrated that global health co-benefits outweigh the mitigation cost for both Paris Agreement climate objectives following different "burden sharing" criteria (2 °C and 1.5 °C stabilization). These results were also confirmed in a recent study (Vandyck et al., 2018), where a range of co-benefits was explored. They concluded that health co-benefits are greater than the mitigation costs, the difference being particularly large in the two regions mentioned above. Another study (Shindell et al., 2018) focused on the location of and variation in these co-benefits depending on the availability of negative-emission-technologies for a decarbonization scenario (RCP2.6); however, in this paper the assumptions on the air pollutant reductions are overly simplified as shown in this work. Additionally, a recent paper found that significant co-benefits could also occur in developed countries, such as USA (Ou et al., 2018). These results are later compared with the outcomes obtained in this work in order to identify potential similarities or discrepancies (see Discussion). Finally, there are several articles that review and classify co-benefits studies, showing a large increase in the number of studies over recent years (Chang et al., 2017; Deng et al., 2017; Gao et al., 2018).

While there exist several studies, which assess the potential health co-benefits associated with different decarbonization futures, the divergences in co-benefit estimations due to different technological deployments have not been analyzed in the literature. This study applies an integrated modelling framework to estimate global and regional health co-benefits, mitigation costs, and possible trade-offs of different technological deployments for achieving the 2 °C target of the Paris Agreement. The technology scenarios are based on the IPCC's Fifth Assessment Report (Anderson and Peters, 2016) and assume different levels of deployment and use of some critical mitigation technologies such as bioenergy, nuclear power, and carbon capture and storage (CCS). For each scenario we assess the emission pathways for GHGs (CO_2, CH_4, N_2O, halocarbons) and air pollutants, with the associated GHG mitigation costs and health co-benefits.

In the modelling framework applied in this study an integrated model of energy, land, and emissions (Global Change Assessment Model, GCAM) is used to generate GHG and air pollutant emissions for each set of pathways examined. The air pollutant emissions are then used in an air quality model (TM5-FASST model), which provides $PM_{2.5}$ and O_3 concentration levels and estimates health impacts in terms of premature mortality. Finally, the Value of Statistical Life (VSL) approach, based on data from the OECD, is used to monetize these impacts, incorporating into the analysis some additional estimates of morbidity costs (Lindhjem et al., 2012; OECD, 2014, 2016). The main innovation of this study is the global modelling of technology-based mitigation scenarios, coupled with an air quality model, in order to obtain health co-benefits under different energy supply pathways.

2. Materials and methods

2.1. Methodology

The study presents an integrated modelling framework which sequentially connects the Global Change Assessment Model (GCAM) (version 4.3), the Fast Scenario Screening Tool (TM5-FASST) and an economic valuation approach which computes monetized health co-benefits of mitigation. A combined use of these models and methods enables an integrated assessment of health impacts of different scenarios and quantify the impact of different technological deployment pathways on air-pollution co-benefits. Due to differences between the models used in this framework, we developed an automated procedure to connect the models used. First, where necessary, e.g. OC, emission units are changed to those expected by TM5-FASST. Second, the emissions obtained from GCAM are downscaled to country level before re-aggregating them to the regions used in TM5-FASST (see Supplementary Data).

The combined use of the tools presented in the integrated modelling framework allows the modeler to control all the features of each scenario such as socioeconomic narratives, energy and land use characteristics, regional emission reduction efforts and future technological pathways. The detailed design of these scenarios makes it possible to explore health co-benefits of future pathways that could not be analyzed by taking future emission trajectories from published databases or model ensembles, which facilitates new research as presented herein. Fig. 1 shows the structure of the integrated modelling framework and further details can be found in a previous study (Markandya et al., 2018).

GCAM is an integrated assessment model developed by the Joint Global Change Research Institute that connects different modules (economy, energy, land use, emissions, and climate), and operates in 5-year time steps from 1990 to 2100. It is divided into 32 geopolitical regions and includes the capability to incorporate carbon taxes, carbon trading, regulations, and accelerated deployment of energy technology. The model also reports the mitigation costs calculated as the area below the marginal abatement curve for GHG reduction, but it does not affect to GDP, which is exogenously defined. There are representative studies regarding GCAM details and applications (Brenkert et al., 2003; Calvin et al., 2014; Clarke et al., 2008; Wise et al., 2009) with on-line documentation also available (http://jgcri.github.io/gcam-doc/).

Focusing on the emissions module, GCAM tracks the GHG and air-pollutants emissions from energy and land-use systems. It covers the major pollutant species, namely black carbon (BC) and organic carbon (OC), nitrous oxides (NOx), sulfur dioxide (SO_2), carbon monoxide (CO), ammonia (NH_3), and non-methane volatile organic compounds (NMVOC). In particular, the sum of BC and OC is an approximation of primary $PM_{2.5}$ emissions (Kanakidou et al., 2005). Most of the pollutants are calibrated based on data from the Emissions Database for Global Atmospheric Research (EDGAR, Janssens-Maenhout et al., 2019), except for BC and OC, where additional studies are used (Bond et al., 2007; Lamarque et al., 2010). All these gases are the main precursors for both atmospheric $PM_{2.5}$ and O_3. Several studies make use of the GCAM emissions module (Shi et al., 2017; Smith et al., 2005; Smith and Wigley, 2006; Wang et al., 2016).

The TM5-FASST scenario screening tool is a global air quality source receptor model developed by the European Commission's Joint Research Centre that enables users to analyze different scenarios or emission pathways and their effects in terms of human health impacts and damage to ecosystems. The model uses parametrizations of meteorology and atmospheric chemistry drawn from more complex models and estimates the concentrations of $PM_{2.5}$ and O_3 in a receptor (gridded cell or region) driven by the emissions of different precursors in different sources (i.e. as reported by GCAM). Thus, it covers effects from not only primary but also secondary pollutants. For O_3 exposure the model uses the 6mDMA1 metric (Jerrett et al., 2009).

In terms of health impacts assessment, TM5-FASST calculates premature mortality attributable to $PM_{2.5}$ based on the integrated exposure-response functions (IER) from Burnett et al. (2014). It includes 5 causes of death, namely ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD), stroke, lung cancer (LC), and acute lower respiratory infection (ALRI). For premature mortality related to O_3 exposure, the model uses exposure-response functions from Jerrett et al. (2009). Even though recent studies have updated the parameters for estimating mortalities attributable to O_3 (Turner et al., 2016), they are not included in the version of the model used.

The model defines, for each cause of death, a theoretical minimum concentration below which there is considered to be no health impact (hereinafter Zcf). In the default TM5-FASST version, for $PM_{2.5}$ exposures, Zcf values are 7.58 μg/m^3 for COPD, 6.91 μg/m^3 for LC, 6.79 μg/m^3 for ALRI, 8.80 μg/m^3 for Stroke and 6.86 μg/m^3 for IHD. These values are consistent with the literature and are used for the calculations in this study. However, literature has defined different Zcf levels that would have a direct effect on health co-benefit estimation. Burnett et al. (2014) define the Zcf as a uniform distribution, Zcf ~ U [5.8, 8.8]. Similarly, another study sets the Zcf at 7.3 μg/m3 for all causes of death (Lelieveld et al., 2015). However, these values can be considered relatively high compared to the Global Burden of Disease study, which defines the lower bound (2.4 μg/m3), median (4.15 μg/m3), and upper bound (5.9 μg/m3) Zcf values (Forouzanfar et al., 2016). Since Zcf is a relevant driver for calculation of health co-benefits, this study includes a sensitivity analysis for this variable (see results). For O_3 exposure the Zcf value chosen is 33.3 ppbv (Jerrett et al., 2009).

Cause-specific mortalities are calculated at region level, based on the population-attributable fraction approach (Murray et al., 2003). Base mortality rates for each cause are taken from WHO, (2011), and population projections from the SSP database (Samir and Lutz, 2017), which is equal to the socioeconomic data used both in GCAM and in the economic assessment in this paper. Specifically, some of the causes of death apply only to adults (> 30 years) (IHD, stroke, COPD, LC) and ALRI applies only to infants (< 5 years). In order to estimate the proportion of adults and infants we adjust these population projections based on historical shares from the United Nations Population Division (2015) revision. Although population levels change over time following SSP2 assumptions, the population structure is constant during the analyzed time horizon, which is a limitation as it does not capture the effects of population aging over time. More technical features of TM5-FASST model are described in Van Dingenen et al., (2018).

To monetize the physical health impacts calculated with TM5-FASST, this study uses the Value of Statistical Life (VSL). VSL is based on the willingness to pay (WTP) approach, defined as the monetary value of a relatively small change in mortality risk reduction (Narain and Sall, 2016). Since it is a survey-based method with limited data across different countries and this is a global study, the authors adjusted the current VSL value for OECD countries, to further regions based on an adaptation of the "unit transfer value" method, described by the following equation:

$$VSL_{c,t} = VSL_{OECD,2005} * \left(\frac{Y_{c,2005}}{Y_{OECD,2005}}\right)^{b} * (1 + \%\Delta Y)^{b} \tag{1}$$

where $VSL_{c,t}$ is the VSL for country c in year t; $VSL_{OECD,2005}$ is the base value; Y is the GDP per capita; b is the income elasticity of the VSL and $\%\Delta Y$ is the annual income growth rate. Results for OECD countries result in a consistent range of base values ranging from US$2005 1.8 to 4.5 million (OECD, 2014). These lower and upper bounds are incorporated in the sensitivity analysis performed (see results), with the default value used taken to be the median of this range. The VSL income elasticity used in this paper is 0.8, as proposed by the OECD.

When regional VSLs are calculated, the associated morbidity costs are included as an additional cost. Morbidity costs include a wide range of effects covering direct market costs related to the health system and other indirect implications such as disability and opportunity costs. Searl et al. (2016) lists some reference endpoints to create a core set of effects to be covered when estimating the cost of morbidity. Due to the lack of methodologies for assessing such costs, this study follows the OECD's guidelines (OECD, 2014), where morbidity costs are taken to be 10% of the estimated mortality damages. By default, the study uses the median value of the range of VSL, but for the sensitivity analysis the VSL lower and upper bounds are used.

Finally, avoided premature mortalities are monetized into health benefits following this equation:

$$HB_{scen,i} = (PD_{Ref,i} * VSL_i) - (PD_{scen,i} * VSL_i) \tag{2}$$

where $HB_{scen,i}$ is the health co-benefit for each scenario and region (i), PD is the estimate obtained for premature deaths and VSL_i the VSL value calculated for region i. Consequently, the global co-benefit is obtained by adding up all these regional co-benefits. Details of how the models are connected, calculations of regional VSLs, and further information can be found in Markandya et al. (2018).

2.2. Scenarios

The scenarios in this study have two main components: a general socioeconomic storyline represented by the Shared Socioeconomic Pathways work (SSP) and the technological pathways represented by different technology options for achieving the 2 °C target defined in the Paris Agreement. For the distribution of mitigation across regions, this study adopts a "least cost" approach with a global carbon price on energy and industrial CO_2 emissions.

In terms of socioeconomic storylines the authors chose the SSP2 narrative, considered as representative of "the middle of the road" (O'Neill et al., 2014). This storyline makes several assumptions, such as central projections for population growth, gradually lower energy and material intensity, continued use of fossil fuels with an increasing share of renewables as their costs fall, and a gradual decrease in inter-regional inequalities. To implement this scenario, the authors used the SSP2 set-up scenario in the GCAM 4.3 release, which has since been updated recently in the GCAM 5.1 release. Further information on how to incorporate SSP narratives into integrated assessment models can be found in different studies (Rao et al., 2017; Riahi et al., 2016).

Moreover, online documentation provides a detailed description of the SSP implementation in GCAM (https://github.com/JGCRI/gcam-doc/blob/gh-pages/ssp.md).

All the GCAM scenarios, with or without a climate policy, have implicit emission controls for different air pollutants. This implies that emissions would also decrease over time in the baseline scenario. Indeed, the applied GCAM implementation of the SSP scenarios incorporates region, sector, and fuel-specific pollutant emission factor pathways. Their temporal evolution and sectorial information is detailed Rao et al., (2017). The SSP implementation in the version of GCAM used in this work uses these same emission factors but has a slightly different future energy trajectory. The resulting differences in global air pollutant emissions in the SSP2 case between the version used here and the SSP2 release range from 5% (NOx) to −6% (SO_2) in 2050 (Markandya et al., 2018).

For the definition of the different technological deployments, the study follows the IPCC 5th Assessment Report (IPCC, 2014). The study defines four pathways in the energy supply sector for achieving a 2 °C target based on different levels of deployment of several technology groups considered critical for achieving low emission targets (i.e. bioenergy, carbon capture and storage, and nuclear power). Literature has extensively analyzed the potential side-effects of different non-CO_2 emitting energy sources (Luderer et al., 2019). Concretely, a substantial increase in bioenergy has implications for agricultural land, which might be countered by policies to limit on the amount of cropland used for dedicated bioenergy crops. Additionally, changes in air pollutant emissions (e.g. OC) and land use change GHG emissions and potential water scarcity are also directly related with the expansion of bioenergy technologies (Harper et al., 2018; Pulighe et al., 2019). In addition, CCS technologies have not yet been implemented at a large scale, as there are several technical (storage and leakages) and financial risks and uncertainties (Leung et al., 2014; Stigson et al., 2012). Therefore, it is useful to consider scenarios where CCS is not widely deployed. According to the IPCC, deployment of nuclear energy also presents relevant risk and barriers, such as operational risks, adverse public opinion or uranium mining risks (IPCC, 2014). In that report, the IPCC also generated a scenario with maximum of 20% global electricity generation from solar and wind power annually ("Limited Solar/Wind"). However, this study does not consider that scenario for the analysis as the decrease on costs of those technologies over recent years has made them fully competitive and their share has been continuously increasing in the electricity mix (IRENA, 2016, 2019). The scenarios considered here are summarized in the Table 1 with more detailed scenario descriptions in the supplementary information (hereafter SI).

3. Results

This section presents the characteristics and associated impacts of the different technological pathways in terms of the energy and electricity mix, emission pathways, $PM_{2.5}$ concentrations, premature mortality, mitigation costs, and health co-benefits for 18 world regions up to 2050. Additional results are reported in the SI.

Table 1
Scenarios. All the scenarios, except the baseline, are constrained to achieve the 2 °C temperature stabilization target of the Paris Agreement by applying a long-term temperature stabilization target (2 °C). However, each results in different patterns of technological deployment.

Scenario	Description
Baseline	No climate policy
All available	All technologies available, no explicit limits
Bioenergy limitation	Maximum global bioenergy consumption of 100 EJ/yr.
Low CCS	Low availability of CCS technologies
Nuclear Phase-out	Phase-out of current nuclear power plants and no installation of new ones

Note that in all cases resource limits, such as fossil fuel resources, wind potential, regional carbon sequestration capacities, and land-productivity, are in place.

3.1. Energy and electricity mix

Each technological pathway results in a different structure of the energy system. Fig. 2 summarizes the energy and electricity mix for 2050 under the different technological assumptions:

In the baseline scenario, fossil fuels (without CCS) account for 83% of the energy mix in 2050, followed by bioenergy (no CCS), renewable energy and nuclear power, which account for 9%, 4% and 2% of the mix respectively in that scenario. A similar structure can be seen in the electricity system, which accounts for between 20 and 24% of final energy consumption by 2050. There, fossil fuels with no carbon capture and storage account for around 70%, while other technologies such as renewables (19%), nuclear (9%), and bioenergy (2%) play a smaller part.

In the 2 °C scenarios, global energy demand decreases from 6% to 16% by 2050 compared to the baseline scenario, depending on the technological pathway. In terms of technological changes, the main difference is in the use of fossil fuels, with and without CCS, with the share of those FF being reduced drastically, in the range of 38–46%, depending on the technological pathway. The global expansion of renewable energy sources demonstrates their importance for achieving the temperature target in all the scenarios presented. Focusing on the electricity mix, they more than double their share from 19% (baseline) to 44% in the nuclear phase-out scenario by 2050. The largest increments occur in wind and solar technologies, increasing from 6 and 3% of total electricity in the baseline to 17–23% and 10–12% in the policy scenarios, respectively. Additionally, total electricity consumption significantly increases in the policy scenarios (up to 20%, when bioenergy is limited), which makes the relative share of renewables relatively even more important.

As expected, the deployment of other technologies such as bioenergy, CCS, and nuclear power is directly related to the scenario analyzed, but they are always significantly more important than in the baseline scenario. Moreover, depending on the technological pathway, they could account for large proportions of the total energy mix: CCS technologies make up around 20% in the bio-limited scenario, biomass (no CCS) up to 13% in the Low CCS scenario, and nuclear power around 8% in the scenario with the bioenergy limitation. The technological pathways have significant implications at a regional level. For example, the global limitation of bioenergy (100 EJ/yr, see above) substantially decreases the biomass consumption in each region, compared to the "All Available" scenario (on average, around −48%). These differences range from −33% in Brazil to −76% in South Korea. Detailed information about current and future regional energy electricity mix, and regional biomass consumption can be found in the Supplementary Data.

3.2. GHG and air pollutant emissions

Variations in energy and electricity mix result in different emission pathways for each scenario, since the emission factors for pollutants are not the same across the technologies. Consequently, even though the stabilization target is equal, there are differences in emission levels. Fig. 3 shows some of these differences in the cumulative (2020–2050) CO_2 reductions in each of the regions defined and Fig. 4 shows the projections for the main air pollutants.

Regarding the spatial distribution, Fig. 3 shows that the biggest reduction in cumulative fossil CO_2 emissions is found in China (around 28% of the total reduction), followed by India (15–16%) and the USA (10–11%). To achieve the target, the model follows a "least cost" approach, so there are larger reductions in those regions where it is more feasible and cost effective to decrease emissions. Large CO_2 emissions, along with potential to accomplish cost-effective emission reductions,

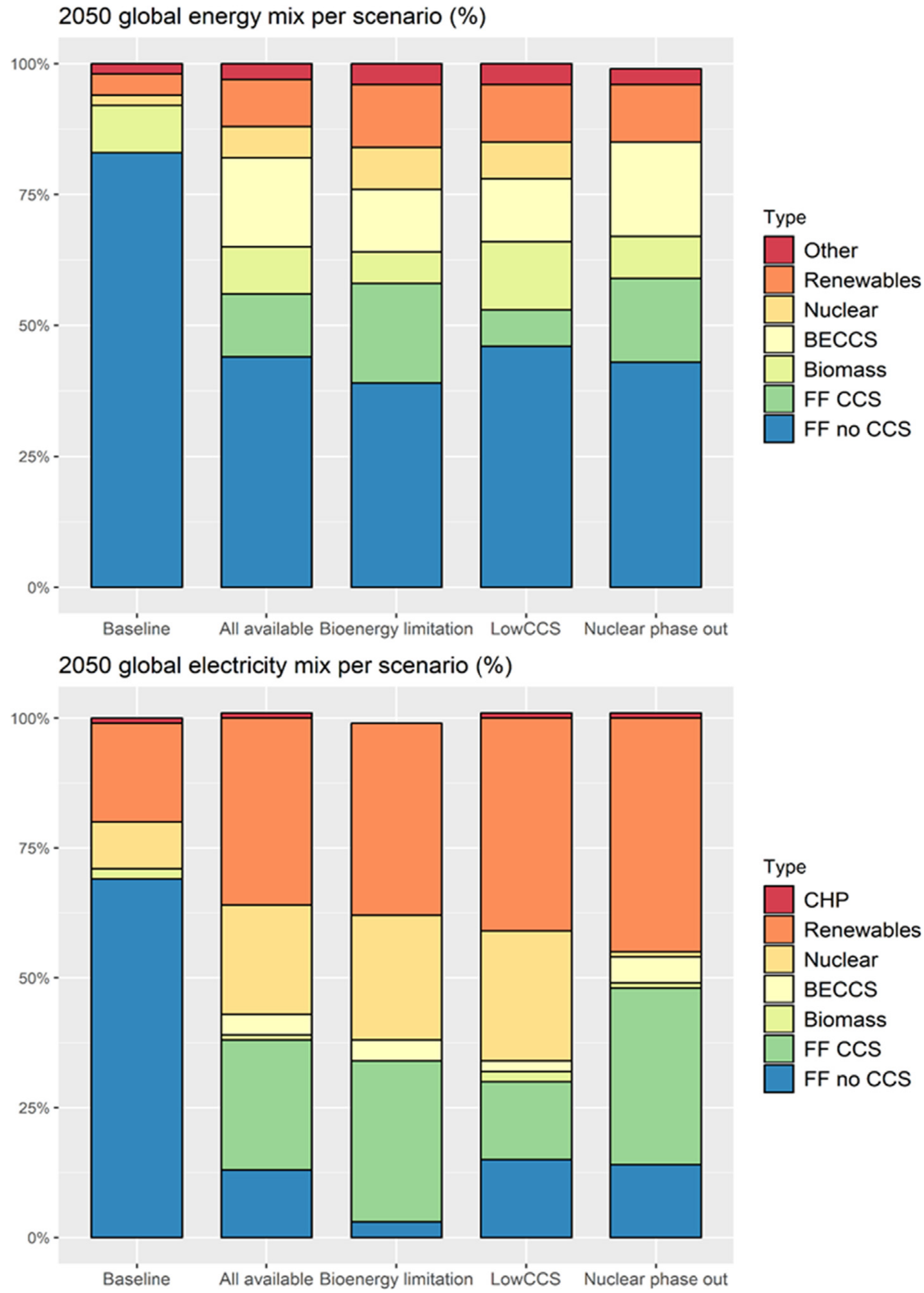

Fig. 2. 2050 global energy and electricity mix per scenario (%). Note that *FF* refers to fossil fuels; *CCS* to carbon capture and storage; *BECCS* to Bioenergy with Carbon Capture and Storage (BECCS) and *CHP* to combined heat and power.

result in China and India having the largest cumulative CO_2 reductions in these scenarios.

These results show that the time path of CO_2 emissions can be quite different from one scenario to another. When bioenergy is limited, emissions decrease more rapidly, as the possibility of having net negative emissions in future periods will depend entirely on the availability of biomass-related technologies (see the SI). So, while in the other policy scenarios cumulative CO_2 emissions decrease by around 40% by 2050 compared to the baseline, in the Bioenergy limitation scenario the reduction is 55%.

It is important to note that the stabilization targets, in order to be aligned with the temperature target of the Paris Agreement, are set for 2100, but we are focusing on results in 2050. While all the scenarios achieve the 2 °C stabilization target set by 2100, cumulative emissions of different pollutant species up to 2050 differ, as each technological pathway also shifts abatement over time, both globally and regionally, closely related to the availability of negative-emission-technologies.

3.3. $PM_{2.5}$ concentrations

As explained in Section 2, the gases tracked are the main precursors for the formation of both $PM_{2.5}$ and O_3 (Klimont et al., 2017; Turner et al., 2016). Thus, their spatial distribution is directly driven by regional emissions from GCAM. Since $PM_{2.5}$ is the most hazardous element in terms of damage to health, Fig. 5 compares worldwide concentration levels in 2050 for the baseline and one of the mitigation scenarios. For this comparison we have chosen the Bioenergy limitation scenario, as it has the most notable reductions. The spatial distribution of both $PM_{2.5}$ and O_3 concentrations for all the scenarios (relative to the reference) can be found in the SI.

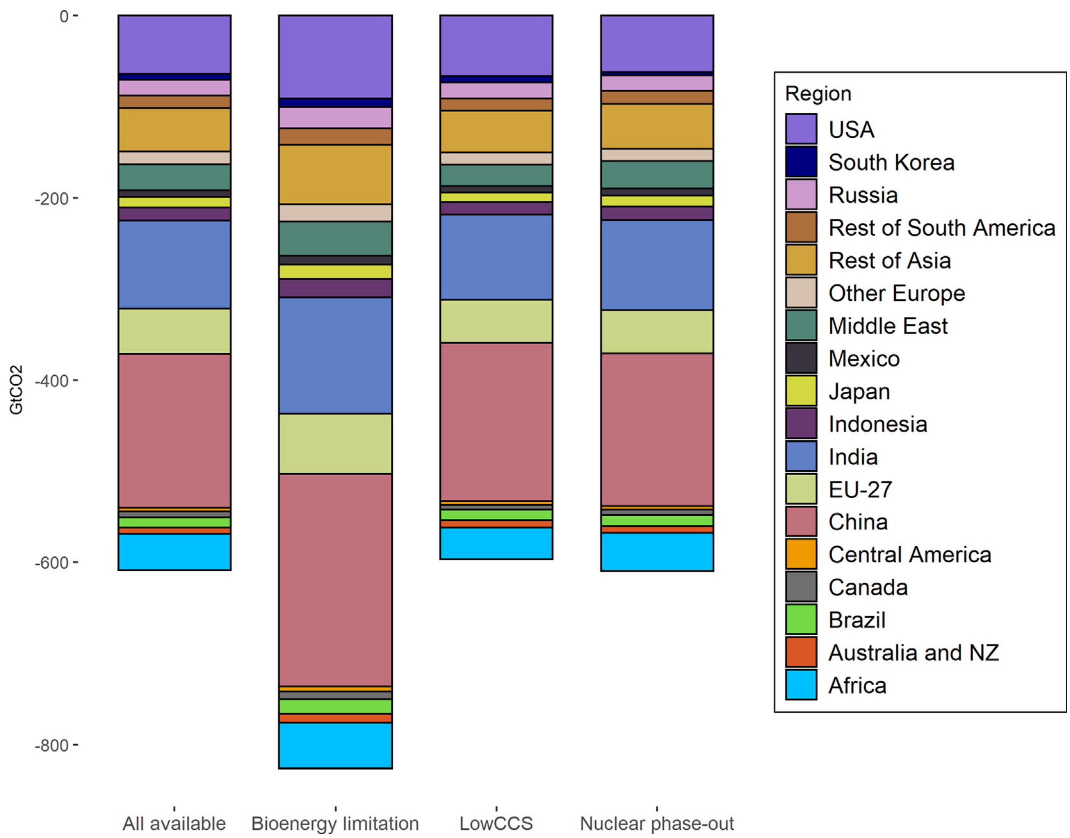

Fig. 3. Cumulative reduction in fossil CO_2 (2020–2050) emissions per region and scenario. Note that Croatia is included in "Other Europe", so results are shown for EU-27 instead of EU-28.

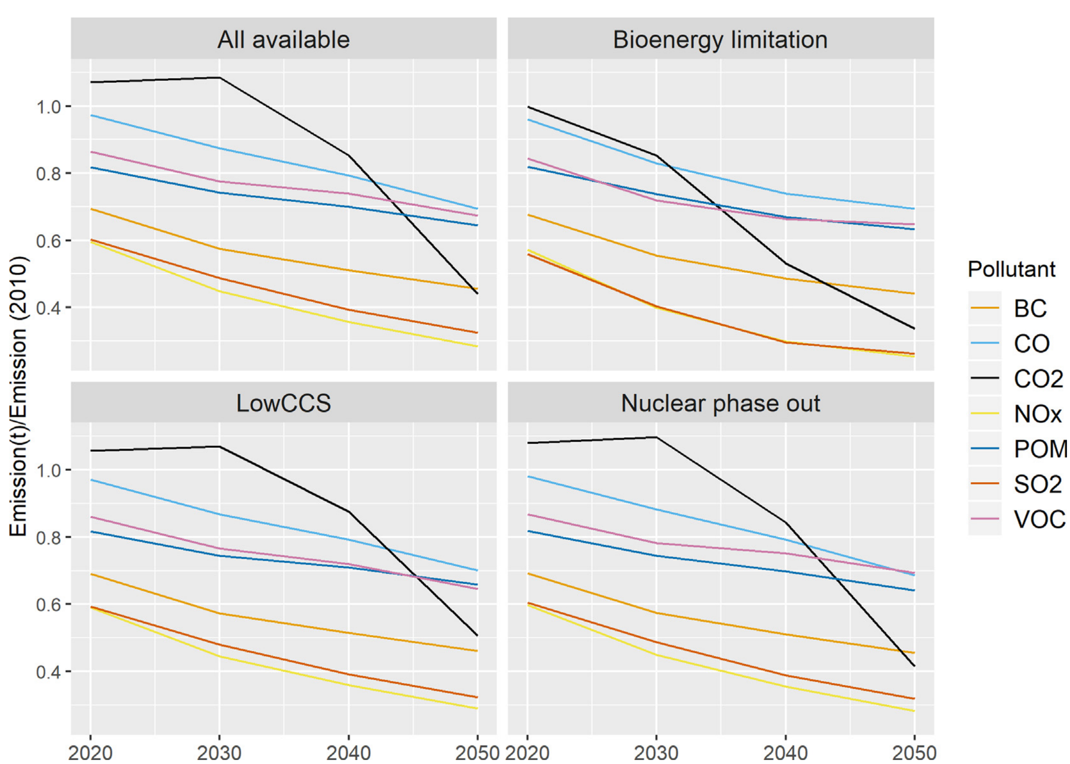

Fig. 4. Projection for main air pollutants per period and scenario. Index = 2010.

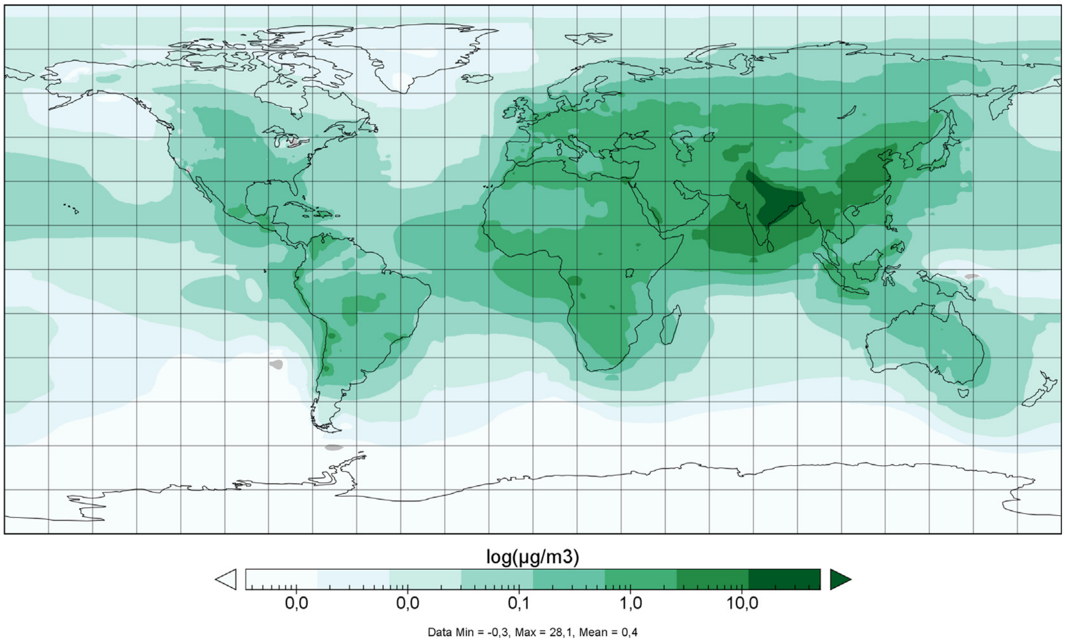

Fig. 5. Difference in $PM_{2.5}$ concentrations between Baseline and Bioenergy Limitation scenario for 2050 (log(μg/m^3)).

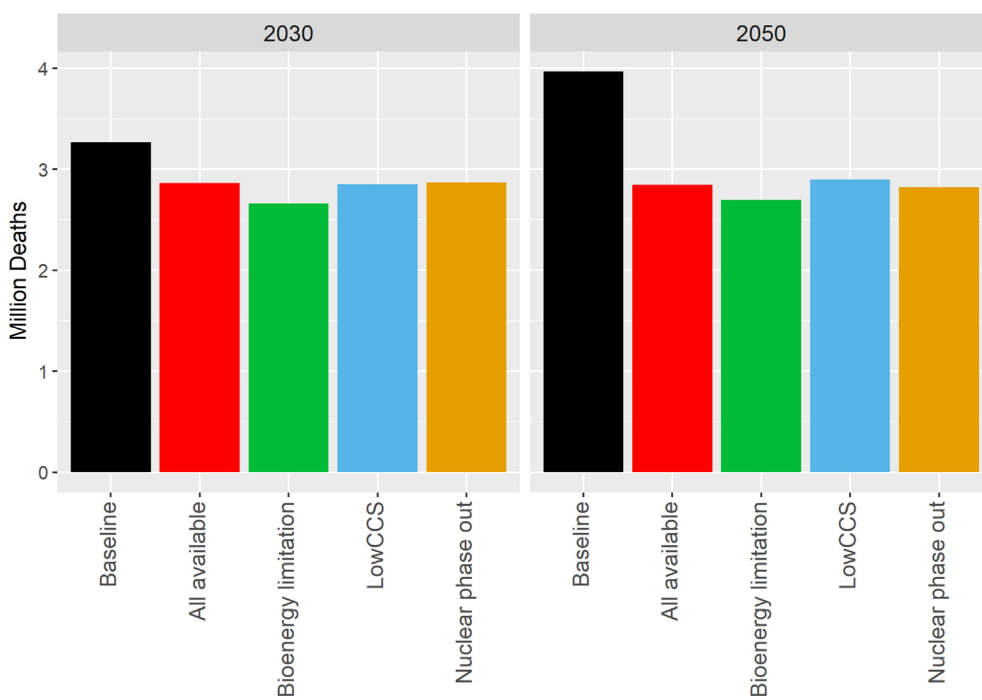

Fig. 6. Worldwide premature mortality attributable to ambient air pollution per scenario and period (million).

Fig. 5 shows that the largest reductions are achieved in India and China. As mentioned, the "least cost" approach results in these regions showing the largest reductions.

3.4. Health impacts: premature mortality

Once the regional concentration levels are calculated, they are converted into health impacts in terms of premature mortality using the TM5-FASST model. Fig. 6 shows the premature deaths attributable to air pollution per scenario for different time horizons.

Fig. 6 shows the premature mortality in the medium (2030) and long term (2050). When no climate policy is set, premature deaths increase continuously. Specifically, they reach almost 4 million in 2050, compared to 3.2 million in 2030. These results are attributable to a combination of changing air pollutant concentrations, implicit air pollution controls and generally increasing population levels. Concretely, world population increases around 10% from 2030 to 2050. This increase directly affects air pollution driven premature mortality, with more population exposed to air pollution. In China, population decreases 8.5% from 2030 to 2050, that indicates that a relatively small fraction of the avoided mortality would be attributable to socio-economic drivers there. On the other hand, population increases in India around 13% from 2030 to 2050. Therefore, a decrease in air pollutant emissions would be the driver for any decrease in premature mortality there, compensating for positive population growth and subsequent increase in exposure. The projected premature mortality

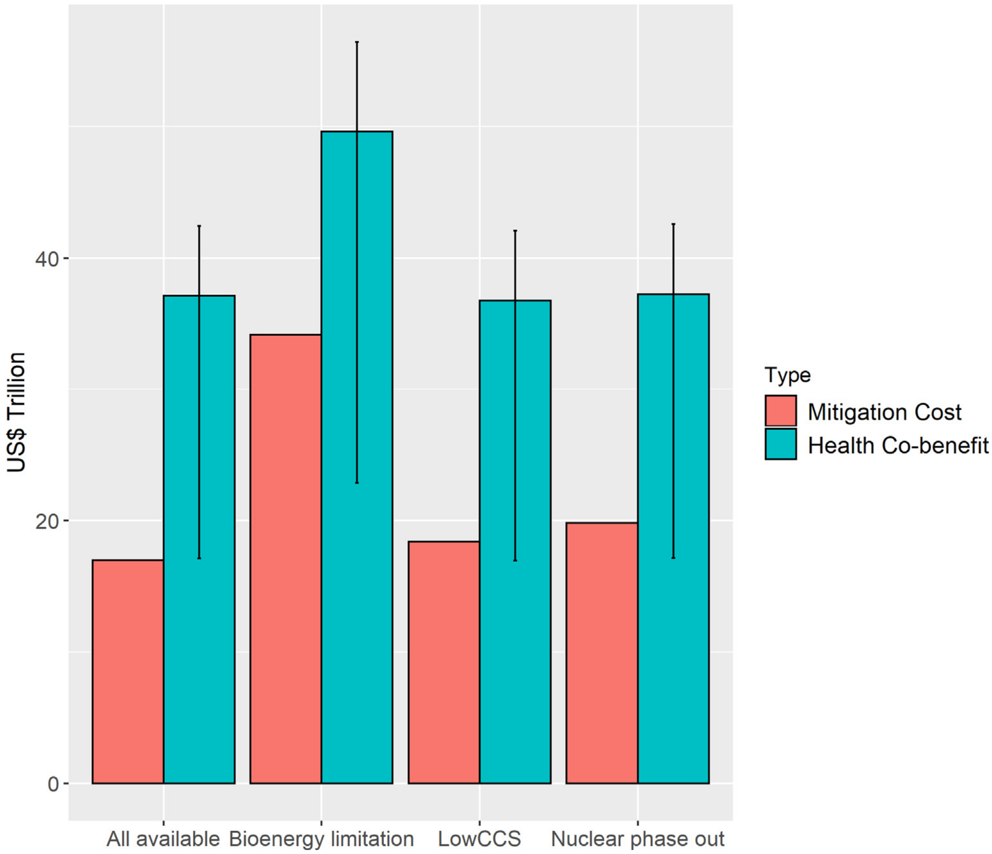

Fig. 7. Cumulative (2020–2050) health co-benefits and mitigation costs per scenario (US$ trillion). The uncertainty bars represent the consistent lower and upper bounds, combining the "theoretical minimum concentration below which there is considered to be no health impact" (Zcf) and VSL values. The discount rate used is 3%.

decreases and stabilizes across the 2 °C scenarios, with the values determined by the technological deployment pathway chosen. Because of an overall increase in population, the stabilization of premature mortalities across the mitigation scenarios, therefore, means a decrease of $PM_{2.5}$ exposure, driven by a relatively larger emission reduction. Compared to the baseline, reductions in premature mortality amount to 12–19%, and 27–32% in the medium (2030) and long term (2050) respectively, depending on the scenario. In cumulative terms (2020–2050), mortality falls by around 16–17% when a stabilization target is applied. Moreover, when a bioenergy limitation is established the effect increases to 23% as the GHG and air pollutant emission reductions are larger than in the other 2 °C scenarios (see Fig. 4). As expected, taking into consideration the spatial concentration levels, the highest numbers of avoided deaths are in India and China. Some additional results such as cumulative (2020–2050) deaths and their spatial distribution are presented in the SI.

3.5. Health co-benefits vs mitigation costs

The monetary valuation of health co-benefits is determined following the VSL approach. In this framework, Fig. 7 shows cumulative (2020–2050) health co-benefits per scenario, using a 3% discount rate, which is in the middle of the range used in the literature to discount climate impacts (Nordhaus, 1994; Stern, 2006). A previous study has demonstrated changing this rate does not significantly change the main conclusions (Markandya et al., 2018).

Two key messages can be derived from this figure: First, globally, health co-benefits outweigh mitigation costs in almost all cases, irrespective of what technological deployments, limitations, or VSL values are assumed. Second, there is a significant divergence when there is a limit to bioenergy. The Bioenergy Limitation scenario has the highest co-benefit, as its net present value (NPV) is US$ 50 trillion, while the co-benefits in other mitigation scenarios are in the range of US$ 36–37 trillion. However, there is also a significant difference in the cost side: in the scenario with the bioenergy limitation the cost is US$ 34 trillion, almost double the costs of the other mitigation scenarios (US$ 16–20 trillion).

In order to address the uncertainty in these calculations, a sensitivity analysis has been performed to assess the extent to which results depend on the two key inputs of the analysis: theoretical minimum concentration below which there is considered to be no health impact (Zcf) for $PM_{2.5}$, and the VSL. By combining these elements, the lowest co-benefits are found using the lowest VSL and the highest Zcf. By contrast, the highest co-benefits are defined by combining the upper bound of the VSL and the lowest Zcf. We consider 0 $\mu g/m^3$ as the lowest Zcf, since some studies suggest that significant damage could be obtained from exposures that are under the current GBD thresholds (Di et al., 2017). The Supplementary Data presents a more detailed sensitivity analysis, by applying different combinations and showing the individual effects of these two variables. The cost-effectiveness of each scenario is calculated as the health co-benefit divided by the cost and can be seen in Fig. 8.

Health co-benefits outweigh mitigation costs by very different proportions depending on the technological deployment, ranging from 1.45 (Bioenergy limitation) to around 2.19 (all available scenario). With no limitation on any particular technology, global health co-benefits would be twice as great as the cost of the policy for achieving the 2 °C target. As shown in Fig. 7, even though the bioenergy limited scenario presents higher co-benefits, it has also significantly larger mitigation cost.

We also examine the regional disaggregation of the costs and co-benefits, with Fig. 9 showing the co-benefit to cost ratio for 18 regions. Regarding burden sharing, we have applied a single global CO_2 market, so the reductions are undertaken where they are cheapest.

The figure shows that there are major differences around the world. Even though values are different between scenarios, some regional

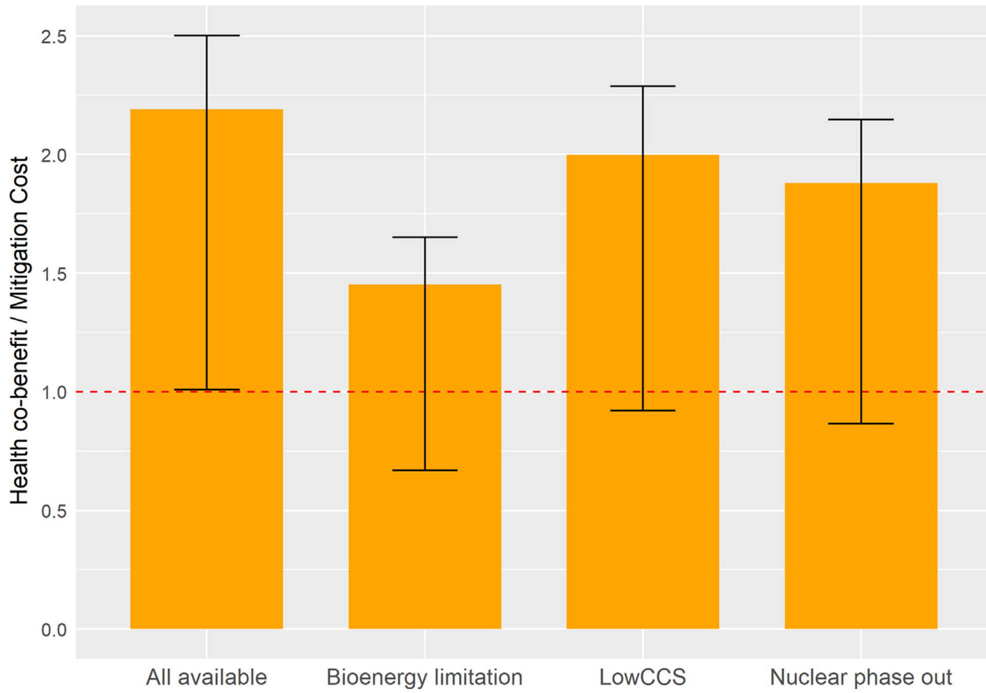

Fig. 8. Ratio of health co-benefit to mitigation cost per scenario (health co-benefit/mitigation cost). The uncertainty bars represent the consistent lower and upper bounds, combining Zcf and VSL values. The discount rate used is 3%.

patterns can be identified. First, there are some regions where the co-benefits are significantly greater than the mitigation costs, particularly for India and China. These two countries have ratios of 3.75–5.17 and 1.95–3.15 respectively. Between them they account for 33–37% and 37–38% of global co-benefits while bearing around 14 and 24% of global mitigation costs, respectively. Factors such as economic development stage, high population densities and current high concentration levels mean that all the mitigation strategies considered produce high

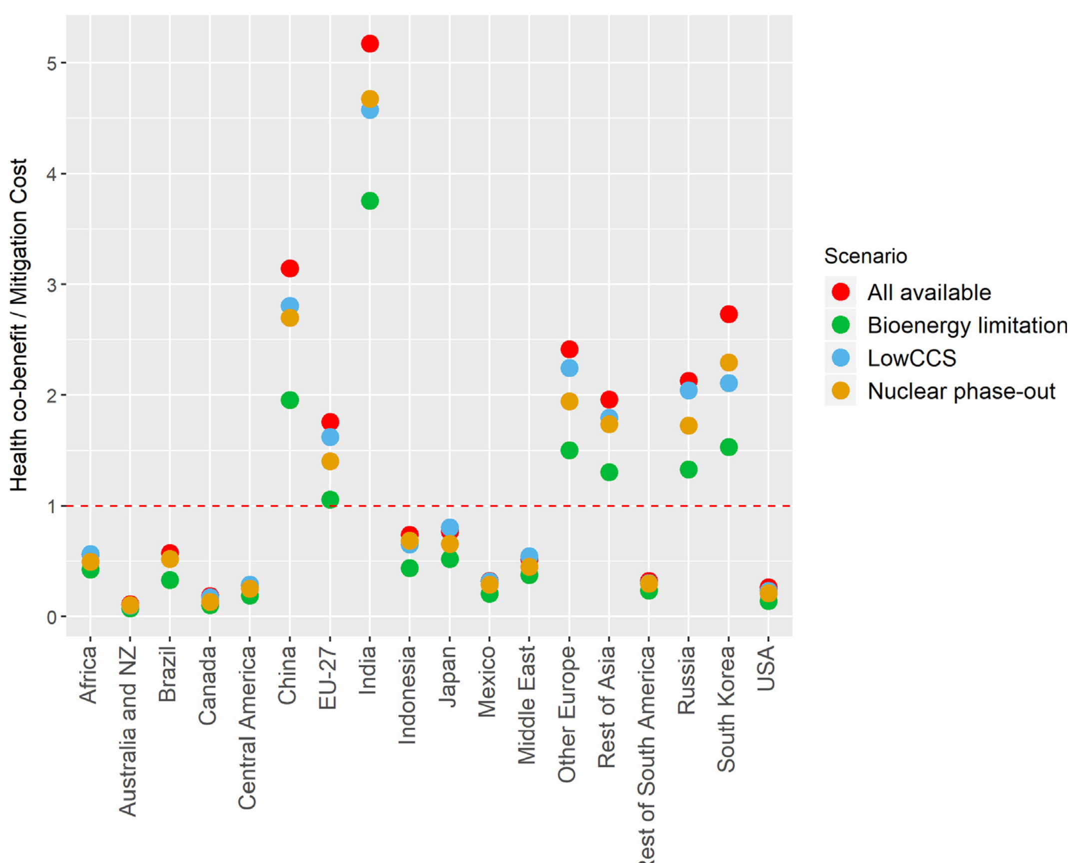

Fig. 9. Ratio of cumulative (2020–2050) health co-benefit to mitigation cost per scenario (health co-benefit/mitigation cost). The discount rate used is 3%.

co-benefits in these regions.

We find that other regions such as Europe, Russia or Asia (all except for Indonesia), also have health co-benefits that are larger than mitigation costs, even though they have different national characteristics. These results can be explained by the ease and relative cheapness with which they can implement low carbon strategies, present-day air pollution levels, and the assumed improvements in pollution controls in the baseline scenario.

Finally, there are other countries and regions where health co-benefits are not larger than mitigation costs, even though co-benefits sometimes are still relatively large. These regions include Canada, Australia, South America and the USA, where there are low population densities and, in some cases, where significant air pollution policies have already been implemented. However, we note that the health co-benefits need to be taken into consideration for policy design in these regions as well. Detailed information on the cumulative health co-benefits, mitigation costs, and ratios per region and scenario can be found in the SI.

4. Discussion

This study demonstrates that health co-benefits exceed the mitigation costs across different scenarios for energy supply technologies. This is consistent with conclusions from studies that analyze different emission targets (Scovronick et al., 2019), individual sectors (Cai et al., 2018) or individual regions (Xie et al., 2016). We show that effects of climate policies on air pollutant emissions, and therefore co-benefits, vary substantially by region and pollutant species. This means it is essential to capture these dynamics by developing a detailed integrated methodology that fully captures the evolution of the key technologies. We have found that emission reductions of each species would have its own behavior over time, not necessarily following CO_2, as has been assumed in some previous work (Shindell et al., 2018). This is shown in the SI (Figs. S14 and S15).

The largest co-benefits are concentrated in China and India. We note, however, that recent studies (Zheng et al., 2018) show that air pollutant emissions in China could be smaller than was initially expected due to the effective implementation of clean air policies in recent years. This would decrease pollutants in the baseline scenario and, therefore, the required effort to avoid pollutants in every policy scenario would also be reduced. Consequently, the calculated co-benefit for this region may be smaller than estimated here. While these newer emission factors were not included in the SSP assumptions used in this study, the SI includes an additional calculation estimating results for China with these recent policies applied, which clearly underlines the importance of these assumptions. We focus this comparison on SO_2 because it varies the most when updating the EFs, and as it is the most influential pollutant for the formation of secondary $PM_{2.5}$. Given the magnitude of the estimated co-benefits in this region, further research ought to focus on baseline emission trends in China (and India) in order to explore in higher detail their health co-benefits potential.

In addition, we also compare our results for USA co-benefits in 2050 with those presented in Ou et al. (2018) in order to compare results for a developed country. In that study the co-benefits range from US$ 200–350 billion, while in this they are estimated here at between US$ 41 and US$ 75 billion. However, in Ou et al (2018), the authors use a different methodology and different emission assumptions. For emissions, they apply a $PM_{2.5}$ emission factor directly instead of using BC and OC emission factors, which results in future (2050) $PM_{2.5}$ levels that differ between the two studies by a factor of 2 in the baseline scenarios. Moreover, to calculate health impacts they derive the mortality impact per ton of $PM_{2.5}$ from literature and multiply the unitary-damage by the units of $PM_{2.5}$ avoided. This comparison illustrates that assumptions for emissions projections and methods used for estimating health impacts can impact co-benefit estimates.

The methodology applied here has some limitations. First, we identify that co-benefits estimates depend significantly on baseline scenario assumptions. Some critical aspects such as population structure and projections have a direct effect on the results (Xie et al., 2018). For clarity, this study uses publicly available socioeconomic data (Samir and Lutz, 2017). Further research should focus on exploring the implications of a dynamic population structure in order to capture the effects of population aging. Moreover, we note that GHG mitigation here was based on a global, least cost allocation (a situation where there is a single global CO_2 market). Although this measure gives an optimal or cost-effective set of results, it is difficult to apply in the real world. Alternative GHG mitigation policies are likely to have higher or lower air pollution co-benefits relative to mitigation costs. In order to assess the importance of the structure of the climate policy, we have compared the results obtained for Europe with a previous study using the same models used here (Markandya et al., 2018). That study does not follow the "least cost" approach for the allocation of the mitigation effort and the results are significantly different. This demonstrates that policy design would also have large impact on health co-benefit estimation. The comparison of the results of the two studies for Europe can be found in the SI (Fig. S8).

In terms of population exposure and health impacts, the present integrating modelling framework uses annual mean $PM_{2.5}$ as exposure metric for fine particulate matter. This is well-aligned with the recommendations by WHO (2013), as well as the methodology used in the Global Burden of Disease assessments. Our modelled $PM_{2.5}$ contains both primary (BC, POM) and secondary (SO_4, NO_3, NH_4) components. However, other primary emitted $PM_{2.5}$ such as fly ash, re-suspended road dust, abrasive emissions from vehicles or primary sulfate are not considered. Therefore, the resulting impacts are conservative estimates. Health impacts from exposure to other pollutants (e.g. NO_2 or SO_2) are currently not being evaluated in TM5-FASST. Some evidence suggests that NO_2 exposure generates the second highest impact on health after $PM_{2.5}$ (U.S. EPA, 2016). However, at the present time, difficulty in modelling NO_2 exposure and determining the extent of overlap between the $PM_{2.5}$ and NO_2 functions introduces too high uncertainties (Holland, 2017). We do however acknowledge that omitting NO_2 (gas) impacts leads to an underestimation of impacts attributable to NOx emissions. Further, potential changes in exposure to secondary organic aerosol are also not included. Additionally, exposure response functions for estimating health impacts attributable to $PM_{2.5}$ and O_3 are based on evidence from countries in North America and Europe. Due to the lack of data, we apply those functions to other countries in the world for estimating the potential health co-benefits. This is a limitation that should be explored. Finally, we have identified that the method for monetizing health co-benefits directly affects the results. Different assumptions, such as the approach for expanding VSL-OECD values to different regions or the selection of the income elasticity of the VSL, impact the calculations of monetized co-benefits (see methodology). In particular, some studies suggest that the income elasticity for the VSL should be modified based on the regional average income levels (Masterman and Viscusi, 2018; Viscusi and Masterman, 2017). Given the importance of this variable (see SI), further research ought to focus on exploring different monetization approaches.

5. Conclusions

In the context of climate change mitigation, the most innovative finding of this paper is that no matter which technological strategy is chosen or, equivalently, which technology constraints turn out to be binding in the future, global health co-benefits outweigh global mitigation costs up to 2050. Each scenario shows significant differences in the energy or electricity mixes or in GHG and air pollutant emissions. Therefore, in cumulative terms (2020–2050), the central ratio of health co-benefits to mitigation costs has a dependence on technological pathway. The bioenergy limitation scenario shows the lowest ratio (1.5) of co-benefits to policy costs, while for the other technology scenarios, the ratio averages 2.0. When bioenergy is limited, the absolute health co-benefits are larger than in the rest of the 2 °C scenarios (additional 33%, compared with the All available). However, the mitigation cost of achieving the target with this technological limitation more than doubles compared to the other scenarios, making the bioenergy limitation the least cost-effective case. A sensitivity analysis shows the results are robust to the assumed "safe concentration level (Zcf)" and VSL. India and China stand to have the highest co-benefits, and their cumulative health co-benefit to mitigation cost ratios range from 3.75 to 5.17 (India) and 1.95–3.15 (China) in the bioenergy limitation and all available scenarios respectively. It is worth noting that India shows larger cumulative net benefits, but China is the country that benefits most in the mid-term. In other regions such as Europe or Russia we also find that health co-benefits could also outweigh mitigation costs. In some parts of the world, such as Canada, Australia, and the USA, countries with more land surface and lower population density, estimated health co-benefits are not enough to compensate mitigation costs. However, they still can amount to a large portion of mitigation costs, so it is important to include co-benefits in policy design in those countries as well.

The temperature stabilization objectives defined in the Paris Agreement require a transformation of the energy system, largely completed by 2040 (Iyer et al., 2015). Each technological deployment for achieving the climate goals will entail a wide set of ancillary co-benefits and adverse effects (Luderer et al., 2019). These side effects include air pollutant and land use change GHG emissions, O_3-related agricultural damages, water pollution or ecosystem damages. Moreover, technological futures will directly affect different Sustainable Development Goals. In this context, this study demonstrates the possibility of exceeding mitigation costs with health co-benefits for different possible future technological pathways. Additionally, it identifies which technological pathways would be the most cost effective in terms of health co-benefits, what is an important implication for stakeholders and policy-makers. It has been shown that co-benefits can provide an incentive for decarbonization (Bain et al., 2016), so these results might encourage countries to undertake mitigation actions, especially in cases such as China and India.

CRediT authorship contribution statement

Jon Sampedro: Corresponding author, Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing -original draft, Writing - review & editing. **Steven J. Smith:** Conceptualization, Methodology, Software, Supervision, Validation, Writing - review & editing. **Iñaki Arto:** Conceptualization, Supervision, Validation, Writing - review & editing. **Mikel Gonzalez-Eguino:** Conceptualization, Supervision, Project administration, Validation, Writing - review & editing. **Anil Markandya:** Conceptualization, Supervision, Validation, Methodology, Writing - review & editing. **Kathleen M. Mulvaney:** Data curation, Formal analysis, Visualization, Writing - review & editing. **Cristina Pizarro-Irizar:** Conceptualization, Writing - review & editing. **Rita Van Dingenen:** Investigation, Methodology, Software, Supervision, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank Dirk-Jan Van de Ven, Bosco Lliso and Sha Yu for their comments, which have improved the document, and Dr. Zarrar Khan, Caleb Braun, and Kalyn Dorheim for their support with data processing. This research is supported by the Basque Government through the BERC 2018-2021 program and by Spanish Ministry of Economy and Competitiveness MINECO through BC3 María de Maeztu excellence accreditation MDM-2017-0714. Additionally, this study received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 642260 (TRANSrisk project). Mikel González-Eguino, Iñaki Arto, Cristina Pizarro Irizar, and Jon Sampedro acknowledge financial support from the Ministry of the Economy and Competitiveness of Spain (ECO2015-68023) and from the Ministry of Science, Innovation and Universities of Spain (RTI2018-093352-B-I00). Mikel González-Eguino and Jon Sampedro acknowledge financial support from the Basque Government (IT-799-13 and PRE_2017_2_0139).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2020.105513.

References

Anderson, K., Peters, G., 2016. The trouble with negative emissions. Science 354, 182–183.

Bain, P.G., Milfont, T.L., Kashima, Y., Bilewicz, M., Doron, G., Garðarsdóttir, R.B., Gouveia, V.V., Guan, Y., Johansson, L.-O., Pasquali, C., 2016. Co-benefits of addressing climate change can motivate action around the world. Nat. Clim. Change 6, 154.

Bond, T.C., Bhardwaj, E., Dong, R., Jogani, R., Jung, S., Roden, C., Streets, D.G., Trautmann, N.M., 2007. Historical emissions of black and organic carbon aerosol from energy-related combustion, 1850–2000. Glob. Biogeochem. Cycles 21.

Brauer, M., Freedman, G., Frostad, J., van Donkelaar, A., Martin, R.V., Dentener, F., van Dingenen, R., Estep, K., Amini, H., Apte, J.S., Balakrishnan, K., Barregard, L., Broday, D., Feigin, V., Ghosh, S., Hopke, P.K., Knibbs, L.D., Kokubo, Y., Liu, Y., Ma, S., Morawska, L., Sangrador, J.L.T., Shaddick, G., Anderson, H.R., Vos, T., Forouzanfar, M.H., Burnett, R.T., Cohen, A., 2016. Ambient air pollution exposure estimation for the global burden of disease 2013. Environ. Sci. Technol. 50, 79–88. https://doi.org/10.1021/acs.est.5b03709.

Brenkert, A.L., Smith, S.J., Kim, S.H., Pitcher, H.M., 2003. Model Documentation for the MiniCAM.

Burnett, R.T., Pope III, C.A., Ezzati, M., Olives, C., Lim, S.S., Mehta, S., Shin, H.H., Singh, G., Hubbell, B., Brauer, M., Anderson, H.R., Smith, K.R., Balmes, J.R., Bruce, N.G., Kan, H., Laden, F., Prüss-Ustün, A., Turner, M.C., Gapstur, S.M., Diver, W.R., Cohen, A., 2014. An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. Environ. Health Perspect. https://doi.org/10.1289/ehp.1307049.

Cai, W., Hui, J., Wang, C., Zheng, Y., Zhang, X., Zhang, Q., Gong, P., 2018. The Lancet Countdown on PM 2·5 pollution-related health impacts of China's projected carbon dioxide mitigation in the electric power generation sector under the Paris Agreement: a modelling study. Lancet Planet. Health 2, e151–e161. https://doi.org/10.1016/S2542-5196(18)30050-0.

Calvin, K., Wise, M., Kyle, P., Patel, P., Clarke, L., Edmonds, J., 2014. Trade-offs of different land and bioenergy policies on the path to achieving climate targets. Clim. Change 123, 691–704. https://doi.org/10.1007/s10584-013-0897-y.

Chang, K.M., Hess, J.J., Balbus, J.M., Buonocore, J.J., Cleveland, D.A., Grabow, M.L., Neff, R., Saari, R.K., Tessum, C.W., Wilkinson, P., 2017. Ancillary health effects of climate mitigation scenarios as drivers of policy uptake: a review of air quality, transportation and diet co-benefits modeling studies. Environ. Res. Lett. 12, 113001.

Clarke, L., Kyle, P., Wise, M., Calvin, K., Edmonds, J., Kim, S., Placet, M., Smith, S., 2008. CO2 emissions mitigation and technological advance: An updated analysis of advanced technology scenarios. PNNL Rep. Pac. Northwest Natl. Lab. Richmond.

Deng, H.-M., Liang, Q.-M., Liu, L.-J., Anadon, L.D., 2017. Co-benefits of greenhouse gas mitigation: a review and classification by type, mitigation sector, and geography. Environ. Res. Lett. 12, 123001.

Di, Q., Wang, Yan, Zanobetti, A., Wang, Yun, Koutrakis, P., Choirat, C., Dominici, F., Schwartz, J.D., 2017. Air pollution and mortality in the Medicare population. N. Engl. J. Med. 376, 2513–2522.

Forouzanfar, M.H., Afshin, A., Alexander, L.T., Anderson, H.R., Bhutta, Z.A., Biryukov, S., Brauer, M., Burnett, R., Cercy, K., Charlson, F.J., et al., 2016. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2015. Lancet.

Gao, J., Kovats, S., Vardoulakis, S., Wilkinson, P., Woodward, A., Li, J., Gu, S., Liu, X., Wu, H., Wang, J., Song, X., Zhai, Y., Zhao, J., Liu, Q., 2018. Public health co-benefits of greenhouse gas emissions reduction: a systematic review. Sci. Total Environ. 627, 388–402. https://doi.org/10.1016/j.scitotenv.2018.01.193.

Harper, A.B., Powell, T., Cox, P.M., House, J., Huntingford, C., Lenton, T.M., Sitch, S., Burke, E., Chadburn, S.E., Collins, W.J., 2018. Land-use emissions play a critical role in land-based mitigation for Paris climate targets. Nat. Commun. 9, 2938.

Holland, M., 2017. Benefit assessment methodologies for the LCP BREF implementation. Health Environ. Alliance.

IPCC, 2014. Summary for Policymakers. In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., von Stechow, C., Zwickel, T., Minx, J.C. (Eds.), Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
IRENA, 2016. The Power to Change: Solar and Wind Cost Reduction Potential to 2025.
IRENA, 2019. Renewable Power Generation Costs in 2018. International Renewable Energy Agency, Abu Dhabi.
Iyer, G.C., Edmonds, J.A., Fawcett, A.A., Hultman, N.E., Alsalam, J., Asrar, G.R., Calvin, K.V., Clarke, L.E., Creason, J., Jeong, M., 2015. The contribution of Paris to limit global warming to 2 C. Environ. Res. Lett. 10, 125002.
Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Bergamaschi, P., Pagliari, V., Olivier, J.G., Peters, J.A., 2019. EDGAR v4. 3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970–2012. Earth Syst. Sci. Data 11, 959–1002.
Jerrett, M., Burnett, R.T., Pope III, C.A., Ito, K., Thurston, G., Krewski, D., Shi, Y., Calle, E., Thun, M., 2009. Long-term ozone exposure and mortality. N. Engl. J. Med. 360, 1085–1095.
Kanakidou, M., Seinfeld, J., Pandis, S., Barnes, I., Dentener, F., Facchini, M., Dingenen, R.V., Ervens, B., Nenes, A., Nielsen, C., 2005. Organic aerosol and global climate modelling: a review. Atmospheric Chem. Phys. 5, 1053–1123.
Klimont, Z., Kupiainen, K., Heyes, C., Purohit, P., Cofala, J., Rafaj, P., Borken-Kleefeld, J., Schöpp, W., 2017. Global anthropogenic emissions of particulate matter including black carbon. Atmospheric Chem. Phys. 17, 8681–8723. https://doi.org/10.5194/acp-17-8681-2017.
Lamarque, J.-F., Bond, T.C., Eyring, V., Granier, C., Heil, A., Klimont, Z., Lee, D., Liousse, C., Mieville, A., Owen, B., Schultz, M.G., Shindell, D., Smith, S.J., Stehfest, E., Van Aardenne, J., Cooper, O.R., Kainuma, M., Mahowald, N., McConnell, J.R., Naik, V., Riahi, K., van Vuuren, D.P., 2010. Historical (1850–2000) gridded anthropogenic and biomass burning emissions of reactive gases and aerosols: methodology and application. Atmospheric Chem. Phys. 10, 7017–7039. https://doi.org/10.5194/acp-10-7017-2010.
Lelieveld, J., Evans, J., Fnais, M., Giannadaki, D., Pozzer, A., 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525, 367–371.
Lelieveld, J., Klingmüller, K., Pozzer, A., Burnett, R., Haines, A., Ramanathan, V., 2019a. Effects of fossil fuel and total anthropogenic emission removal on public health and climate. Proc. Natl. Acad. Sci 201819989.
Lelieveld, J., Klingmüller, K., Pozzer, A., Pöschl, U., Fnais, M., Daiber, A., Münzel, T., 2019b. Cardiovascular disease burden from ambient air pollution in Europe reassessed using novel hazard ratio functions. Eur. Heart J. 40, 1590–1596.
Leung, D.Y., Caramanna, G., Maroto-Valer, M.M., 2014. An overview of current status of carbon dioxide capture and storage technologies. Renew. Sustain. Energy Rev. 39, 426–443.
Lindhjem, H., Navrud, S., Biausque, V., Braathen, N., 2012. Mortality risk valuation in environment, health and transport policies.
Luderer, G., Pehl, M., Arvesen, A., Gibon, T., Bodirsky, B.L., de Boer, H.S., Fricko, O., Hejazi, M., Humpenöder, F., Iyer, G., 2019. Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies. Nat. Commun. 10, 1–13.
Markandya, A., Sampedro, J., Smith, S.J., Van Dingenen, R., Pizarro-Irizar, C., Arto, I., González-Eguino, M., 2018. Health co-benefits from air pollution and mitigation costs of the Paris Agreement: a modelling study. Lancet Planet. Health 2, e126–e133.
Masterman, C.J., Viscusi, W.K., 2018. The income elasticity of global values of a statistical life: stated preference evidence. J. Benefit-Cost Anal. 9, 407–434.
Murray, C.J., Ezzati, M., Lopez, A.D., Rodgers, A., Vander Hoorn, S., 2003. Comparative quantification of health risks: conceptual framework and methodological issues. Popul. Health Metr. 1, 1.
Narain, U., Sall C. 2016. Methodology for Valuing the Health Impacts of Air Pollution: Discussion of Challenges and Proposed Solutions. World Bank, Washington DC. License: Creative Commons Attribution CC BY 3.0 IGO.
Nordhaus, W.D., 1994. Managing the Global Commons: The Economics of Climate Change. MIT Press, Cambridge, MA.
OCDE, 2014. Cost of Air Pollution: Health Impacts of Road Transport. OECD Publishing.
OECD, 2016. The Economic Consequences of Outdoor Air Pollution. OECD Publishing. https://doi.org/10.1787/9789264257474-en.
O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim. Change 122, 387–400. https://doi.org/10.1007/s10584-013-0905-2.
Ou, Y., Shi, W., Smith, S.J., Ledna, C.M., West, J.J., Nolte, C.G., Loughlin, D.H., 2018. Estimating environmental co-benefits of US low-carbon pathways using an integrated assessment model with state-level resolution. Appl. Energy 216, 482–493.
Pulighe, G., Bonati, G., Colangeli, M., Morese, M.M., Traverso, L., Lupia, F., Khawaja, C., Janssen, R., Fava, F., 2019. Ongoing and emerging issues for sustainable bioenergy production on marginal lands in the Mediterranean regions. Renew. Sustain. Energy Rev. 103, 58–70.
Rao, S., Klimont, Z., Smith, S.J., Van Dingenen, R., Dentener, F., Bouwman, L., Riahi, K., Amann, M., Bodirsky, B.L., van Vuuren, D.P., Aleluia Reis, L., Calvin, K., Drouet, L., Fricko, O., Fujimori, S., Gernaat, D., Havlik, P., Harmsen, M., Hasegawa, T., Heyes, C., Hilaire, J., Luderer, G., Masui, T., Stehfest, E., Strefler, J., van der Sluis, S., Tavoni, M., 2017. Future air pollution in the Shared Socio-economic Pathways. Glob. Environ. Change 42, 346–358. https://doi.org/10.1016/j.gloenvcha.2016.05.012.
Riahi, K., Van Vuuren, D.P., Kriegler, E., Edmonds, J., O'neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., 2016. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob. Environ. Change.
Samir, K., Lutz, W., 2017. The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. Glob. Environ. Change 42, 181–192.
Scovronick, N., Budolfson, M., Dennig, F., Errickson, F., Fleurbaey, M., Peng, W., Socolow, R.H., Spears, D., Wagner, F., 2019. The impact of human health co-benefits on evaluations of global climate policy. Nat. Commun. 10, 2095.
Searl, A., Ferguson, J., Hurley, F., Hunt, A., 2016. Social Costs of Morbidity Impacts of Air Pollution (OECD Environment Working Papers No. 99).
Shi, W., Ou, Y., Smith, S.J., Ledna, C.M., Nolte, C.G., Loughlin, D.H., 2017. Projecting state-level air pollutant emissions using an integrated assessment model: GCAM-USA. Appl. Energy 208, 511–521. https://doi.org/10.1016/j.apenergy.2017.09.122.
Shindell, D., Faluvegi, G., Seltzer, K., Shindell, C., 2018. Quantified, localized health benefits of accelerated carbon dioxide emissions reductions. Nat. Clim. Change. https://doi.org/10.1038/s41558-018-0108-y.
Smith, S.J., Pitcher, H., Wigley, T.M.L., 2005. Future sulfur dioxide emissions. Clim. Change 73, 267–318. https://doi.org/10.1007/s10584-005-6887-y.
Smith, S.J., Wigley, T.M.L., 2006. Multi-gas forcing stabilization with Minicam. Energy J. 373–391.
Stern, N., 2006. Stern review report on the economics of climate change.
Stigson, P., Hansson, A., Lind, M., 2012. Obstacles for CCS deployment: an analysis of discrepancies of perceptions. Mitig. Adapt. Strateg. Glob. Change 17, 601–619.
Thompson, T.M., Rausch, S., Saari, R.K., Selin, N.E., 2014. A systems approach to evaluating the air quality co-benefits of US carbon policies. Nat. Clim. Change 4, 917.
Turner, M.C., Jerrett, M., Pope III, C.A., Krewski, D., Gapstur, S.M., Diver, W.R., Beckerman, B.S., Marshall, J.D., Su, J., Crouse, D.L., 2016. Long-term ozone exposure and mortality in a large prospective study. Am. J. Respir. Crit. Care Med. 193, 1134–1142.
U.S. EPA, 2016. Integrated Science Assessment (ISA) For Oxides Of Nitrogen – Health Criteria (Final Report, 2016). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-15/068, 2016.
Van Dingenen, R., Dentener, F., Crippa, M., Leitao, J., Marmer, E., Rao, S., Solazzo, E., Valentini, L., 2018. TM5-FASST: a global atmospheric source–receptor model for rapid impact analysis of emission changes on air quality and short-lived climate pollutants. Atmos. Chem. Phys. 18, 16173–16211. https://doi.org/10.5194/acp-18-16173-2018.
Vandyck, T., Keramidas, K., Kitous, A., Spadaro, J.V., Van Dingenen, R., Holland, M., Saveyn, B., 2018. Air quality co-benefits for human health and agriculture counterbalance costs to meet Paris Agreement pledges. Nat. Commun. 9. https://doi.org/10.1038/s41467-018-06885-9.
Viscusi, W.K., Masterman, C.J., 2017. Income elasticities and global values of a statistical life. J. Benefit-Cost Anal. 8, 226–250.
Wang, L., Patel, P.L., Yu, S., Liu, B., McLeod, J., Clarke, L.E., Chen, W., 2016. Win-Win strategies to promote air pollutant control policies and non-fossil energy target regulation in China. Appl. Energy 163, 244–253. https://doi.org/10.1016/j.apenergy.2015.10.189.
West, J.J., Smith, S.J., Silva, R.A., Naik, V., Zhang, Y., Adelman, Z., Fry, M.M., Anenberg, S., Horowitz, L.W., Lamarque, J.-F., 2013. Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health. Nat. Clim. Change 3, 885–889. https://doi.org/10.1038/nclimate2009.
WHO, 2011. Causes of Death 2008: Data Sources and Methods. Geneva World Health Organ.
WHO, 2013. Health risks of air pollution in Europe-HRAPIE project. New Emerg. Risks Air Pollut.-Results Surv. Experts.
WHO, 2016. Ambient air pollution: A global assessment of exposure and burden of disease. In: Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease.
Wise, M., Calvin, K., Thomson, A., Clarke, L., Bond-Lamberty, B., Sands, R., Smith, S.J., Janetos, A., Edmonds, J., 2009. Implications of Limiting CO2 Concentrations for Land Use and Energy. Science 324, 1183–1186. https://doi.org/10.1126/science.1168475.
Xie, Y., Dai, H., Dong, H., Hanaoka, T., Masui, T., 2016. Economic impacts from PM2. 5 pollution-related health effects in China: a provincial-level analysis. Environ. Sci. Technol. 50, 4836–4843.
Xie, Y., Dai, H., Xu, X., Fujimori, S., Hasegawa, T., Yi, K., Masui, T., Kurata, G., 2018. Co-benefits of climate mitigation on air quality and human health in Asian countries. Environ. Int. 119, 309–318. https://doi.org/10.1016/j.envint.2018.07.008.
Zheng, B., Tong, D., Li, M., Liu, F., Hong, C., Geng, G., Li, H., Li, X., Peng, L., Qi, J., 2018. Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. Atmospheric Chem. Phys. 18, 14095–14111.