D5.2

Focus Report on Health Impacts and External Costs due to Air Pollution

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About this report

Within the framework of the REEEM project this report analyses health impacts and external costs due to air pollution as one indicator of a sustainable energy system as part of the REEEM Work Package 5 on Environment, Health and Resources. To achieve clean air and a low-carbon society, climate change mitigation and air pollution control policies need to be considered simultaneously in an integrated assessment since both interact with each other. For this task the energy system model is linked with an impact assessment model. In a comparative scenario analysis based on detailed estimations of impacts and external costs due to air pollution interactions and co-benefits between climate change mitigation and air pollution control are identified The three considered decarbonisation pathways are all characterized by ambitious decarbonisation targets, with one also having a dedicated target for a high share of renewable energy sources. To be also able to analyse the effect of air pollution control on the European energy system and its decarbonisation, marginal damage costs are estimated for several air pollutants and fed back to the energy system model as unit cost factors in the third pathway.

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About REEEM

REEEM aims to gain a clear and comprehensive understanding of the system-wide implications of energy strategies in support of transitions to a competitive low-carbon EU energy society. This project has four main objectives: (1) to develop an integrated assessment framework (2) to define pathways towards a low-carbon society and assess their potential implications (3) to bridge the science-policy gap through clear communication using decision support tools and (4) to ensure transparency in the process.

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Abbreviations

CRFs: Concentration-response function

CTM: Chemistry Transport Model

DALY: Disability Adjusted Life Year

DEHM: Danish Eulerian Hemispheric Model

ETS: EU Emission Trading System

GHG: Greenhouse gas

RES: Renewable energy sources (share in gross final energy consumption)

YOLL: Years of Life Lost

1 Introduction

A sustainable energy system does not only have to meet ambitious decarbonisation targets leading to a low-carbon society in an effort to mitigate climate change, but do so while minimizing other adverse impacts on society. Since air pollution is considered to be the biggest environmental threat to human health[1], reducing air pollution and its related impacts is part of several UN sustainable development goals[2]. Similarly, the EU strives to reduce air pollution and associated health impacts as stated in their "Clean Air Programme" (European Commission, 2013). Despite having achieved high reductions for most air pollutants over the last years, air quality standards are still not met across Europe, with most emissions still being energy-related (European Environment Agency, 2018). Since both greenhouse gases (GHG) and air pollutants are mainly released by combustion processes involving fossil fuels, climate change mitigation often also results in reduced air pollution, providing attributable co-benefits to society which may even exceed initial GHG mitigation costs (Kitous et al., 2017; Markandya et al., 2018). Thus, effects on air pollution and related impacts need to be considered when assessing possible pathways to a decarbonised and sustainable European energy system. Similarly, air pollution control itself can facilitate decarbonisation, partly compensating GHG mitigation costs and thus increasing incentives for climate change mitigation. Changes to the energy system prompted by GHG mitigation and air pollution control may, however, cause them to interfere with each other. An example for this is the use of biomass as an energy carrier. While biomass may be an important factor on the way to a carbon-neutral society, it may not help to reduce air pollution since it still emits high amounts of particulate matter when burned in its solid form. These implications of different climate change mitigation and air pollution control policies need to be considered simultaneously in an integrated assessment to achieve both goals, clean air and a low-carbon society. The aim of this study is therefore to assess possible pathways to a sustainable European energy system, as defined within the project, with regard to their effects on air pollution, associated impacts and external costs, focusing especially on health impacts. Additionally, external costs due to biodiversity losses are estimated as an indicator for other environmental impacts due to air pollution. Health impacts are estimated by processing emissions of air pollutants as given by an energy system optimisation model with an impact assessment model which follows the "Impact Pathway Approach". To also analyse the possible effect of air pollution control on decarbonising the energy system, unit cost factors, i.e. costs of health impacts per kilogram of emissions released, are calculated for main air pollutants and fed back to the energy system model. This makes it possible to include costs of air pollution control in the optimisation function as an additional driver for changes in the energy system, enabling an integrated assessment of climate change mitigation and air pollution control efforts.

In the first part of this report, the applied methodologies and models are presented. First, the general principle of the "Impact Pathway Approach" is briefly described, together with the model framework applied, including

[1] As stated by UNECE: https://www.unece.org/environmental-policy/conventions/envlrtapwelcome/cross-sectoral-linkages/air-pollution-and-health.html (last checked: 30-01-2019).
[2] An overview of the sustainably development goals (SDG) is given at:
https://www.un.org/sustainabledevelopment/sustainable-development-goals/ (last checked: 30-01-2019).
Air pollution is mentioned in SDG 7 (affordable and clean energy) and SDG 11 (sustainable cities and communities).
Tackling air pollution and its related impacts is a direct goal of SDG 3 (good health and well-being).

the feedback loop with the energy system model. Afterwards, the methodologies used to calculate the unit cost factors as well as estimating specific health impacts and costs of biodiversity losses are explained in detail. The second part is an assessment of the effects of three possible decarbonisation pathways on air pollution, including both a detailed analysis of health impacts and external costs and a detailed description of unit cost factors to be used in energy system models. Finally, some uncertainties are discussed, before conclusions are drawn and limitations of the study are treated.

2 Methodology

2.1 General approach

The assessment of health impacts and external costs due to air pollution follows the principles of the *Impact Pathway Approach* as developed in the *ExternE*[3] project series (Bickel and Friedrich, 2005). The *Impact Pathway Approach* is a bottom-up method to estimate environmental benefits and costs by following the complete impact chain from source emissions to physical impacts, which can be monetized in a final step. The impact chain for health impacts is depicted in Figure 1.

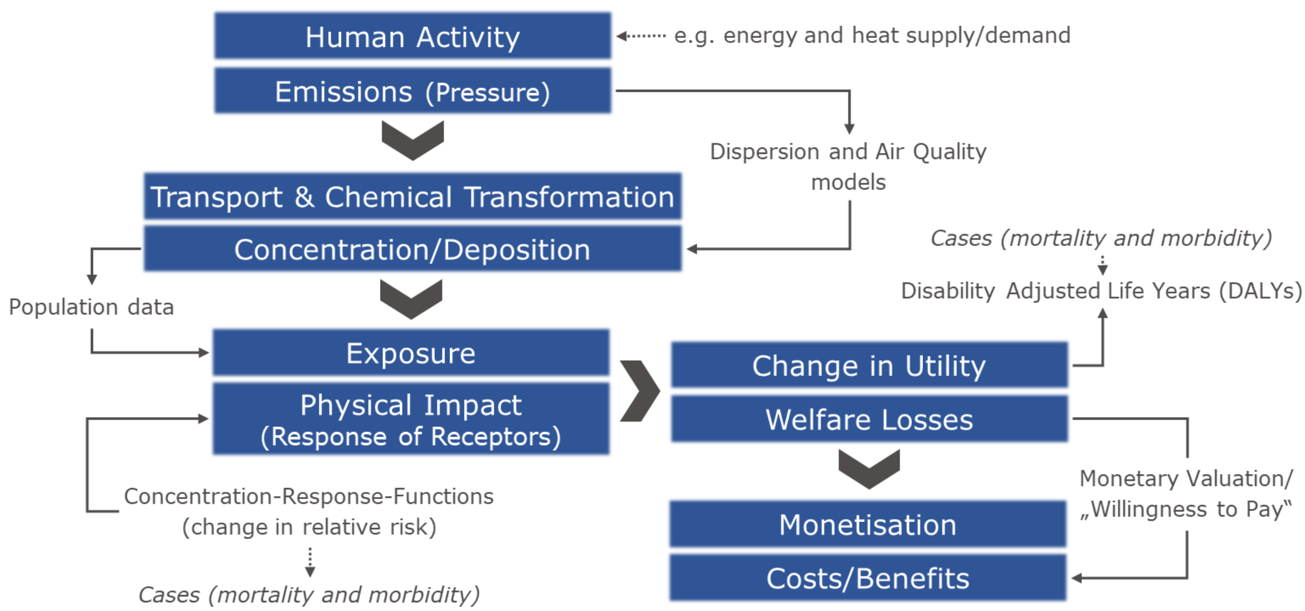

Figure 1: Impact Pathway Approach for estimating health impacts and related external costs due to air pollution.

First, changes in anthropogenic emissions are translated into changes in air pollutant concentration levels by using dispersion and air quality models. Air pollutants are transported and transformed over long distances; a change in emissions in one country may lead to a change in concentration levels in a different country. Additionally, some pollutants may react chemically with each other, leading to secondary pollutants such as secondary aerosols or ozone. To account for these complex, partially non-linear chemical transformation processes, a chemistry-transport model (CTM) can be applied. CTMs are full atmospheric dispersion models to

[3] http://www.externe.info (last checked: 13-12-2018).

estimate concentration and deposition levels of air pollutants by taking into account meteorology and chemical transformation schemes, reflecting the complex mechanisms in the atmosphere. Due to the inherited complexity and non-linearity, these models are computationally expensive. Particularly in policy assessment, where often many different scenarios need to be analysed, computer time and power are, however, critical resources. Alternatively, surrogate models, such as source-receptor-matrices, can be used instead. These surrogate models sacrifice some accuracy for a substantial reduction in computation time. For regional analysis, these models are most often either based on selected CTM simulations or incorporate their results to account for non-linear chemical processes. Source-receptor matrices, for example, represent a standardized and parameterized version of CTM simulations, by linking a specific change in emissions in the source region to a change in concentration at the receptor grid (Wind et al., 2004). Overall, these simplified models perform well for small to medium changes in emissions and annual mean concentrations as these are not significantly characterized by non-linear effects (Bachmann, 2015; Bartnicki, 2000; Clappier et al., 2017; Pisoni et al., 2017; Thunis et al., 2015).

Next, spatially resolved changes in concentration levels are combined with population data to estimate the exposed population. By applying concentration-response functions (CRFs), the marginal physical impacts, i.e. the effects on human health caused by an increase or decrease of 10 µg/m³ in concentration levels, are assessed and multiplied with the respective change in concentration levels. CRFs combine information about the change in risk due to a specific change in ambient concentration levels (relative risk) with background rates of certain health outcomes. Relative risks are derived based on epidemiological studies and are provided for each pollutant-outcome pair, usually together with their 95 % confidence interval to account for uncertainties (e.g. Héroux et al., 2015). When combined with background disease rates and population data, this results in impact factors, which state the additional cases per µg/m³, exposed person and year. Physical impacts comprise both mortality and morbidity. As mortality due to air pollution is mainly caused by long-term exposure (chronic mortality), it is usually estimated as average loss in life expectancy based on life table calculations, which results in "Years of Life Lost" (YOLL) (Bickel and Friedrich, 2005; Rabl, 2003; Rabl et al., 2014). To assess the combination of different health impacts, especially if some impacts are difficult to monetize, the common indicator 'Disability Adjusted Life Years' (DALY) can be used. DALY reflect the impact of a specific health outcome on both the quality and quantity of a life lived by providing scores for each health outcome according to its severity between 1 (death) and 0 (perfect health). When this is combined with the typical duration of an illness, it is possible to calculate a weighted sum of mortality (one YOLL equals one DALY) and morbidity as a combined indicator for health impacts due to air pollution. Additionally, or alternatively, different health impacts can be assessed together in terms of monetary values. Monetary values can be derived by different methods, e.g. based on willingness-to-pay or based on market costs. In the case of health impacts, mortality is usually valued by a willingness-to-pay approach either in form of a value of prevented fatality/value of statistical life[4] (typically applied for accidents) or a value of life year (which can then be applied on YOLL). For morbidity, a cost-of-illness approach is applied (Bickel and Friedrich, 2005; Leksell and Rabl, 2001; Rabl et al., 2014). Similarly, effects on ecosystems can be estimated as biodiversity losses in terms of fractions lost due to deposition of NO_X and SO_2 (measured in potentially

[4] The value of prevented fatality reflects the willingness-to-pay to avoid an anonymous premature death and is not equal to an intrinsic value of life.

disappeared fraction). These biodiversity losses can be monetized by applying restoration costs, i.e. the costs to restore a specific land use type with fewer species to one with more species (Bachmann, 2015; Rabl et al., 2014).

Integrated impact assessment models which implement the *Impact Pathway Approach* can thus vary in their complexity, depending on their geographical scale and spatial resolution, the pollutants considered, CRFs and monetary values applied, their population distribution and projections as well as the method used to model concentration levels (Anenberg et al., 2016). The variety of model approaches also reflects the complexity and uncertainty of estimating environmental and health impacts due to air pollution. Differences in concentration estimates in Europe when using a CTM may vary up to a factor of three and overall uncertainty across the full impact pathway is estimated to range between a factor of two and four (Im et al., 2018; Spadaro and Rabl, 2008).

The two impact assessment models applied in this study implement different versions of the *Impact Pathway Approach* to assess health impacts. In the remainder of this report, the two models and their main underlying assumptions are described before both models and their results are compared to each other, highlighting the differences and common features. The comparison and application of both models also contributes to a better assessment of the uncertainty of the results.

2.2 Modelling framework

2.2.1 EcoSense

EcoSense is an integrated impact assessment model following the *Impact Pathway Approach* to estimate health impacts caused by different air pollutants (Friedrich et al., 2011; Roos, 2017). It is primarily designed to support and inform assessments of different air pollution mitigation strategies and related cost-benefit analyses. To reduce computation time, *EcoSense* implements a parameterized atmospheric dispersion model in form of country-to-grid source receptor matrices based on the EMEP/MSC-W[5] CTM. The source-receptor matrices allocate changes in emissions of SO_2, NO_X, non-methane volatile organic compounds (NMVOC), NH_3 and primary particles ($PM_{2.5}$ and PM_{10}) in a given country to changes in concentration levels of ozone, NO_2 and particulate matter (separated in $PM_{2.5}$ and PM_{10})[6] across Europe. The matrices are based on 15 % reduction scenarios which are run with the full atmospheric dispersion model individually for each pollutant species and country (Wind et al., 2004). The resulting concentration changes are then linearly inter- or extrapolated according to the emission reduction ratio of a scenario of interest. The source-receptor matrices currently implemented in *EcoSense* have a spatial resolution of 0.25° × 0.5° and their domain covers Europe completely, including neighbouring regions in Asia and Africa. *EcoSense* has source-receptor matrices for four meteorological years (2006-2010) which are based on 2020 emission projections, which makes them suitable for estimating future emission reduction impacts. For these future estimates, a source-receptor matrix averaged over the four meteorological years is usually applied. The model implements CRFs for short- and long-term effects as recommended by the WHO (Héroux et al., 2015). The WHO has classified pollutant-outcome pairs according to uncertainties related to varying data availability. Additionally, only subsets of these classes are to be included in a holistic analysis in which all impacts are considered simultaneously, i.e. these impacts can be directly summed up without risking

[5] http://emep.int/mscw/index_mscw.html (last checked: 14-12-2018).

[6] All concentration levels except ozone are stated in µg/m³. Ozone is measured in the metric SOMO35 (µg/m³ days).

overlapping estimations (set A* and B* in Héroux et al., 2015). As *EcoSense* strives to achieve a holistic cost analysis, only these CRFs are applied to annual mean concentration levels. Impact factors, given in Table 13 in the Appendix, are calculated based on background disease rates as recommended in Héroux et al. (2015) and Holland (2014). Additionally, *EcoSense* contains impact factors for the lower and upper level of the 95 % confidence interval of the relative risk, providing a range of possible results to account for uncertainties.

To estimate the change in future exposure, detailed population data is needed. The population data in *EcoSense* considers the spatial distribution of the high-resolution population density grid as described in Batista e Silva et al. (2013). This population grid has been combined with UN population data to include country-specific age structures and population projections. This means that *EcoSense* considers demographic change for future years, yet internal migration effects, such as urbanization, are not included. While the age structure may change over time, the spatial distribution is always taken from the original dataset. The final dataset thus includes spatially resolved population data and projections with 5-year age-bands and a final resolution of 2.5' × 2.5'.

Intermediate results in terms of individual health outcomes such as increased chronic mortality, hospital admissions or restricted activity days are aggregated to two common metrics: monetary values and DALY. The applied severity weights and assumed duration to calculate associated DALY for each endpoint are given in Table 1 and based on results from the HEIMTSA/INTARESE project (Friedrich et al., 2011).

Table 1: Severity and duration weights used in EcoSense to aggregate different impacts to Disability Adjusted Life Years.

	Severity	**Duration** (years)
Mortality, YOLL:	1	1
Infant Mortality:	1	80
Chronic bronchitis:	0.099	10
Prevalence of bronchitis in children:	0.001	0.0384
Incidence of asthma in children:	0.043	0.00274
Minor restricted activity days:	0.07	0.00274
Work loss days:	0.099	0.00274
Restricted activity days:	0.099	0.00274
Cardiovascular hospital admissions:	0.71	0.038
Respiratory hospital admissions:	0.64	0.038

As monetary valuation, especially if based on willingness-to-pay studies, is partly influenced by risk perception and always subject to uncertainty, *EcoSense* implements three levels of cost factors for each endpoint. For cost-benefit analysis and unit cost calculations, the mid-value is usually used; the lower and upper values are only applied to reflect the possible range of external costs. Monetary values per endpoint are mainly based on the HEIMTSA/INTARESE project results (Friedrich et al., 2011). For endpoints that were not part of this project, cost factors are based on Holland (2014). The cost factors can be found in Table 14 in the Appendix.

2.2.2 EVA

EVA (Brandt et al., 2013a, 2013b) is a health impact assessment model developed at Aarhus University. It is also based on the *Impact Pathway Approach* (Bickel and Friedrich, 2005); in contrast to *EcoSense*, it requires hourly gridded concentration values from a regional CTM. For this reason, *EVA* utilizes the Danish Eulerian Hemispheric Model (DEHM), a regional Eulerian CTM that covers Europe with a spatial resolution of 50 km × 50 km (Brandt et al., 2012). This means that, in contrast to *EcoSense*, non-linear effects due to complex atmospheric dispersion and chemical transformation are directly considered. The latest description of the health impact assessment module and its numerical assumptions is given in Im et al. (2018). *EVA* considers health impacts caused by exposure to annual mean levels of particulate matter ($PM_{2.5}$), CO and SO_2 as well as hourly ozone concentrations (SOMO35). The respective exposure-response coefficients or impact functions are given in Table 13 in the Appendix. For population data, the GEOSTAT 2011 population density raster[7] with a resolution of 1 km × 1 km is used. To take into account the demographic aspects and sensitivity of different health impacts to age, five age groups are included at grid level: infants, children (younger than 15 years) and three groups for adults (older than 15 years; older than 30 years; older than 65 years). The fractions of the different age groups are derived from the EUROSTAT 2000 database. Monetary valuation is based on several previous studies of willingness-to-pay to avoid a specific health outcome as well as cost-of-illness assessments (Brandt et al., 2013b; Im et al., 2018). The respective cost factors are given in Table 14 in the Appendix.

2.2.3 Feedback to the Energy System Model

To be able to take into account negative effects due to air pollution control in the energy system analysis, the respective costs due to health impacts are included in the Integrated Energy System Model (Welsch et al., 2017). The latest version of the Integrated Energy System Model is described in the forthcoming deliverable D6.1. This is also the version used to derive the results in this report. The modelling framework of *TIMES PanEU* provides options to model local externalities in form of additional costs and to explicitly in- or exclude these costs in the optimization. In the latter case, the optimal solution shifts from a merely economic one to a rather social optimum in the sense of welfare maximization. External effects are then efficiently avoided as long as their avoidance costs do not exceed their damage cost. The exact implementation of these cost factors in *TIMES PanEU* is described in D6.1, while this report focuses on how respective cost factors are estimated. By establishing a two-way link between the energy system model *TIMES PanEU* and an impact assessment model, such as *EcoSense* or *EVA*, marginal damage costs per pollutant are estimated and fed-back to the energy system model. As an example, the feedback loops between *TIMES PanEU* and *EcoSense* are depicted in Figure 2.

First, emission factors of local air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_X, NMVOC, NH_3, CO) in *TIMES PanEU* are updated to reflect future emissions standards and expected penetration of technical mitigation options (e.g. filters and catalysts) in line with EU legislation (European Commission, 2013). Whenever possible, process-specific, i.e. technology-specific emission factors are chosen. If technology-specific emission factors were not available, sector and/or fuel specific emission factors reflecting average technological conditions are used instead. Emission factors for all categories except railway and road transport are based on the *Eclipse V5a*

[7] https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat (last checked: 19-12-2018).

Scenario[8], as developed within the EU FP7 project *Eclipse*[9]. For Europe, their policy assumptions and data reflect the latest *National Emissions Ceiling* revision scenarios (Amann et al., 2014a; Amann et al., 2015) and a comprehensive list of included emission control legislation can be found in (Amann et al., 2014b). Future emission factors thus reflect the requirement for industrial processes to follow the best available techniques as proposed by the *Industrial Emissions Directive* (European Union, 2010). Emissions due to the combustion of fuels and process emissions are reported separately and are usually applied to the amount of fuel consumed (combustion) or the quantity of product produced (process emissions).

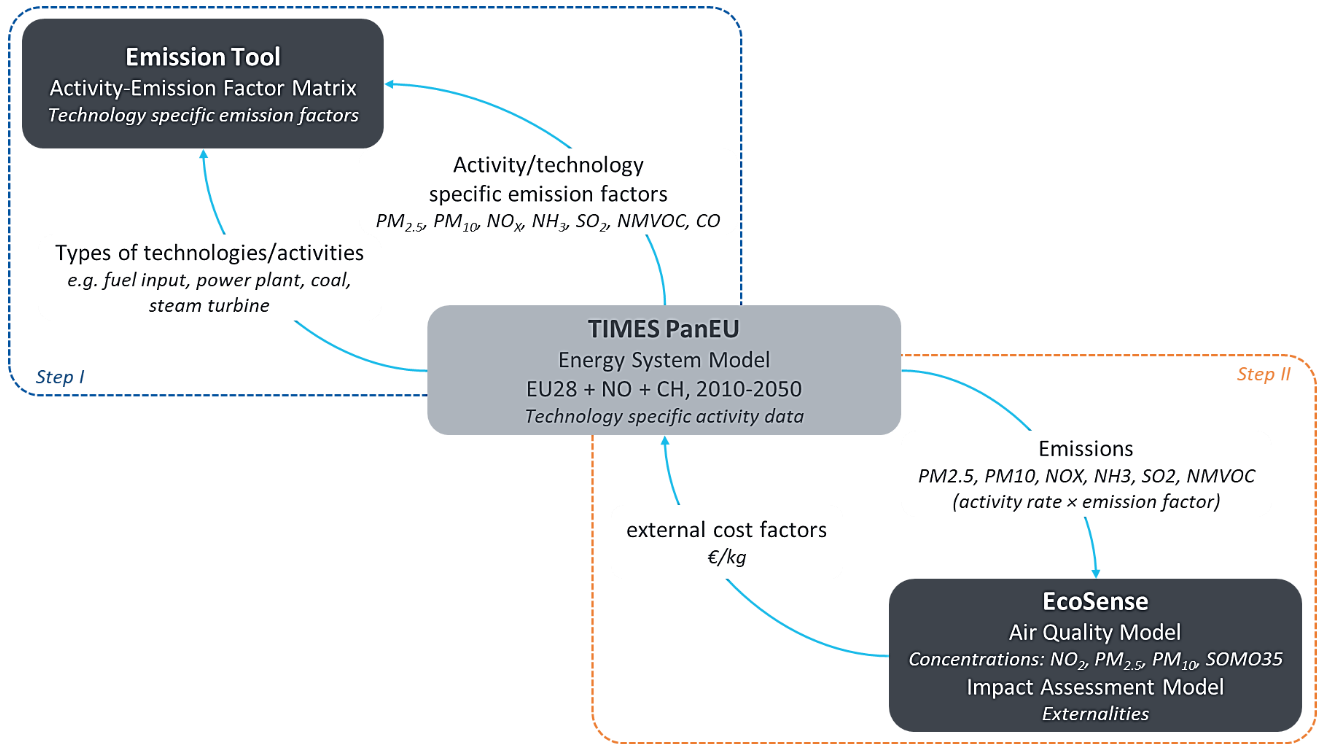

Figure 2: Feedback loops between TIMES PanEU and EcoSense to include external costs in the energy system model.

For road transport and railways, emission factors are implemented based on vehicle kilometres driven to also account for particulate matter emissions due to abrasion and tyre/brake wear. Additionally, NMVOC emissions due to evaporation processes are included. For road transport, all emission factors are based on the *COPERT 5*[10] model, including updated NO_X emission factors for diesel cars. Since *TIMES PanEU* does not differentiate activities in road transport by European vehicle emission standards, which is needed to determine an accurate emission level, average emission factors based on national fleet mixes as given by the *TREMOVE 3.3.2*[11] model are applied instead for the base-year technologies. For future technologies, the appropriate European emission standard is used, i.e. Euro 6 for all new cars in 2015 and Euro 6d from 2020 on. Emission factors for railway are based on the EMEP/EEA Guidebook (2016).

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[8] http://www.iiasa.ac.at/web/home/research/researchPrograms/air/ECLIPSEv5a.html (last checked: 20-12-2018).
[9] http://eclipse.nilu.no/language/en-GB/ProjectOverview.aspx (last checked: 20-12-2018).
[10] http://emisia.com/products/copert/copert-5 (last checked: 20-12-2018).
[11] http://www.tmleuven.be/methode/tremove/home.htm (last checked: 20-12-2018).

Next, unit cost factors, i.e. marginal damage costs, are calculated with an impact assessment model. These cost factors can be calculated based on the actual emission streams as provided by the energy system model. This would then result in scenario-specific unit cost factors and may result in an iterative process depending on the specific scenario assumptions. When assuming a linear relation between the amount of emissions released or reduced and resulting impacts, the marginal damage costs are constant and thus scenario independent. In this case, marginal damage costs can be estimated based on already existing emission reduction scenarios and a one-way link between the impact assessment model and the energy system model, resulting in a simpler model configuration. As shown by previous studies (Bachmann, 2015; Bartnicki, 2000; Clappier et al., 2017; Pisoni et al., 2017; Thunis et al., 2015), the relation between changes in emissions and changes in annual mean concentrations can be approximately linearized. Since also only linear CRFs are applied (Héroux et al., 2015; Holland, 2014), marginal damage costs are calculated based on the simpler setup, i.e. the impact assessment model is run independently of the energy system model. Marginal damage costs are then calculated separately for each pollutant, year and country. It is assumed that damages occurring in one year only relate to the emissions released in this year, i.e. that there is no time lag between cause and impact and that all impacts are additive, with impacts due to $PM_{2.5}$ and PM_{10} relating to different health outcomes. This means that total damage costs can be calculated simply by summing up the product of the annual amount of emissions and the respective pollutant-specific, annual unit cost factors. Damages across Europe are allocated according to the "polluter pays" principle, which means that all damages across Europe caused by emissions of a specific country are allocated to this very country.

2.3 Unit cost calculations

As already mentioned unit cost factors (marginal damage cost) are calculated independently of scenario and pathway by running a specific reduction scenario separately for each pollutant, country and year. Even when assuming a linear relation between estimated impacts and change in emissions, unit cost factors for future years are still affected by assumptions regarding population growth and future levels of background concentrations which are influenced by future meteorological conditions and assumed levels of future emissions including natural sources. As *EcoSense* is based on pre-calculated source-receptor matrices, it is not possible to consider other meteorological conditions and background emissions than the ones used to derive the source-receptor-matrices. This limitation is partly compensated by applying source-receptor-matrices based on average meteorological conditions and 2020 emission estimates. As forecasts are always subject to uncertainty, the strengths of lower computational power requirements and shorter running times are valued higher than the ability to simulate different future conditions. *EVA* with its integrated CTM, on the other hand, is flexible enough to consider varying future meteorology and background emissions. Due to the computational power and resulting runtime required, it is, however, not possible to run the model for all pollutants, all countries and all future years. Hence, unit cost factors are estimated by applying both models and finally integrating their results, building on the strengths of both models.

For the initial estimate, unit cost factors for all pollutants (except CO) and years were calculated with *EcoSense* assuming a reduction of all pollutants and all sectors in one country at once, which corresponds to the optimization function in energy system models like *TIMES PanEU*. As the source-receptor-matrices do not take into account any cross-dependencies between different precursors, the balance or ratio of emission changes between different precursors does not affect the unit cost results. Additionally, as all relations within *EcoSense* are fully linear[12], assuming that results can be linearly extra- or interpolated, estimated unit costs are also not dependent on the chosen amount of emissions. A value of 1000 t was chosen for each pollutant in each country, since this is also the reference unit of emissions of air pollutants in *TIMES PanEU*.

To improve the accuracy of the result set, unit cost factors for NO_X and SO_2 with release heights typical for the electricity and heat sector[13] are calculated with the *EVA* model for current (2013) and future (2030) conditions. These two pollutants are chemically reactive and are precursors for organic aerosols which are subject to non-linear chemistry. The non-linear effects are most relevant for emissions with high release heights since these are transported the furthest, linger in the atmosphere the longest and are thus available even for slower chemical reactions. By including these cost-factors, it is possible to consider the cross-dependencies of these two precursors. All unit cost factors estimated by *EVA* are based on a 15 % reduction in emissions, which is small enough to account for marginal changes, yet large enough to provide a clear signal in emission changes. For current years, simulations are run based on 2013 conditions and with officially reported national emissions provided by EMEP[14]. To reflect future conditions, the year 2030 was chosen, since official emission projections exist for that year. Emission projections are again based on EMEP emission inventories and include national reduction commitments within the course of the *National Emissions Ceiling* directives, since these directives and emission projections are also the basis of future emission factors as implemented in *TIMES PanEU*. While this increases consistency between the emission factors applied in TIMES PanEU (and thus estimated emissions of air pollution) and the estimated unit cost factors by considering the same technical regulations, including future meteorological conditions for the year 2030 does neither increase consistency nor reduce uncertainty. Since long-term meteorological forecasts are not possible due to the complexity of atmospheric and meteorological processes, future conditions can only be based on climate models. These models themselves show a wide range in predictions and downscaling their results to fit the needed input format for a CTM involves a huge amount of data processing. Additionally, studies examining the effect of emission reduction and climate change on health impacts due to ambient air pollution showed that the effect of climate change is dominated by the effect of reduced emission levels (Geels et al., 2015; Geels et al., 2016; Hedegaard et al., 2013), especially within the time horizon until 2050. Due to these reasons, future runs with *EVA* only consider the effects of reduced emission levels and are still run with current meteorological conditions. A detailed comparison of the two models and their results is given in chapters 3.1 and 3.2.

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[12] The only non-linear assumption relates to the threshold value of NO_2 for mortality impacts. As this depends on the background concentration levels and actual amount of emissions reduced (the fraction of emissions leading to concentration changes above and below 20 µg/m³), this cannot be properly reflected by unit costs (as it cannot be known which additional tonne of emissions will lead to a change above/below 20 µg/m³). These impacts are thus only included in the unit costs if the background scenario of the source-receptor matrices shows concentration levels above 20 µg/m³. As this is only one of many health impacts considered, the introduced inaccuracy is considered negligible.

[13] SNAP1 emissions according to the *Selected Nomenclature for sources of Air Pollution*.

[14] *European Monitoring and Evaluation Programme*. Officially reported country emissions can be downloaded from http://www.ceip.at/ms/ceip_home1/ceip_home/webdab_emepdatabase/ (last checked: 21-12-2018).

2.4 Health impacts and external costs of decarbonisation pathways

2.4.1 Health impacts across Europe

To provide a detailed assessment of health impacts across Europe, these impacts are calculated for selected pathways ex post based on emissions of air pollutants as provided by the energy system model. By running *EcoSense* with annual total national emissions of NO_X, $PM_{2.5}$, PM_{10}, NH_3, NMVOC and SO_2, Europe-wide health impacts due to exposure to particulate matter (primary and secondary), NO_2 and ozone are estimated for each milestone year (see also Figure 2). *EcoSense* is chosen over *EVA* for this task due to the better running time and expected number of scenarios.

In contrast to the calculation of unit costs, the ex post calculations consider all changes in emissions (in all species and all countries) to happen at once. This is especially relevant with respect to the applied threshold for mortality impacts due to NO_2, as the sum of emissions from multiple countries may lead to concentration levels above this threshold in places were the contribution of a single country would not be high enough to reach these levels. Since country-specific unit cost factors should only reflect the contribution of emissions from this country, these cost factors are estimated with the emissions of other countries held constant. Thus, the effect of elevated levels caused by different contributions of several countries due to long-range transport of air pollutants cannot be reflected in linear cost-factors. The spatial distribution of emissions within each country is inherited from the applied source-receptor matrix and thus kept constant for all years. For a detailed analysis, endpoint specific health impacts and related costs are estimated by applying the recommended relative risk factors from Héroux et al. (2015) and the resulting impact factors as given in Table 13, with average monetary valuation as stated in Table 14 (see Appendix).

To account for uncertainties, the same calculations are repeated with the upper and lower limits of the relative risk's 95 % confidence interval[15] in combination with low and high monetary valuations as given in Table 14 in the Appendix, respectively. Impacts are also clustered according to the two WHO groups (A* and B*) recommended for cost-benefit analysis to reflect their uncertainty. All impacts are expressed as DALYs, which helps to identify regions most affected by air pollution by aggregating impacts across a defined region. Associated costs are always allocated according to the "polluter pays" principle reflecting all impacts across the whole model domain caused by emissions from a specific country. In this way, it is possible to compare the estimated costs with ex post calculations based on unit cost factors.

[15] Applied relative risks were cut-off at zero, i.e. that if the lower limit is stated as negative, it is assumed that exposure of air pollution does not have an effect on this specific health outcome. Negative relative risk would lead to a positive effect of air pollution, which is unrealistic.

2.4.2 Biodiversity losses

Biodiversity losses/gains are used as an indicator for the impact of air pollution on ecosystems. In contrast to health impacts, impacts on biodiversity are only estimated with a unit cost approach, since running the full impact pathway needs additional models and the overall costs of biodiversity losses due to the deposition of air pollutants are relatively low compared to costs of health impacts. The applied cost factors are taken from Preiss et al. (2008) and transferred to €$_{2010}$ values. All cost factors are originally based on the NEEDS/CASES approach (Kuik et al., 2007; Ott et al., 2006), which estimates biodiversity losses as the change in potentially disappeared fractions (PDF×m²×year) per kilogram deposition of acidifying substances. These impacts are then valued with restoration costs (from a habitat with low biodiversity to one with higher biodiversity). As deposition of acidifying substances is not limited to any specific land use, the lowest costs across all variations of land use categories are taken as an approximation (see also Ott et al., 2006). Additionally, a background acidification and eutrophication pressure index is taken into account to value impacts higher if the pressure is already high, as ecosystems under low pressure can absorb pollutants until a critical load is reached. Separate, country-specific unit cost factors are provided for SO_2, NO_X, NMVOC and NH_3 and for different release heights (low and high), yet the same cost factors are applied throughout the years. Average, minimal and maximal unit cost factors across Europe for high and low release heights are given in Table 2. Again, all unit cost factors follow the “polluter pays” principle.

Table 2: Average (minimum, maximum) unit cost factors (€$_{2010}$/kg) for biodiversity losses due to air pollution differentiated by height of release.

pollutant / release height	NH_3	NO_X	SO_2	NMVOC
high	4.15 (0.24;11.09)	1.07 (0.05;2.24)	0.36 (-0.04;0.92)	-0.07 (-0.27;0.00)
low	4.15 (0.24;11.09)	1.10 (0.05;2.24)	0.34 (-0.04;0.77)	-0.07 (-0.27;0.00)

To associate the sector-specific emissions from the energy system model *TIMES PanEU* with their release heights, effective pollutant release heights are used (Pregger and Friedrich, 2009), which state the relative share of release heights for each sector as given in Table 3.

Table 3: Effective pollutant release height for different sectors according to Pregger and Friedrich (2009).

Sector	Low release height	High release height
Agriculture	1	0
Commercial	1	0
Residential	1	0
Transport	1	0
Industry (Energy)	0.5	0.5
Industry (Process)	0.9	0.1
Electricity	0	1
Conversion/Supply	0	1

3 Results and Discussion

3.1 EcoSense – EVA comparison

3.1.1 Main assumptions

Although both applied models follow the same basic methodology, the models differ in their implementation, underlying data and numerical assumptions. The main differences and data sources used are given in Table 4. Numerical assumptions regarding the CRFs and monetary valuation can be found in the Appendix in Table 13 and Table 14, respectively. The biggest differences are found in the dispersion modelling with *EVA* running a full CTM with a coarser resolution and *EcoSense* using a simplified approach (country-to-grid matrices) but with a higher spatial resolution. Although *EVA* results are actually based on a finer population density grid, the spatial quality of the final results is always determined by the coarsest resolution, in this case by the estimated concentration levels (50 × 50 km). Both models include population data with several age-bands specific to the respective CRFs applied. Differences in the impact factors (Table 13) and monetary valuation (Table 14) themselves are well within the range of uncertainty, yet health outcomes differ considerably. While both models take into account similar outcomes for particulate matter, only *EcoSense* applies CRFs for health impacts caused by direct exposure to NO_2 and only *EVA* considers mortality and morbidity effects of increased SO_2 and CO concentration levels.

Table 4: Main differences between EVA and EcoSense and used data sources.

	EVA	**EcoSense**
DISPERSION MODELLING	Full atmospheric dispersion model (DEHM)	Country-to-grid source-receptor relationships (based on EMEP MSC-W model)
Resolution:	50 km × 50 km	0.5° × 0.25° (approximately: 36 km × 28 km)
Derived concentrations:	O_3 (SOMO35), PM ($PM_{2.5}$), CO, SO_2	O_3 (SOMO35), PM ($PM_{2.5}$/PM_{coarse}/PM_{10}), NO_2
Meteorological data:	MM5v3 (1979-2016)	IFS-ECMWF (2006-2010, average)
POPULATION DATA	Eurostat population grid 2011[16]	"JRC population density grid" (Batista e Silva et al., 2013)
Maximal resolution:	1 km x 1 km	2.5′ × 2.5′
age groups:	infants, children (< 15 yr), adults (> 15 yr, > 30 yr, > 65)	5-year age bands
Projections:		UN projections for 2010, 2020, 2030, 2050 (interpolation in-between)

[16] Eurostat, EFGS (https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat#geostat11, last accessed 23-11-2018).

The effect of these different assumptions on total results was tested for different reduction scenarios for Germany based on 2013 EMEP emissions. Despite these differences, premature deaths[17] due to the different levels of emission reductions when all emissions are reduced at once are similar, with differences well within the typical range of uncertainty for impact assessment models (Figure 3). The anticipated linear relation between impacts and level of emission reductions is also supported by these results.

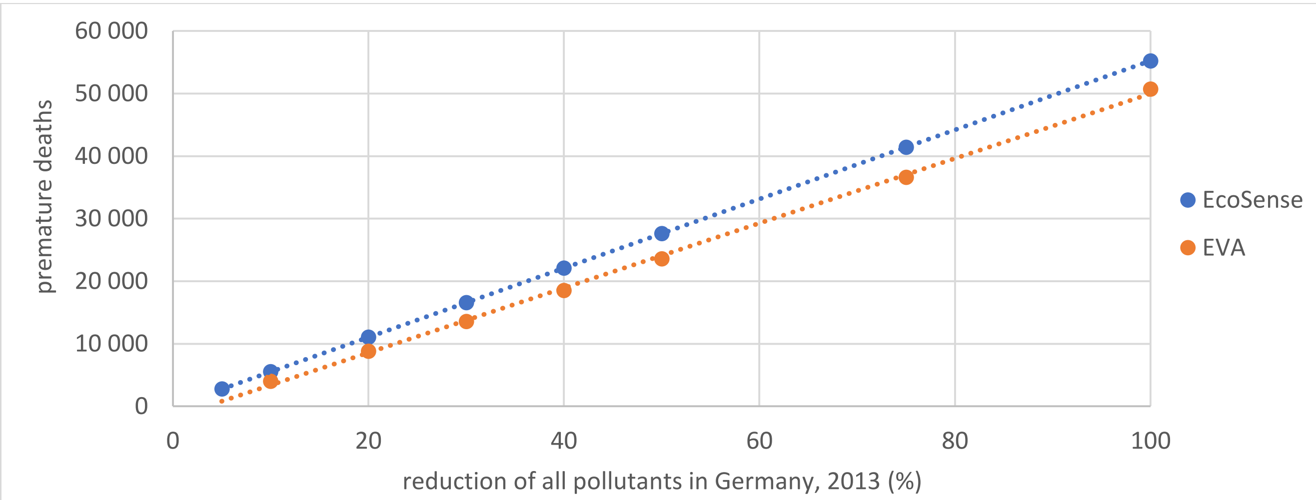

Figure 3: Premature deaths as estimated by EcoSense and EVA for different reduction scenarios off all pollutants in Germany in 2013.

3.1.2 Combining EcoSense and EVA results

To provide again a full set of unit cost factors to be used in energy system models, *EVA* unit cost factors need to be integrated with *EcoSense* cost factors for pollutants and sectors not contained in the *EVA* result set. Therefore, it is first necessary to process *EVA* result sets to match the structure of *EcoSense* as they differ in their monetary base year and reference unit. *EVA* provides unit cost factors in $€_{2013}$ per kg-N and kg-S whereas *EcoSense* cost factors are given in $€_{2010}$ per kg of SO_2 and NO_X emissions as also needed by *TIMES PanEU*. Additionally, *EVA* cost factors are only provided for a current (2013) and future (2030) year due to the resource-intensive runs. To be able to provide unit cost factors for all years, these need to be inter- and extrapolated accordingly.

First, *EVA* cost factors were transferred to $€_{2013}$ per kg of SO_2 and NO_X, respectively. For this, the original cost factors were divided by the respective conversion factor (2 for S → SO_2, 3.2857 for N → NO_X). Afterwards, they were adjusted to $€_{2010}$ values by discounting them with an average inflation rate of 2.17 %[18]. To not lose any spatial information contained in the *EVA* data set, the cost factors should directly replace *EcoSense* data for sectors with high release heights (conversion and electricity and heat sector) as long as they lie within the range of uncertainty of the corresponding *EcoSense* cost factors. Thus, the transformed *EVA* cost factors for the current

[17] Comprising chronic and acute mortality. For chronic mortality an average of 10.6 YOLL per death are assumed in both models.

[18] The average inflation rate is calculated based on annual inflation rates in the Euro-Zone for the years 2011-2013 as given at https://de.statista.com/statistik/daten/studie/156285/umfrage/entwicklung-der-inflationsrate-in-der-eu-und-der-eurozone/ (last checked: 22-01-2019).

year[19] were compared to both 2010 and 2015 cost factors from *EcoSense* since EVA cost factors are originally based on 2013 data. By visual inspection, few outliers in the *EVA* dataset could be identified, namely CH, DK, LU, LV for SO_2 and CH, DK, LU and NO for NO_X, which are all more than 1.5 times the interquartile range above the upper quartile. Additionally, the *EVA* dataset is missing Croatia as this is not part of the model. Since there was no reasonable explanation for these extreme outliers, they are treated as missing values and imputed accordingly. To impute missing values, the *Multivariate imputation by chained equations* (*MICE)* as implemented in R (Buuren and Groothuis-Oudshoorn, 2011; R Core Team, 2018) is applied. The model is based on a random forest approach with five iterations and five draws using the full NO_X and SO_2 datasets from *EcoSense* for both *EVA* datasets, but separately for the years 2010 and 2015, resulting in two separate *MICE* models. The density distribution for both *MICE* models and the pooled regression between *EcoSense* and *EVA* factors from the *MICE* models showed a better fit with the 2010 dataset. Therefore, missing values in the EVA dataset were imputed by taking the average across the five draws from the 2010 *MICE* model. Finally, the fit between *EcoSense* (2010) and the full *EVA* dataset was checked by calculating the Spearman correlation coefficient, which shows with 0.83 a better fit for NO_X compared to SO_2 (0.62). Nevertheless, this shows a positive correlation between the two datasets. After correcting the previously identified outliers, all *EVA* cost factors are also within the range of uncertainty when compared to *EcoSense* data, ranging between - 64 % (CH) and 272 % (NO) for SO_2 and - 59 % (CY) and 315 % (MT) for NO_X. Finally, the corrected *EVA* cost factors are extrapolated to future years based on the trend as given by *EcoSense* and integrated in the final dataset as unit costs for the SNAP1 sector (energy and conversion). The differences between the two datasets, purely *EcoSense* and *EcoSense with EVA*, are explained and discussed below.

3.2 Unit costs to be used in Energy System Models

3.2.1 Initial cost factors based only on EcoSense

The initial cost factors as calculated by *EcoSense* and provided to the energy system model are country- and pollutant-specific with 2010 as their monetary reference year. For better visibility, Table 5 shows only the mean value across all EU28 countries plus Norway and Switzerland as well as the minimum and maximum values for all pollutant species and selected years. All other years are linearly interpolated. The costs for PM_{10} do not include impacts due to exposure to $PM_{2.5}$. The two cost factors for particulate matter are thus additive and should always be considered together to assess the full impact of fine particles. The full dataset will be available in the REEEM database[20] under the version *PathwayNA-FrameworkV2-DataV1*, this will also be used to reference this data set for the remainder of this report.

For all species, average cost factors increase over time until 2035 and then start to decrease again in line with population projections, resulting in similar or even lower cost levels in 2050 compared to 2015. PM2.5 clearly dominates unit costs due to its impacts on mortality. This is also reflected in the values for SO_2 as this is one of the main contributors to secondary particles and thus also responsible for mortality impacts. Despite its direct impact on mortality, NO_X unit costs are roughly a fifth of those for $PM_{2.5}$. This is due to the threshold limit of

[19] At the time of writing this report, *EVA* cost factors for the future year were not yet available. The same procedure to combine the two datasets will be applied as soon as the data becomes available.
[20] For more details about the REEEM database please refer to the forthcoming deliverable D6.5.

20 µg/m³ which is almost never exceeded by the contribution of only one country. Additionally, only 66 % of these impacts are taken into account for NO_X since there is a possible overlap with $PM_{2.5}$ (see also Table 13 in the Appendix). The lowest cost factors occur for PM_{10} since these only reflect additional impacts on top of $PM_{2.5}$ which are only minor impacts on morbidity.

Table 5: Average (minimum, maximum) unit cost factors (€$_{2010}$/kg) to be used in energy system models for selected years.

€/kg	NH_3	NO_X	$PM_{2.5}$	PM_{10}	SO_2	NMVOC
2015	16.94 (2.74;43.29)	8.80 (1.08;21.07)	50.93 (7.84;95.72)	1.75 (0.28;3.88)	20.72 (4.31;55.23)	2.33 (0.57;5.65)
2020	17.24 (2.83;44.26)	8.95 (1.10;21.43)	51.87 (7.98;97.76)	1.80 (0.28;3.93)	21.09 (4.40;56.27)	2.38 (0.61;5.72)
2030	17.26 (2.95;44.18)	8.98 (1.10;21.63)	52.13 (8.03;99.35)	1.80 (0.28;3.99)	21.19 (4.43;56.92)	2.39 (0.64;5.61)
2040	16.92 (3.02;42.79)	8.83 (1.09;21.29)	51.26 (7.94;97.70)	1.78 (0.28;4.01)	20.85 (4.37;56.00)	2.35 (0.63;5.61)
2050	16.57 (3.09;41.41)	8.68 (1.08;20.94)	50.39 (7.84;96.04)	1.77 (0.28;4.04)	20.51 (4.30;55.08)	2.31 (0.63;5.51)

The minimum and maximum values show a wide range for all species, reflecting the spatial variability of impacts across Europe. This spatial variability also reflects the natural influence of population density and geographic location on unit cost factors. Both of these factors directly influence exposure to air pollution independent of the actual amount of emissions released. The more people live in an area, the more can be affected by air pollution in this area. Additionally, emissions from central European countries with many neighbours affect more people through long-range transport. This is why countries such as Cyprus, Malta or Finland typically tend to have lower unit cost factors, while Switzerland's are generally higher. The spatial variability of unit cost factors across Europe further indicates that a pan-European energy system model should at least apply country- and pollutant-specific unit cost factors to be able to evaluate impacts of air pollution control accurately. Neglecting this information may lead to an ineffective or inefficient distribution of emission reductions since the critical issue are not emissions of air pollutants themselves but exposure to air pollution in general.

3.2.2 Improvements by including EVA results

During the comparison of *EcoSense* and *EVA* and the process of integrating both datasets, the *EcoSense* model domain was minimally adjusted to also include non-European neighbour countries in order to increase consistency with the EVA model. This also lead to minor differences in the unit cost factors, with the previously discussed range and spatial variability of unit cost factors still being valid as indicated in Table 6. The distributional patterns of the merged datasets from the two models also seem to be similar, despite any differences that still exists with respect to implementation and underlying assumptions. The range between lowest and highest sector-specific unit cost factors as estimated by *EVA* reflects again their high spatial variability, though it is in general smaller compared to *EcoSense* unit cost factors with unspecified release height. The reason for this does not necessarily have to relate to the sector characterization. One explanation could also be the different spatial resolutions of the two models. The finer the spatial resolution, the better a model can capture exposure to air pollution, especially with respect to hot spots characterized by high population density. The coarser resolution in *EVA* may lead to averaging out extremely low and high exposure points, while the finer resolution in *EcoSense* results in a better representation of these points and thus a wider range of minimum and maximum values.

Table 6: Average (minimum, maximum) unit cost factors (€$_{2010}$/kg) for selected years from both EcoSense and EVA.

€/kg		NH_3	NO_X	$PM_{2.5}$	PM_{10}	SO_2	NMVOC
2015	*EcoSense*	17.23 (2.75;43.53)	9.25 (1.81;21.26)	52.00 (7.97;96.30)	1.81 (0.28;3.88)	21.68 (5.25;55.55)	2.60 (0.68;6.05)
	EVA (SNAP1)	-	10.97 (3.79;15.74)	-	-	15.62 (5.82;28.67)	-
2020	*EcoSense*	17.56 (2.84;44.49)	9.44 (1.86;21.64)	53.03 (8.12;98.36)	1.83 (0.28;3.94)	22.13 (5.33;56.62)	2.67 (0.70;6.17)
	EVA (SNAP1)	-	11.18 (4.18;15.96)	-	-	15.69 (6.47;29.13)	-
2030	*EcoSense*	17.62 (2.96;44.40)	9.54 (1.85;21.85)	53.44 (8.16;100.00)	1.84 (0.29;3.99)	22.41 (5.32;57.32)	2.73 (0.71;6.23)
	EVA (SNAP1)	-	11.26 (4.96;15.92)	-	-	16.15 (7.36;29.16)	-
2040	*EcoSense*	17.31 (3.03;43.00)	9.45 (1.80;21.52)	52.70 (8.07;98.37)	1.83 (0.28;4.01)	22.23 (5.22;56.44)	2.74 (0.71;6.19)
	EVA (SNAP1)	-	11.12 (5.07;15.33)	-	-	16.01 (7.23;28.50)	-
2050	*EcoSense*	17.00 (3.10;41.61)	9.37 (1.76;21.18)	51.96 (7.97;96.73)	1.81 (0.28;4.04)	22.04 (5.13;55.55)	2.75 (0.71;6.15)
	EVA (SNAP1)	-	10.98 (4.95;15.15)	-	-	15.88 (7.10;27.85)	-

Average, sector specific *EVA* results for NO_X are generally higher than the updated *EcoSense* values, with the opposite being true for SO_2. Since emissions from high stacks are usually transported further and thus remain longer in the atmosphere, NO_X from these sources contributes more to the formation of ozone than directly affecting NO_2 concentration levels, leading to higher impacts. Similarly, SO_2 emissions from these release heights have less impact on particle formation, as they are deposited or washed out of the atmosphere as sulphur.

The new dataset with EVA values for SNAP1 emissions and corrected *EcoSense* cost factors for all other emissions will be made available in the REEEM database under the version *PathwayNA-FrameworkV2-DataV2*. This name is also used in the remainder of this report to identify this dataset. These values are used for an ex post analysis based on unit cost factors as a comparison to the full *EcoSense* runs. Final unit cost factors including *EVA* cost factors for future years will be made available under the version *PathwayNA-FrameworkV2-DataV3*, which can then be used in the final version of the Integrated Energy System Model[21], either as a common input for all upcoming pathways or as part of sensitivity analyses for selected pathways.

3.3 Effects of decarbonisation pathways on air pollution and related impacts

3.3.1 Pathway description

In this chapter, the effect of decarbonising the energy system on air pollution and related health impacts are analysed for three different pathways. Each pathway is characterized by a consistent description of a possible future, decarbonisation targets and further technological, social and environmental developments. All three pathways are placed within the same possible future and the two main pathways, *BASE* and *HighRES*, are further described in detail in Avgerinopoulos et al. (2018) and Gardumi et al. (2018). The main assumptions are summarized in Table 7 and briefly described hereinafter.

Table 7: Main assumptions and used TIMES PanEU data for the considered pathways.

	BASE	**BASE_DAM**	**HighRES**
GHG ETS	2020 Climate and Energy Package 2030 Climate and Energy Framework 2050: -83 % rel. to 2005		
GHG non-ETS	Effort Sharing Decision/Regulation 2050: country clusters (-75 % in EU28 rel. to 2005)		
RES	-		Renewable Energy Directive 2050: country clusters (75 % in EU28)
Env. tax	-	✓	-
TIMES PanEU	*BASE-FrameworkV1-DataV4*	*BASE-FrameworkV2-DataV2*	*HighRES-FrameworkV1-DataV4*

For all pathways it is assumed that, instead of a EU wide common energy policy, different countries will form clusters following similar policies, with some setting more ambitious decarbonisation targets than others, also depending on assumed economic growth across member states. Hence, clusters are formed according to their socioeconomic situation, availability of resources and geographic locations. This may lead to additional, cluster based targets for greenhouse gas reduction as well as the share of renewables in gross final energy consumption (RES), despite shared EU targets. In line with this future, all existing and binding EU-wide GHG reduction targets as outlined in the “2020 Climate and Energy Package” (European Union, 2009a) and the “2030 Climate and Energy Framework” (European Commission, 2014) are considered in both the *BASE* and *HighRES* pathway. This includes both EU-wide reduction targets according to the *EU Emissions Trading System* (ETS, European

[21] The full model framework, i.e. the final Integrated Energy System Model, is described in the forthcoming deliverable D6.1.

Commission, 2017) and country-specific targets for non-ETS emissions following the binding "Effort Sharing Decision" and "Effort Sharing Regulation" (European Union, 2009a, 2018). Reductions targets for 2050 are chosen in line with the "Energy Roadmap 2050" (European Commission, 2012), with the concept of effort sharing being applied to the defined country clusters. In contrast to the *BASE* pathway, the *HighRES* pathway also considers explicit targets for the share of renewable energy sources (RES) in 2050. For 2020 these targets follow the "Renewable Energy Directive" (European Union, 2009b). Targets in 2050 are again chosen in line with the "Energy Roadmap 2050" (European Commission, 2012) and the chosen country clusters. All country and cluster specific targets are also given in Avgerinopoulos et al. (2018). For the variant *BASE_DAM*, which follows the same assumptions as the *BASE* pathway, costs of air pollution are included in the energy system model *TIMES PanEU* as part of the optimization, which can be interpreted as an additional environmental tax. This environmental tax matches the unit cost factors[22] and is applied from 2020 on, following a stepwise introduction starting with only half of the actual unit costs in 2020. A detailed description of how it is implemented in the energy system model is given in the forthcoming deliverable D6.1. To assess possible impacts on air pollution and related external costs, a comparative scenario analysis is performed based on outputs of the energy system model *TIMES PanEU*. The result sets used will be available in the REEEM database under the respective version stated in Table 7.

3.3.2 Levels of air pollution and greenhouse gases

The change in emissions of air pollutants and CO_2-equivalents (CO_2eq) as an indicator for greenhouse gas emissions relative to 2015 levels is given for all three pathways and each milestone year in Figure 4. Overall, air pollutants (except SO_2) are reduced by 30 % to 70 % in 2050 compared to 2015 levels. When comparing the three pathways, a striking difference is the development over time for certain pollutants, especially SO_2, for which the *BASE* and *HighRES* pathway both show increases over time. Similar patterns can be found for particulate matter and NO_X between the years 2030 and 2045 for the *BASE* pathway.

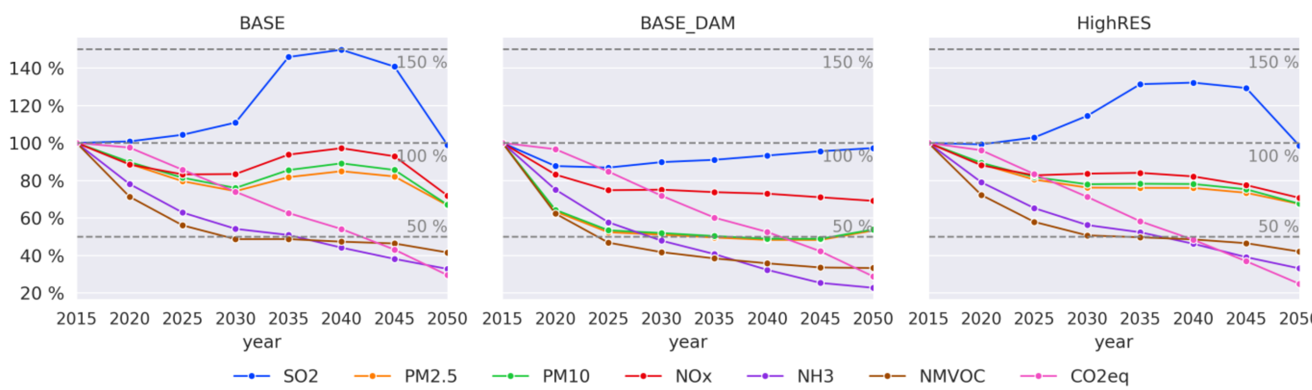

Figure 4: Changes in emissions of air pollutants(EU28) for the considered pathways relative to 2015 levels.

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[22] All runs considered in this analysis apply the first version of unit costs provided by *EcoSense* (*PathwayNA-FrameworkV2-DataV1*).

The steep increase in SO_2 emissions in the *BASE* and *HighRES* pathways between 2030 and 2045 are attributable to conversion processes (Figure 12 in the Appendix), mainly gasification and synthetic fuel production, which are not utilized in the *BASE_DAM* scenario due to their high external costs. Similarly, biomass utilization in electricity production and lignite used in combined heat and power plants cause higher emissions of particulate matter and NO_X between 2030 and 2045 in the *BASE* pathway (see Figure 13 in the Appendix). While SO_2 emissions also increase again in the *BASE_DAM* pathway after an initial decrease in 2020, they still stay lower than their 2015 levels in every year.

Additionally, *BASE_DAM* also shows a sharper initial decrease of particulate matter in 2020, which is mainly coming from the residential and transport sector (Figure 13 in the Appendix). These reductions are mainly caused by banning coal from the residential sector and replacing fuel oil in maritime transport with diesel. These implications are also valid for the initial reduction in SO_2 emissions. The increase in SO_2 after 2020 is mainly caused by an increase in industrial demand, leading to higher process emissions. These emissions can only be mitigated by additional end-of-pipe mitigation technologies or drastic changes in the process itself. As *TIMES PanEU* does not have any options to apply such additional technologies, these emissions cannot be mitigated within the model. Additionally, increasing transport demand and a lack of alternative low-sulphur fuels in maritime transport keep SO_2 emissions from transport virtually on the same level as in 2015 (Figure 5), even leading to a recent increase of fuel oil in maritime transport after 2045 in the *BASE_DAM* pathway after its initial reduction in earlier years. This, in turn, results in almost the same SO_2-emission levels in 2050 as in 2015, since these are clearly dominated by industrial process emissions (see Figure 12 in the Appendix). The increase in transport demand is also apparent in emissions of particulate matter in the *BASE_DAM* Pathway, which also show an increase in 2050. Emissions of particulate matter in transport include emissions from abrasion processes and tyre wear, which can only be reduced by reducing vehicle kilometres. With an increasing demand, this can only be achieved by modal shifts (e.g. from private cars to public transport). Again, such modal shifts are not part of *TIMES PanEU*, resulting inevitably in an increase of particulate matter if transport demand, especially in road transport, increases.

In contrast to air pollutants, all three pathways show a similar, steady decrease in CO_2-equivalents, which are reduced between 70 % for the *BASE* and 75 % for the *HighRES* pathway in 2050 compared to 2015 levels, driven by the same, fixed decarbonisation targets across all three pathways. The *BASE_DAM* pathway shows slightly lower levels of CO_2-equivalents in 2050 compared to the *BASE* pathway, indicating that air pollution control can have positive effects on decarbonisation, which is even better reflected in CO_2 prices for ETS emissions. While the highest overall reductions are achieved in the *HighRES* pathway, the *BASE_DAM* shows the lowest CO_2 prices[23], which means that greenhouse gas mitigation is partly driven by reducing air pollution, lowering directly attributable mitigation costs.

Figure 5 depicts sector specific reductions in 2050 relative to 2015, indicating that public electricity and heat production is the first sector to be almost completely decarbonized in all three scenarios (up to - 98 % compared to 2015 levels). For all sectors, GHG reduction levels and patterns are similar in the *BASE* and *BASE_DAM* pathway

[23] CO_2 prices for ETS emissions are given directly as an Output of *TIMES PanEU* and are on average 10 % lower in the *BASE_DAM* pathway compared to the *BASE* pathway.

(see also Figure 12 in the Appendix). A higher degree of biomass utilization in industry and a higher share of electricity in combination with ambient heat in the residential and commercial sector lead to lower levels of CO_2-equivalents in the *HighRES* pathway. The commercial sector, in particular, is in the other two pathways not nearly as decarbonized. Overall, greenhouse gas reductions in industry and agriculture remain a challenge, with those sectors still emitting between 40 % and 50 % of their 2015 emissions across all three pathways. The higher share of biomass and biofuels in the *HighRES* pathway also leads to less reductions for certain air pollutants, especially $PM_{2.5}$ from public electricity and heat production and the residential sector.

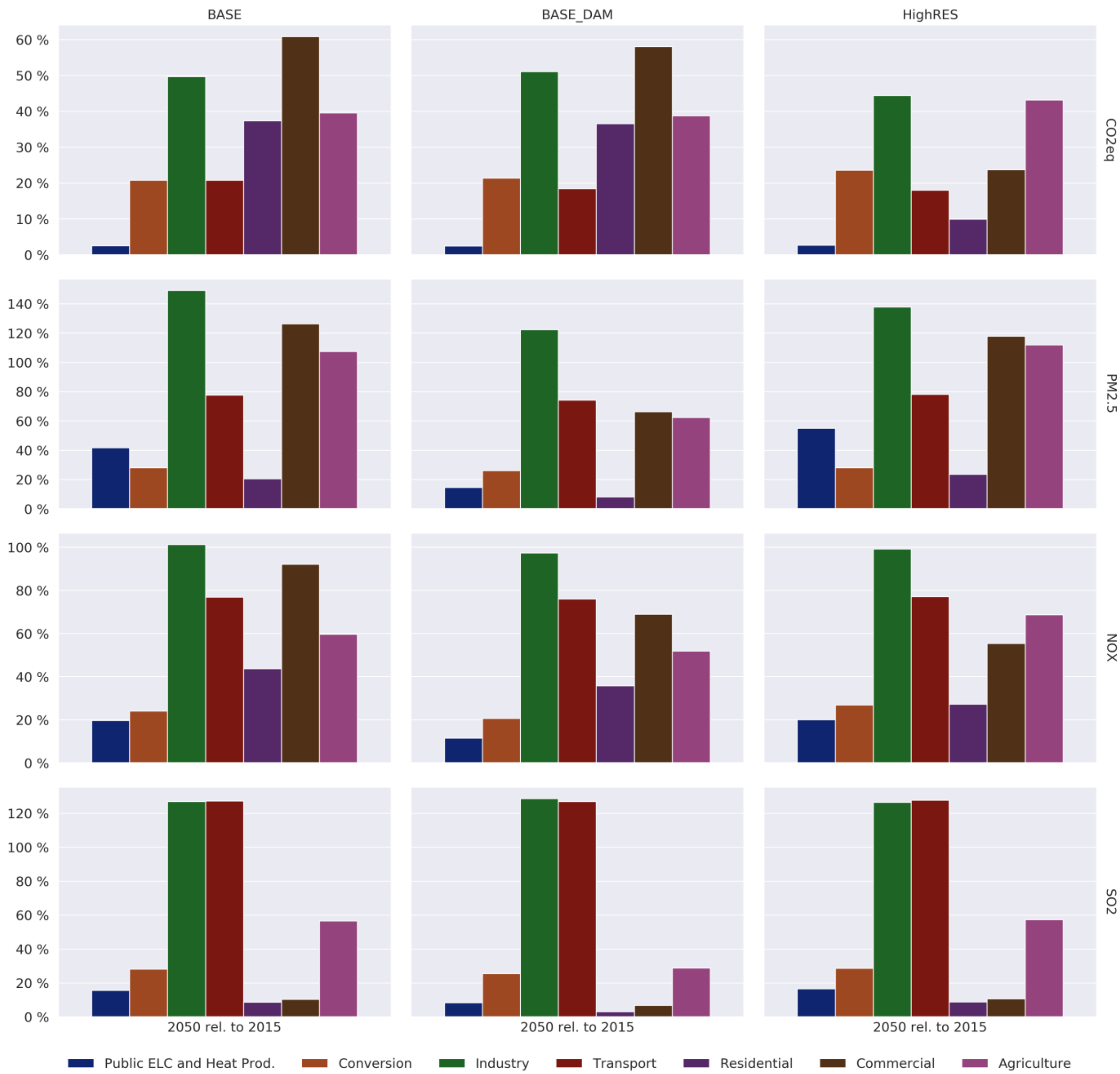

Figure 5: Sector-specific levels of emissions (CO_2-eq., $PM_{2.5}$, NO_X and SO_2) in 2050 relative to 2015.

In both the *BASE* and *HighRES* pathway, $PM_{2.5}$ emissions actually increase over time in industry, agriculture and the commercial sector due to a higher degree of biomass utilization. As a visible effect of considering the costs of air pollution in the optimization function, $PM_{2.5}$ emissions are reduced in all sectors except industry in the *BASE_DAM* scenario. Again, the reduction potential in industry is limited because of the high fraction of process emissions and increasing demand. The effect of air pollution control costs is, however, also apparent in industry, with $PM_{2.5}$ emissions being only increased by 20 % compared to over 40 % in the *BASE* pathway (Figure 5).

Similarly, all three scenarios show similar levels for $PM_{2.5}$ from transport, which is also characterized by emissions from abrasion and tyre wear. As mentioned earlier, these emissions can currently not be mitigated within *TIMES PanEU*. All other sectors show reduction levels nearly twice those in the *BASE_DAM* scenario. Similar patterns can be identified for NO_X and SO_2 emissions with industry and transport showing almost identical reduction levels across all three scenarios, again indicating a lack of mitigation possibilities in these sectors. Because of the initial decrease in fuel oil in maritime transport, the *BASE_DAM* pathway results in a slightly smaller increase of SO_2 emissions from transport. Additionally, the residential sector is almost sulphur-free. In contrast, *BASE_DAM* shows higher levels of NO_X emissions in the residential and commercial sector compared to the *HighRES* pathway. Whereas the *HighRES* pathway is characterized by a high share of electricity and (ambient) heat, natural gas still makes up 29 % of final energy consumption in the residential and about 20 % in the commercial sector in the *BASE_DAM* scenario. In the *BASE* pathway, these sectors are characterized by a high share of biomass on top of natural gas, which leads again to the highest emission values regarding air pollutants. Nevertheless, the *BASE_DAM* pathway still shows the highest emission reductions for all air pollutants when considering all sectors at once, since the high electricity demand in the *HighRES* pathway in combination with renewable as well as decarbonisation targets and a higher utilization of biomass in electricity production results in the lowest reductions of $PM_{2.5}$ and NO_X emissions from public electricity and heat production across all three scenarios.

3.3.3 Detailed analysis of health impacts

The air pollution reduction patterns described above are also found for the reduction in health impacts stated as DALYs. Figure 6. shows health impacts for each pathway separated for morbidity and mortality and attributable to emissions of air pollutants from EU28, Switzerland and Norway. Health impacts are clearly dominated by increased mortality. Impacts on morbidity range between 180 000 and 300 000 DALYs while impacts on mortality are in the range of 1.5 to three million DALYs.

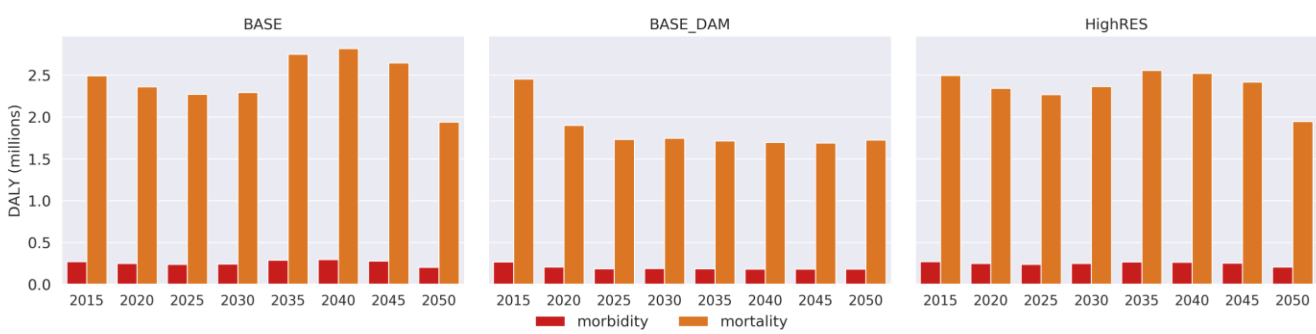

Figure 6: Health impacts in DALYs (mortality and morbidity) attributable to air pollution from EU28, CH and NO for each milestone year.

The lowest impacts are achieved for the *BASE_DAM* pathway in 2045, which is also the only pathway showing a persistent reduction resulting in almost stagnating impacts after 2025. There is a negligible, intermediate increase of total impacts in 2030 (less than 1 % compared to 2025) and a minimal increase in 2050 (2 % compared to 2045), which is caused by the previously discussed increase in emissions of particulate matter. For both the *HighRES* and *BASE* pathway, impacts increase more distinctive after 2030. In the *BASE* pathway, impacts even exceed 2015 levels for 2035 up to 2045. These increases mirror the SO_2 emissions, which especially affect concentration levels of particulate matter and ozone as well as their respective health impacts. When comparing health impacts due to exposure to particulate matter, NO_2 and ozone (SOMO35) separately (Figure 15 in the Appendix), the dominance of impacts on mortality due to $PM_{2.5}$ is apparent, showing orders of magnitude higher impacts. It is interesting to note that for NO_2, mortality impacts are continuously dropping in all three pathways while respective impacts on morbidity are rather constant or even increasing for middle years as seen in the *BASE* pathway. This indicates that, on the one hand, concentration levels are actually reduced below the threshold of 20 µg/m³ (annual mean) in places where this threshold was initially exceeded and, on the other hand, that most increases in NO_2 concentrations do not reach the threshold value. From 2045 on, mortality impacts due to NO_2 are in fact zero, indicating that no fraction of the population is exposed to levels above 20 µg/m³ (annual mean). Note that reductions from 2040 on are not necessarily because of reduced emissions of precursors but may also be due to general population decline assumed for most European countries.

The influence of the assumed population projections is also visible in the spatial distribution of DALYs across all pathways. Figure 7 shows the spatial distribution of DALYS attributable to emissions of air pollutants in the EU28 as well as Switzerland and Norway for the *BASE* pathway and the years 2015 and 2050.

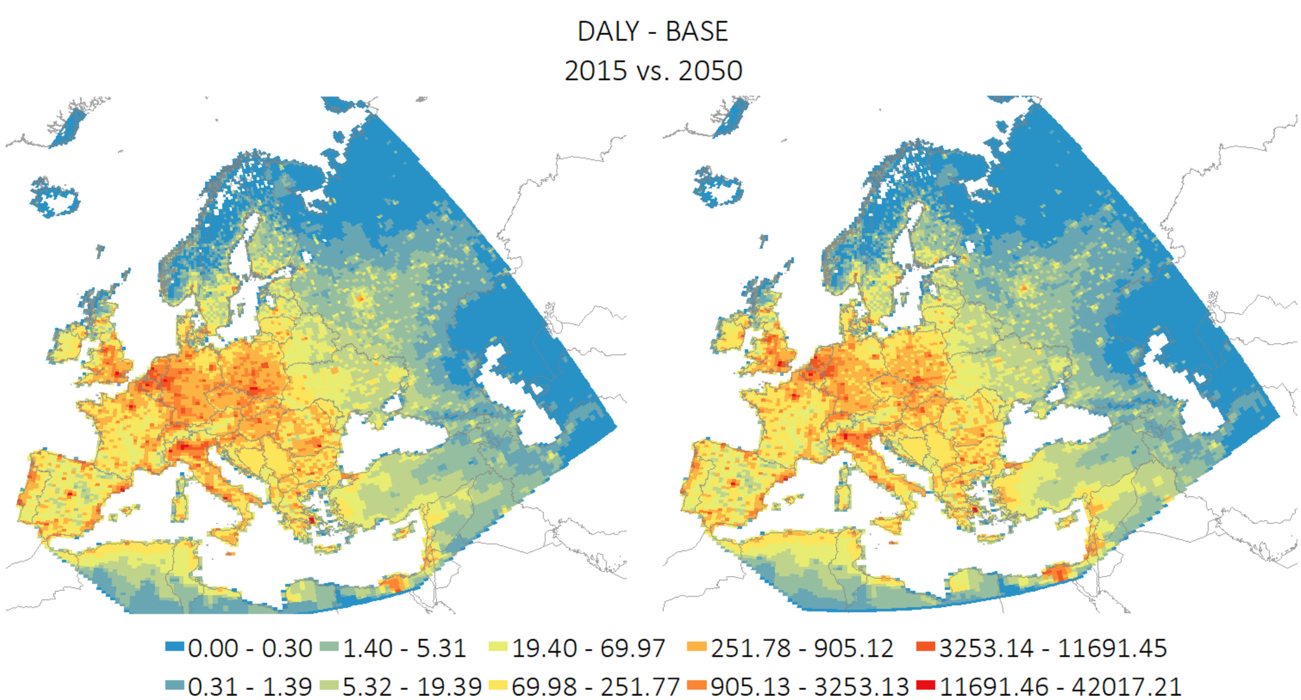

Figure 7: Spatial distribution of DALYs attributable to air pollution from EU28, CH and NO for the BASE pathway in 2015 and 2050.

For both years, hotspots are big cities, Belgium and the Netherlands as well as the Po Valley in Italy. The high population density in combination with high emission density, which is characteristic for these regions, increases general exposure and thus impacts. As the spatial distribution of emissions inherited from the source-receptor matrix as well as the spatial distribution of population data is the same for all three pathways, both the *HighRES* and *BASE_DAM* scenario show similar spatial patterns in exposure and related health impacts with overall lower impacts per grid-cell (see Figure 14 in the Appendix). It seems that there is a shift of exposure from central Europe (Germany, Poland) to south-east Europe (Greece, Bulgaria) and outside of Europe, for example to Turkey. This shift is most likely caused by a shift of emissions from west to east due to higher decarbonisation targets in western Europe as well as the used population projections. Both factors directly affect the exposed population and thus resulting health impacts, either by changes in concentration levels or by changes in the population examined. Despite the overall decrease in health impacts over the whole model domain, some countries can be identified for which health impacts actually increase over time (Figure 8).

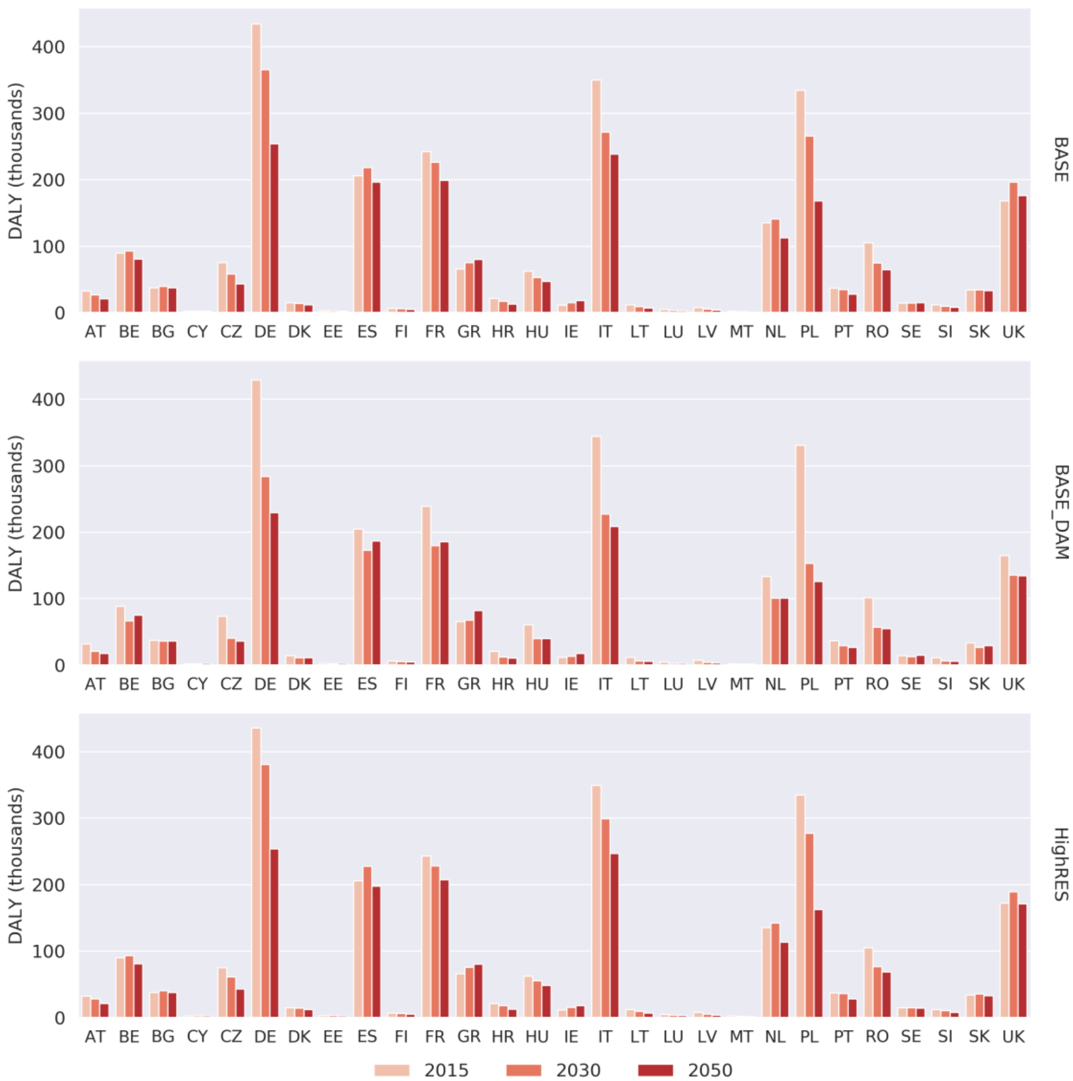

Figure 8: Health impacts in DALY attributable to air pollution from EU28, CH and NO for selected years and for each EU28 member state.

While some countries such as Spain, Belgium or the United Kingdom only indicate increasing health impacts in the middle years (after an initial sharp decrease), still achieving a reduction in 2050 compared to 2015, other countries such as Greece and Ireland show a steady increase over time, even in case of considered air pollution control costs (*BASE_DAM*). This is most likely caused by increasing demand and thus increasing process emissions from industry and transport in these countries. In all three pathways, impacts in countries with the highest levels in 2015 (Germany, Italy and Poland) are reduced continuously over time and by the largest fractions. For most other countries, impacts are either rather constant (in case of the *BASE* and *HighRES* pathway) or only changing by a small fraction, especially after 2030, as is the case in the *BASE_DAM* pathway. This also means that most of the potential cost savings can be attributed to reducing health impacts in only few countries.

3.3.4 External cost due to health impacts and biodiversity losses

In contrast to the previously presented health impacts in DALYs, which are aggregated over the domain of a country in which they occur, monetized health impacts, i.e. external costs, are allocated according to the "polluter pays" principle. This means that costs of impacts are allocated to the country whose emissions are responsible for these impacts, independent of whether these impacts occur in this country or somewhere else. This allocation ensures that countries are held responsible for impacts which they can directly mitigate by reducing their own emissions. As depicted in Figure 9, annual costs of health impacts due to air pollution from EU28 member states range between 150 bn. € and 260 bn. €. Considering the two CRF groups as defined by Héroux et al. (2015), about two-thirds of external costs can be attributed to pollutant-outcome pairs classified as secured (CRF group A*). One-third of external costs relates to pollutant-outcome pairs classified in CRF group B*. These costs are considered to vary more with and depend more on assumptions, since there is still a lack of quantity or quality with regard to the data they are based on. For both groups, external costs show the same patterns as aggregated impacts across Europe (see also Figure 6).

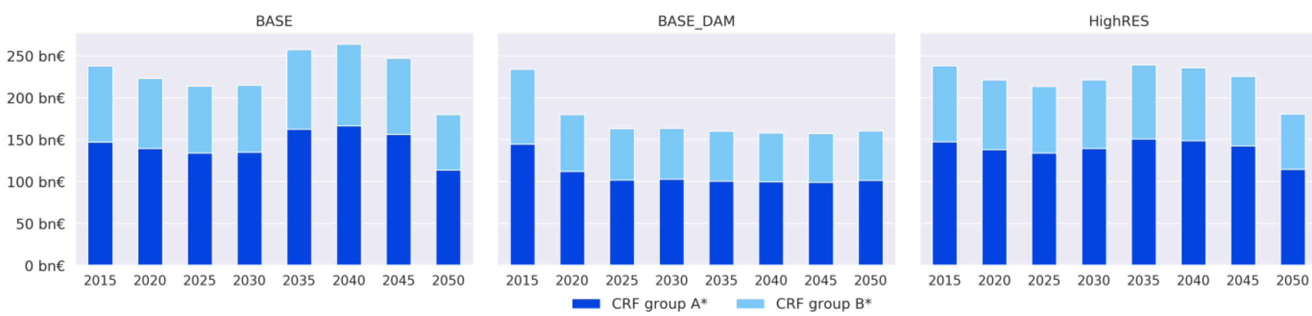

Figure 9: Annual costs of air pollution due to health impacts caused by EU28 and separated by WHO uncertainty groups.

While total external costs rise again in 2035 in the *BASE* and *HighRES* pathway, with costs even exceeding 2015 levels in the *BASE* scenario, the *BASE_DAM* pathway shows a continuous reduction over the years, with only slightly increasing costs in 2050. The lowest annual costs can be observed for the *BASE_DAM* pathway in 2045 and the increase afterwards can be explained by the previously mentioned increase in particulate matter. The highest annual costs occur in the *BASE* pathway in 2040, following the peak in SO_2 emissions. Except for 2050, the *HighRES* pathway shows almost constant costs. While costs due to exposure to NO_2 and ozone decrease constantly over time, costs due to exposure to particulate matter are only minimally fluctuating until 2045 (Figure 16 in the Appendix). Since exposure to $PM_{2.5}$ is associated with costs an order of magnitude higher than all others and is clearly the dominant factor in external costs of health impacts, it overshadows cost reductions due to reduced exposure to other air pollutants.

The sharp decrease in 2050 for the *BASE* and *HighRES* pathway, which is also visible in the underlying emissions and associated health impacts (see Figure 4 and Figure 6), is even more prominent in annual external costs. In contrast, a similar sharp decrease occurs in the *BASE_DAM* pathway already in 2020, afterwards it shows almost stable costs, mirroring $PM_{2.5}$ emissions. This is consistent with the principle of time preferences: As *TIMES PanEU* minimizes total discounted costs with perfect foresight, it tries to reduce existing costs as early as possible and avoid additional costs as long as possible. This is why expensive GHG mitigations, which imply additional costs on the system, are pushed back in the *BASE* and even *HighRES* pathway, resulting in a steeper decarbonisation from 2045 to 2050 when the ambitious reduction targets are in place. Since decarbonisation is the only force driving reductions of emissions of air pollutants, the biggest reductions also occur in 2050. By introducing costs of air pollution in the *BASE_DAM* pathway, the model tries to avoid these costs by reducing emissions of air pollutants as early as possible and as long as additional costs do not exceed the associated cost reductions, leading to the steep initial decrease in external costs in 2020.

Germany and Poland are responsible for the highest country-specific costs in 2015 and also show the highest reductions until 2050 for all three scenarios (Figure 10). The biggest impact of introducing an environmental tax based on costs or air pollution is found in Poland, a country currently characterized by poor air quality, for which costs in 2050 are almost halved compared to the *BASE* pathway. Interestingly, cost of air pollution attributable to emissions from Germany seem to decrease more than actual health impacts occurring in Germany (see Figure 8), with Spain already taking the role of "biggest polluter" in 2030. This highlights the role of trans-national mitigation efforts to reduce health impacts. While the ambitious GHG reduction targets in Germany, especially in combination with the high country-specific unit cost factors as given in the *BASE_DAM* pathway, lead to a high reduction of emissions of air pollutants and associated costs, reductions of actual health impacts are more limited due to the contribution of emissions from other countries.

Despite intermediately increasing costs in 2030 for some countries in the *BASE* and *HighRE*S pathway, almost all countries achieve a visible reduction in 2050 compared to 2015. As previously mentioned, the intermediate increase can be explained by fluctuating emissions as well as by initial population growth assumptions increasing exposure and thus health impacts. In all three pathways, mainly countries in south-east Europe (GR, BG, SK) show an increase in emissions of air pollution and associated costs of health impacts, which is consistent with lower decarbonisation targets as well as the shift in the spatial distribution of health impacts, which is best visible in regions outside of Europe such as Turkey (see Figure 7). Since these countries also show increased external costs in the *BASE_DAM* scenario, the related costs are not high enough to achieve any further emission reductions than already enforced by the binding decarbonisation targets. This may also be a result of EU-wide targets in combination with the chosen country clusters and respective effort sharing decisions. Different country clusters or only EU-wide targets for all sectors may lead to a different distribution of country-specific external costs.

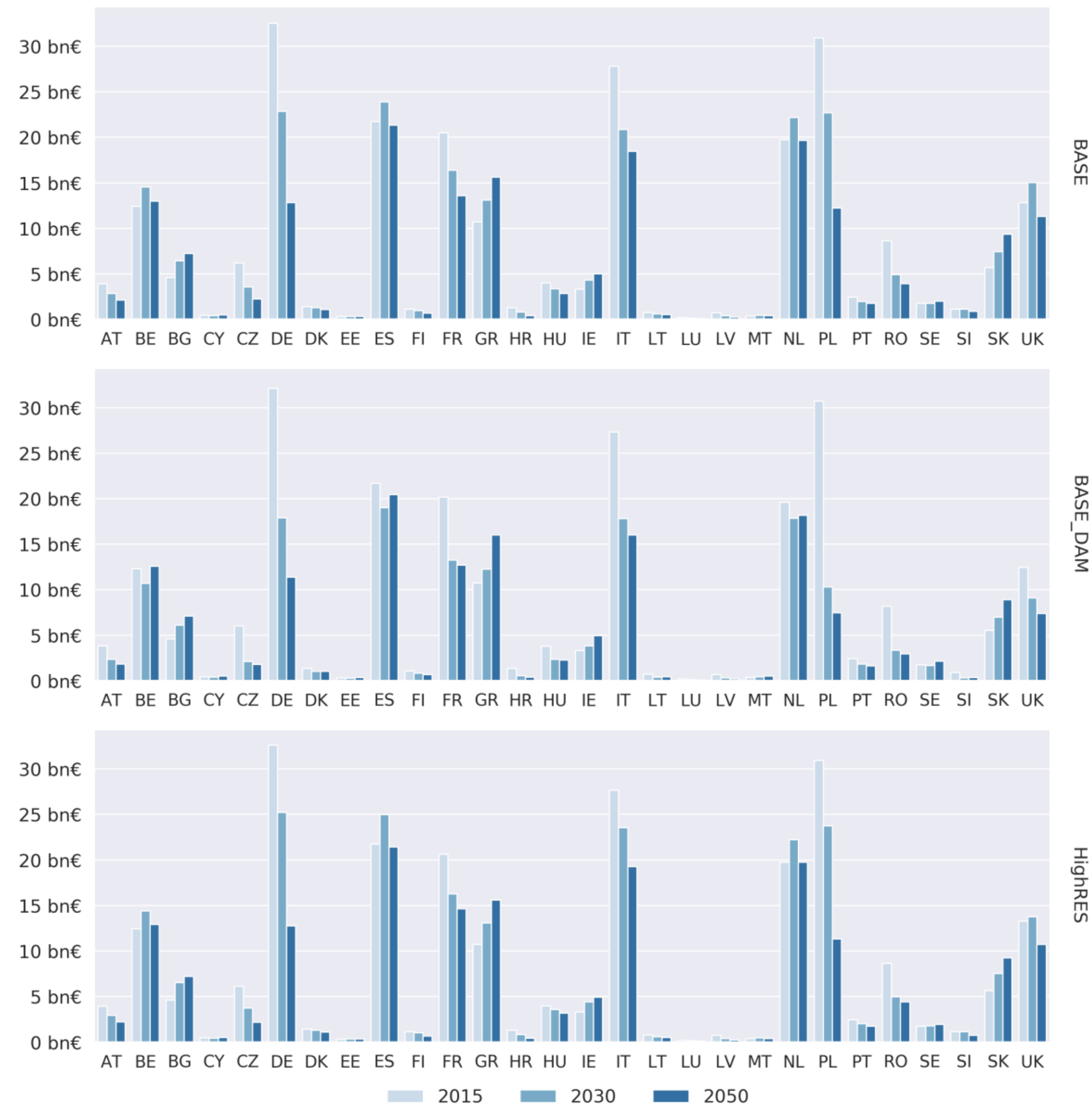

Figure 10: Country-specific costs of air pollution due to health impacts following the "polluter pays" principle for 2015, 2030 and 2050.

Aside from impacts on human health and associated costs, *EcoSense* also estimated costs due to biodiversity losses caused by deposition of sulphur and nitrogen. These costs are an order of magnitude lower than costs due to health impacts, ranging between seven and eleven billion euros for EU28 member states, Switzerland and Norway (Table 8). While these costs are reduced continuously over time for the *BASE_DAM* pathway, there is a visible increase in the *BASE* pathway in 2035 and 2040, which also exists less prominently in the *HighRES* scenario. This increase is mainly caused by the sharp increase in SO_2 emissions. In the case of the *BASE* pathway, the rise in costs due to biodiversity losses is further enforced by a relevant increase in NO_X emissions. Costs of biodiversity losses attributable to other pollutants show similar patterns for all three pathways (see Figure 17 in the Appendix). NMVOC emissions actually lead to overall negative costs since they are, together with NO_X emissions, involved in the formation of ozone, thus reducing possible deposition of nitrogen.

Table 8: Costs of air pollution due to biodiversity losses caused by emissions in EU28, CH and NO.

	BASE	BASE_DAM	HighRES
2015		11.334 bn. €	
2020	10.034 bn. €	9.326 bn. €	9.985 bn. €
2025	9.325 bn. €	8.253 bn. €	9.295 bn. €
2030	9.268 bn. €	8.127 bn. €	9.377 bn. €
2035	10.218 bn. €	7.862 bn. €	9.612 bn. €
2040	10.473 bn. €	7.707 bn. €	9.340 bn. €
2045	9.915 bn. €	7.522 bn. €	8.822 bn. €
2050	7.773 bn. €	7.369 bn. €	7.690 bn. €

All but a few countries are able to reduce costs of biodiversity loss in 2050 compared to 2015 levels or at least maintain the 2015 level in every considered pathway (see Figure 11). This also means that all of these countries mitigate or stabilize their emissions of SO_2, NO_X, NH_3 and NMVOC. This in turn suggests that the increases in health impacts and related costs in certain countries actually stem either from population growth or from increased emissions of particulate matter, which is most crucial for health impacts but does not affect biodiversity losses. In all three scenarios, Belgium and the Netherlands are the only two countries with increasing costs due to biodiversity losses. Both countries are characterized by increasing NO_X and SO_2 emissions. Including costs of air pollution in the optimization function as done in the *BASE_DAM* scenario does not seem to be sufficient to avoid these emission increases caused by growing industrial and transport demand.

The “biggest polluter” in 2015, Germany, also shows the highest reduction until 2050. Again, the lowest external costs are achieved in the *BASE_DAM* pathway, although differences for individual countries, especially in 2050, are not as visible as for health-related costs when comparing to the *BASE* or *HighRES* pathway. Since costs of health impacts associated with air pollution are dominated by exposure to particulate matter, including these costs in an energy system optimization model mainly affects emissions of primary particles which are irrelevant for impacts on biodiversity due to sulphur and nitrogen deposition.

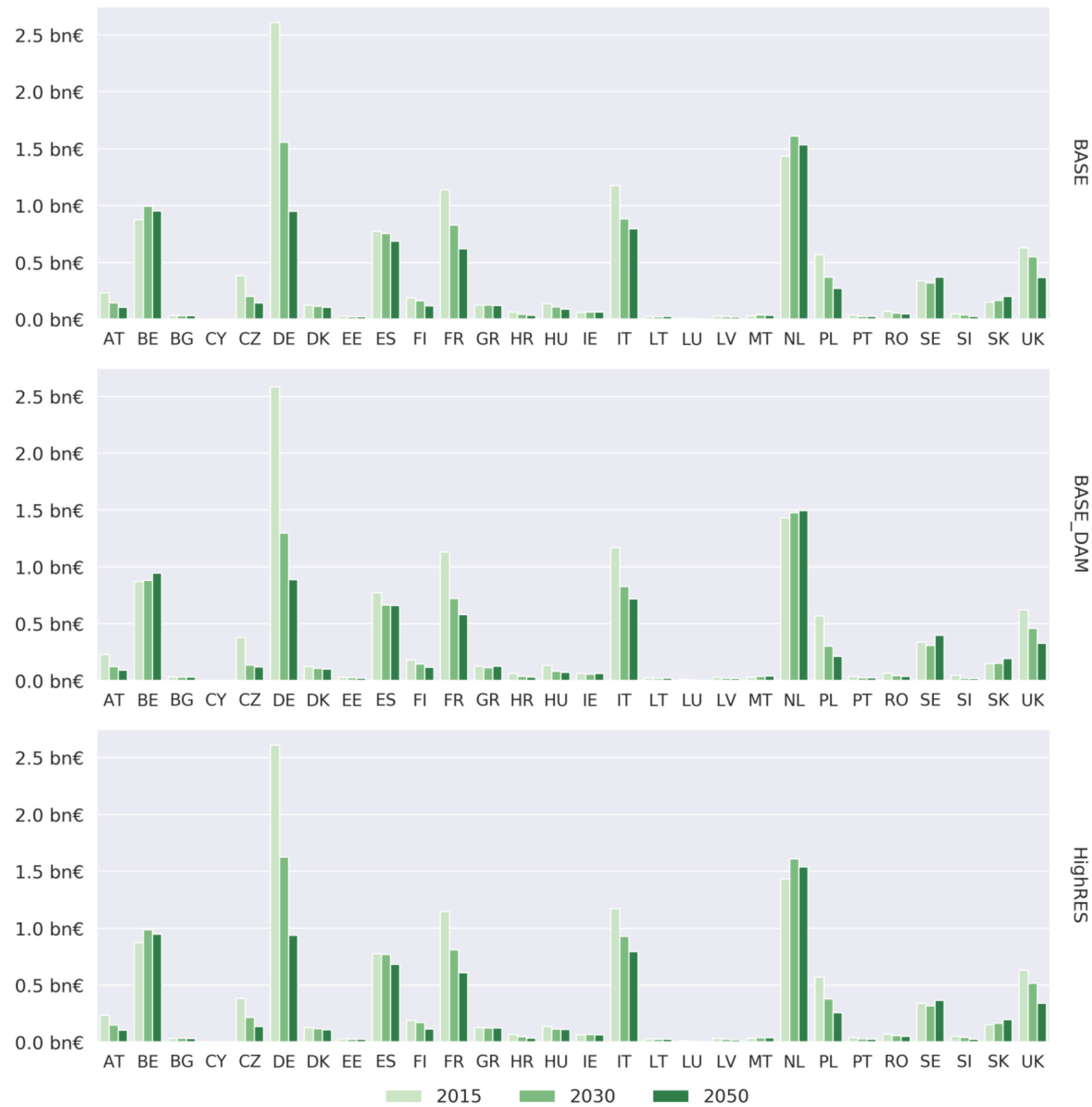

Figure 11: Country-specific costs of air pollution due to biodiversity losses following the "polluter pays" principle for 2015, 2030 and 2050.

3.3.5 Uncertainties

As mentioned earlier, estimates of external costs of air pollution, especially related to health impacts, may vary up to a factor of four, since each step of the impact pathway is subject to uncertainties. *EcoSense* provides the possibility to directly consider uncertainties of pollutant-outcome pairs in terms of relative risk factors and their respective monetary valuation (refer to chapter 2.2.1). This feature is used to calculate a possible range of health impacts and associated costs (see Table 9 - Table 11). In the course of this, three levels of estimated impacts – low, medium, and high – are additionally separated in the two CRF groups, as proposed by the WHO, to also reflect overall uncertainty of data availability (see Héroux et al., 2015). For low-level impacts the lower limit of the 95 % confidence interval of relative risks are applied for all pollutant-outcome pairs (see Héroux et al., 2015) as well as the lowest available monetary valuation as given in Table 14 in the Appendix. The opposite accounts for high level impacts, for which the upper limit of the 95 % confidence interval of relative risks and the highest available monetary valuation are assumed. Thus, low-level impacts reflect the lower limit of health impacts and associated costs, high-level impacts the upper limit. The medium level represents the default configuration in *EcoSense* as also used in the previous analysis and calculation of unit cost factors.

Table 9: Health impacts and associated costs of the BASE pathway estimated with varying CRFs and monetary valuation.

		low		medium		high	
		DALY (m.)	€ (bn.)	DALY (m.)	€ (bn.)	DALY (m.)	€ (bn.)
2020	**A***	1.510	56.877	2.345	141.336	3.143	677.080
	A*+B*	1.650	125.444	2.610	226.472	3.562	808.400
2030	**A***	1.468	55.276	2.280	137.338	3.055	658.048
	A*+B*	1.601	120.582	2.533	218.328	3.456	782.258
2050	**A***	1.241	46.763	1.928	116.178	2.584	556.649
	A*+B*	1.354	101.060	2.143	183.573	2.922	659.544

Table 10: Health impacts and associated costs of the BASE_DAM pathway estimated with varying CRFs and monetary valuation.

		low		medium		high	
		DALY (m.)	€ (bn.)	DALY (m.)	€ (bn.)	DALY (m.)	€ (bn.)
2020	**A***	1.216	45.859	1.890	113.952	2.533	545.741
	A*+B*	1.331	101.264	2.108	183.012	2.879	652.649
2030	**A***	1.119	42.160	1.738	104.741	2.329	501.716
	A*+B*	1.222	92.092	1.934	166.872	2.640	597.258
2050	**A***	1.106	41.671	1.718	103.522	2.302	495.977
	A*+B*	1.207	90.092	1.910	163.683	2.605	587.938

Table 11: Health impacts and associated costs of the HighRES pathway estimated with varying CRFs and monetary valuation.

		low		medium		high	
		DALY (m.)	€ (bn.)	DALY (m.)	€ (bn.)	DALY (m.)	€ (bn.)
2020	**A***	1.498	56.450	2.328	140.277	3.120	671.996
	A*+B*	1.637	124.497	2.590	224.776	3.535	802.331
2030	**A***	1.514	57.012	2.351	141.654	3.151	678.755
	A*+B*	1.652	124.285	2.612	225.040	3.563	806.566
2050	**A***	1.248	47.006	1.938	116.785	2.598	559.569
	A*+B*	1.361	101.570	2.154	184.488	2.936	662.904

Including pollutant-outcome pairs classified as B* results in between 9 % (low level) and 13 % (high level) higher estimations of DALYs per year, which translates into 18 % higher costs in the case of high level assumptions and even doubled costs in the case of low assumptions. In the medium level, costs are about 58 % higher if group B* is included in the assessment. These pollutant-outcome pairs should be included when estimating external costs due to air pollution since these would otherwise be greatly underestimated, especially if there is high willingness-to-pay to avoid health impacts. If both group A* and B* pollutant-outcome pairs are considered, the impact estimates given as DALYs range from ≈ 60 % of the medium estimates to 134 %. After monetization, their range is, however, much bigger, showing 3.5 times higher costs for the high-level estimates and almost halved costs for the lower limit. This indicates that a high portion of uncertainty still comes from monetary valuation of health outcomes. Especially when no market values exist, such as in the case of mortality impacts and YOLL, monetary valuations may show a wide range. Most of the time, contingent studies are used to assess a willingness-to-pay, which is also the method used in *EcoSense*. Yet, as these studies always rely on survey results and are thus partly subjective, their results directly inherit an unavoidable uncertainty, which is then also reflected in total cost estimates of air pollution. This possible range in absolute costs should always be kept in mind when doing cost-benefit analysis involving health impacts of air pollutants, especially when only working with cost factors.

To also account for possible variability between different models and to test the robustness of results, costs of health impacts due to air pollution are also estimated by directly applying the latest version of unit cost factors, which include the integration of *EVA* results. As can be seen in Table 12, total discounted costs of air pollution estimated with the two methods and a 5 % discount rate are in the same range for all three pathways.

Table 12: Total discounted costs of air pollution (EU28) due to health impacts as calculated with EcoSense and based on unit costs.

	EcoSense (detailed)	EcoSense/EVA cost factors
BASE	4014.433 bn. €	4215.792 bn. €
BASE_DAM	3101.038 bn. €	3342.210 bn. €
HighRES	3923.315 bn. €	4113.707 bn. €

For the *BASE* and *HighRES* pathways, estimates based on unit cost factors are about 5 % higher than detailed calculations with *EcoSense*. In the case of internalizing costs of air pollution (*BASE_DAM*), the difference is around 7 %, although it should be noted that the cost factors considered in the optimization did not yet include sector-specific cost factors from *EVA*. As these are higher for SO_2 and NO_X from the energy and conversion sector and both other pathways are characterized by increasing SO_2-emissions, mainly coming from conversion processes, including EVA cost factors in the energy-system model most likely leads to different emissions and thus different overall costs for this specific pathway. Thus the discrepancy between the two models is considered to be low, despite all inherited uncertainty. The comparison between the total costs based on unit-cost calculations and detailed EcoSense model runs indicates that applying unit costs can give a good first estimation of external health costs of air pollution, providing a good alternative to also analyse costs of air pollution with complex models such as energy system models even if they are not part of the optimization.

4 Conclusions and Limitations

This study analysed the effects of possible decarbonisation pathways for the European energy system on air pollution and associated impacts, highlighting the importance of an integrated assessment of climate change mitigation and air pollution control. By carrying out a comparative scenario analysis of three different pathways, which all feature ambitious GHG mitigation targets, the interactions of decarbonisation and air pollution control are studied, with one scenario having ambitious RES targets as an additional decarbonisation measure and the third scenario introducing costs of air pollution control as an environmental tax in the system.

Emissions of all considered air pollutants except SO_2 emissions are reduced in all three scenarios by 30 % to 70 % in 2050 compared to 2015 levels. This indicates that ambitious CO2 targets are also a driving force in reducing air pollution. The potential for reducing SO_2 emissions, which are characterized by a high share of industrial process emissions, seems to be limited due to increasing industrial and transport demand. Process emissions can only be mitigated by changing the production process or by end-of-pipe mitigation technologies, which are not part of the *TIMES PanEU* model, hence these emissions directly correlate with increases in industrial demand and are not mitigable. Additionally, a lack of alternative low-sulphur fuels in maritime transport and increasing demand in transport further limit reduction potentials for SO_2. These emissions could only be reduced by introducing new kinds of fuels or allowing modal shifts, i.e. shifting demand from one transport category to another, which is not possible in the current model configuration. When analysing the spatial distribution of health impacts as well as country-specific external costs, it seems that the principle of burden sharing in GHG reductions in combination with the chosen country clusters leads to a re-distribution of emissions and thus related impacts from central Europe to south-east Europe. This also means that not all countries profit from better air quality and health due to emission reductions. While some countries, such as Germany and Poland, show high reductions in exposure and attributable external costs, clearly identifying them as beneficiaries of climate change mitigation efforts within the European energy system, exposure to air pollution, related health impacts and attributable costs actually increase for other countries. This may lead to conflicts between pan-European climate mitigation policy and national or even local air quality plans. Additionally, the role of trans-national impacts, i.e. impacts occurring in one country caused by emissions of another country, should not be underestimated; Germany, for example, can reduce its attributable costs due to health impacts across Europe far more than the actual decrease in health impacts occurring in Germany. This highlights the necessity for a pan-European strategy to address climate change and air pollution simultaneously. With burden-sharing schemes and national targets aiming to achieve a common target across the EU, integrated policies are even more important.

Similarly, country-specific RES targets may have a negative effect on air pollution due to increased utilization of biomass, depending on the chosen country clusters and assumed availability of renewable resources, overall leading to an increase in external costs. Thus, these targets may not lead to an optimal allocation of resources in Europe. From the three considered scenarios, including costs of air pollution in the optimization and thus considering air pollution control and climate mitigation simultaneously leads to the lowest external costs, providing benefits for society while still achieving the same decarbonisation targets. Because of the principle of time preferences, the model tries in this scenario to avoid these costs by reducing emissions of air pollutants as early as possible and as long as these reductions do not introduce any higher costs to the system. Reducing GHG emissions by introducing fixed targets imposes costs on the system, which the model tries to avoid as long as possible, delaying any expensive decarbonisation measure. Thus, costs of air pollution control result in an early push out of coal in the residential sector and in replacing a big share of fuel oil in maritime transport with diesel already by 2020. Such impacts also reduce GHG emissions earlier in time, resulting in lower ETS CO_2 prices. These CO_2 prices are even lower than in the case of RES targets, which clearly indicates the high potential for co-benefits between air pollution control and climate change mitigation. Once again, this emphasizes the need for integrated policies to exploit these co-benefits as much as possible.

This study has some limitations. First, the results of the three considered pathways may vary substantially with different country clusters and may react sensitive to changes in other input parameters used in *TIMES PanEU*. While the uncertainty assessment undertaken in this study showed that at least the health impact assessment is within the typical range of uncertainty (up to a factor of four) for all three scenarios, the results depend heavily on the assumed emission streams. These depend not only on activities as an outcome of the optimization in *TIMES PanEU*, but also on the chosen emission factors and assumed emission control mechanisms in the future, such as applied end-of-pipe technologies or set limit values. Although future developments are treated by applying technology-specific emission factors, which also change over time, this study also suggests that this may not be enough, as certain emissions are not reduced. This is particularly the case for process emissions from industry and transport which directly correlate with increases in demand. Further, the unit cost factors fed back to the energy system model did not consider any differences in release heights. Thus, sector-specific contributions may not be reflected well enough, especially with respect to the influence of long-range transport of air pollutants from high emission sources. Consequently, introducing sector-specific unit cost factors which take into account different effective release heights may lead to a different distribution of emission reductions, especially in the *BASE_DAM* scenario. Similarly, impacts of air pollution control on road transport may be underestimated in the current study. The ambitious GHG reduction targets already lead to a shift to newer and thus cleaner vehicles, almost achieving the same share of fuels with or without costs of air pollutants. Since there is no differentiation between urban and rural road transport, neither in the energy system model nor in the applied unit cost factors, it seems that there is no possible cost advantage provided by reducing emissions of air pollutants compared to solely achieving the GHG mitigation targets. This might be different if road transport and its respective unit costs were differentiated by urban and rural areas. Due to its low release height in combination with the high population density, emissions of road transport are mainly an issue in urban areas, imposing much higher external costs than in rural areas. Additionally, some emissions in road transport, such as emissions from abrasion processes and tyre wear, can only be mitigated by modal shifts or overall reducing demand. Shifts in transport modes due to the introduced taxes cannot be reflected in the model, thus possible effects of air pollution control costs on these process emissions are partially neglected. Last but not least, all impact assessments are only based on ambient air concentration levels. Some climate change mitigation measures, especially for the building stock, have a bigger effect on indoor air pollution. With increased insulation and sealing of the building envelope, indoor pollutant concentration levels and thus actual exposure may increase due to decreased ventilation. This may especially be true in winter, when people tend to open windows less and if there is no active ventilation system installed. As indoor air pollution is an important factor in total exposure, this should be investigated in the future.

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Appendix

Comparison of EcoSense and EVA: Applied assumptions

Table 13: Concentration-response functions (impact factors per exposed person) as implemented in EVA and EcoSense.

	EVA[1]	EcoSense	WHO classification[2]
PARTICULATE MATTER[3]			
Chronic mortality, YOLL:	1.138×10^{-3} YOLL/µg m^{-3} (adults > 30 yr)	1.0131×10^{-3} YOLL/µg m^{-3} (adults > 30 yr)	A*
Infant mortality:	6.68×10^{-6} cases/µg m^{-3} (infants)	*5.05×10^{-6} cases/µg m^{-3} (infants)*	B*
Chronic bronchitis:	8.2×10^{-5} cases/µg m^{-3} (adults > 18 yr)	*4.563×10^{-5} cases/µg m^{-3} (adults > 18 yr)*	B*
Prevalence of bronchitis in children:	-	*1.488×10^{-3} cases/µg m^{-3} (children age 5-14 yr)*	B*
Asthmatic adults, bronchodilator use:	2.72×10^{-1} cases/µg m^{-3} (5.9% of adults age > 15 yr)	-	
Asthmatic adults, cough:	2.8×10^{-1} days/µg m^{-3} (5.9% of adults age > 15 yr)	-	
Asthmatic adults, lower respiratory symptoms:	1.01×10^{-1} days/µg m^{-3} (5.9% of adults age > 15 yr)	-	
Incidence of Asthma Symptoms in Asthmatic Children:	-	*1.7374×10^{-1} days/µg m^{-3} (4.14% of children age 5-19 yr)*	B*
Asthmatic children, bronchodilator use:	1.29×10^{-1} cases/µg m^{-3} (7.6% of children < 15 yr)	-	
Asthmatic children, cough:	4.46×10^{-1} days/µg m^{-3} (7.6% of children < 15 yr)	-	
Asthmatic children, Lower respiratory symptoms:	1.72×10^{-1} days/µg m^{-3} (7.6% of children < 15 yr)	-	
Respiratory hospital admissions:	3.46×10^{-6} cases/µg m^{-3} (total pop.)	2.2135×10^{-5} cases/µg m^{-3} (total pop.)	A*
Cerebro-/Cardiovascular hospital admissions:	8.42×10^{-6} cases/µg m^{-3} (total pop.)	2.053×10^{-5} cases/µg m^{-3} (total pop.)	A*
Congestive heart failure:	3.09×10^{-5} cases/µg m^{-3} (total pop.)	-	
Lung cancer:	1.26×10^{-5} cases/µg m^{-3} (total pop.)	-	
Work Loss Days	-	3.1326×10^{-2} days/µg m^{-3} (69.36% of adults age 20-64 yr)	B*
(Net) Restricted Activity Days[4]:	8.4×10^{-4} days/µg m^{-3} (adults) $- 3.46\times10^{-5}$ days/µg m^{-3} (adults) $- 8.42\times10^{-5}$ days/µg m^{-3} (adults) $- 2.47\times10^{-4}$ days/µg m^{-3} (adults age > 65 yr)	8.93×10^{-2} days/µg m^{-3} (total pop.) $- 2.2135\times10^{-4}$ days/µg m^{-3} (total pop.) $- 2.053\times10^{-4}$ days/µg m^{-3} (total pop.) $- 3.1326\times10^{-2}$ days/µg m^{-3} (pop. age 20-64 yr) $- 1.7374\times10^{-1}$ days/µg m^{-3} (4.14% of children age 5-19 yr)	B*

	EVA[1]	EcoSense	WHO classification[2]
OZONE (SOMO35)			
Acute mortality:	3.27×10^{-6} cases/µg m^{-3} (total pop.)	2.8×10^{-6} cases/µg m^{-3} (total pop.)	A*
Respiratory hospital admissions:	-	1.023×10^{-5} cases/µg m^{-3} (adults age > 64 yr)	A*
Cardiovascular hospital admissions:	-	4.482×10^{-5} cases/µg m^{-3} (adults age > 64 yr)	A*
Minor restricted activity days:	-	1.201×10^{-2} days/µg m^{-3} (total pop.)	A*
CARBON MONOXIDE (CO)			
Congestive heart failure:	5.64×10^{-7} cases/µg m^{-3} (total pop.)	-	
SULFUR DIOXIDE (SO_2)			
Acute mortality:	7.85×10^{-6} cases/µg m^{-3} (total pop.)	-	
Respiratory hospital admissions:	2.04×10^{-6} cases/µg m^{-3} (total pop.)	-	
NITROGEN DIOXIDE (NO_2)			
Chronic mortality, YOLL[5]:	-	8.987×10^{-4} YOLL/µg m^{-3} (adults age > 30 yr)	B*
Prevalence of bronchitic symptoms in asthmatic children:	-	4.431×10^{-3} cases/µg m^{-3} (10.5% of children age 5-14 yr)	B*
Respiratory hospital admissions:		2.097×10^{-5} cases/µg m^{-3} (total pop.)	A*

[1] See also Im et al. (2018).
[2] According to Héroux et al. (2015).
Category A*: secured concentration-response function;
Category B*: higher uncertainty about used data, but confident concentration-response function.
[3] Both models apply same toxicity to primary and secondary particles. Impacts in italic are related to PM_{10} exposure, others are related to $PM_{2.5}$.
[4] *EVA*: Hospital admissions with an average stay of 10 days are deducted to avoid double counting.
EcoSense: Hospital admissions with an average stay of 10 days as well as work loss days and asthmatic symptoms are deducted to avoid double counting.
[5] With a threshold of 20 µg/m³. In line with the WHO HRAPIE recommendations (Héroux et al., 2015), a maximum overlap of 33 % with chronic mortality due to exposure to $PM_{2.5}$ is assumed. This overlap is also the reason why it is categorized as B*.

Table 14: Monetary valuation applied by EVA and EcoSense to quantify health damage costs.

	EVA[1]	EcoSense[2]	
price year	2013	2010	
currency	€	€	(low;high)
Chronic mortality, YOLL:	57 510 per YOLL	60 000 per YOLL	(37 500;215 000)
Infant mortality:	2 298 148 per case	2 475 000 per case	(1 120 000;11 200 000)
Acute mortality[3]:	1 532 099 per case	89 715 per case	(60 820;220 000)
Hospital admissions:	5 315 per case (respiratory) 6 734 per case (cerebrovascular)	2 990 per case	(2 990;8 074)
Chronic bronchitis:	38°578 per case	60 000 per case	(43 000;100 000)
Prevalence of bronchitis (children):	-	593 per case	-
Incidence of asthma in children:	-	42 per day	-
Bronchodilator use:	16 per case	-	-
Cough:	30 per day	-	-
Lower respiratory symptoms:	9 per day	-	-
Restricted activity days:	98 per day	194 per day	-
Minor restricted activity days:	-	57 per day	-
Work loss day:	-	441 per day	-
Congestive heart failure:	10 998 per case	-	-
Lung cancer:	16 022 per case	-	-

[1] See also Im et al. (2018).

[2] See also Friedrich et al. (2011) and Holland (2014).

[3] *Eva* applies a 'Value of statistical life (VSL)', *EcoSense* implements a 'Value of Life Year (VOLY)' based on one year of life lost per case (see also Holland, 2014).

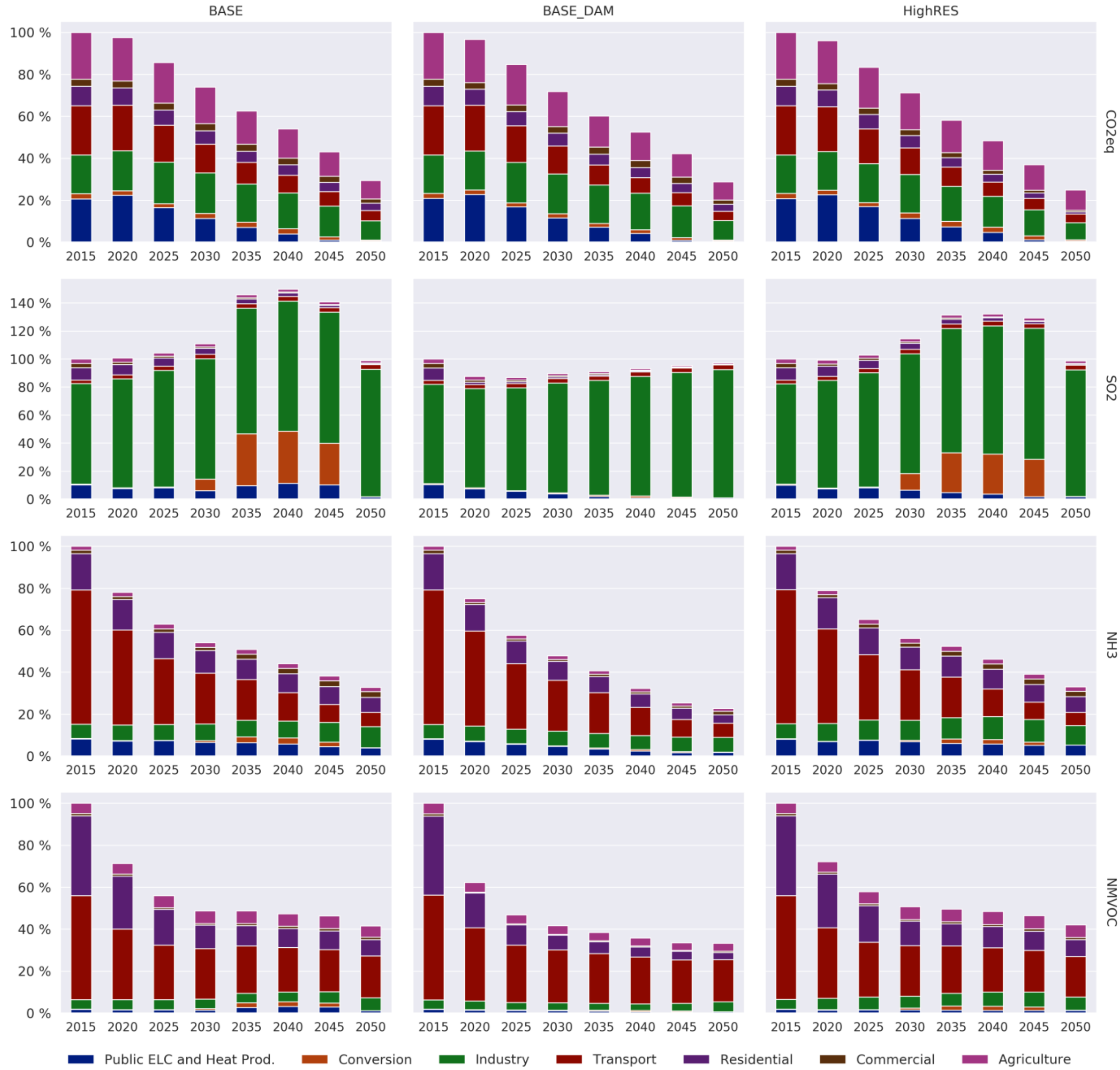

Figure 12: Changes emissions of CO_2-equivalents, SO_2, NH_3 and NMVOC relative to 2015 levels split to sectors.

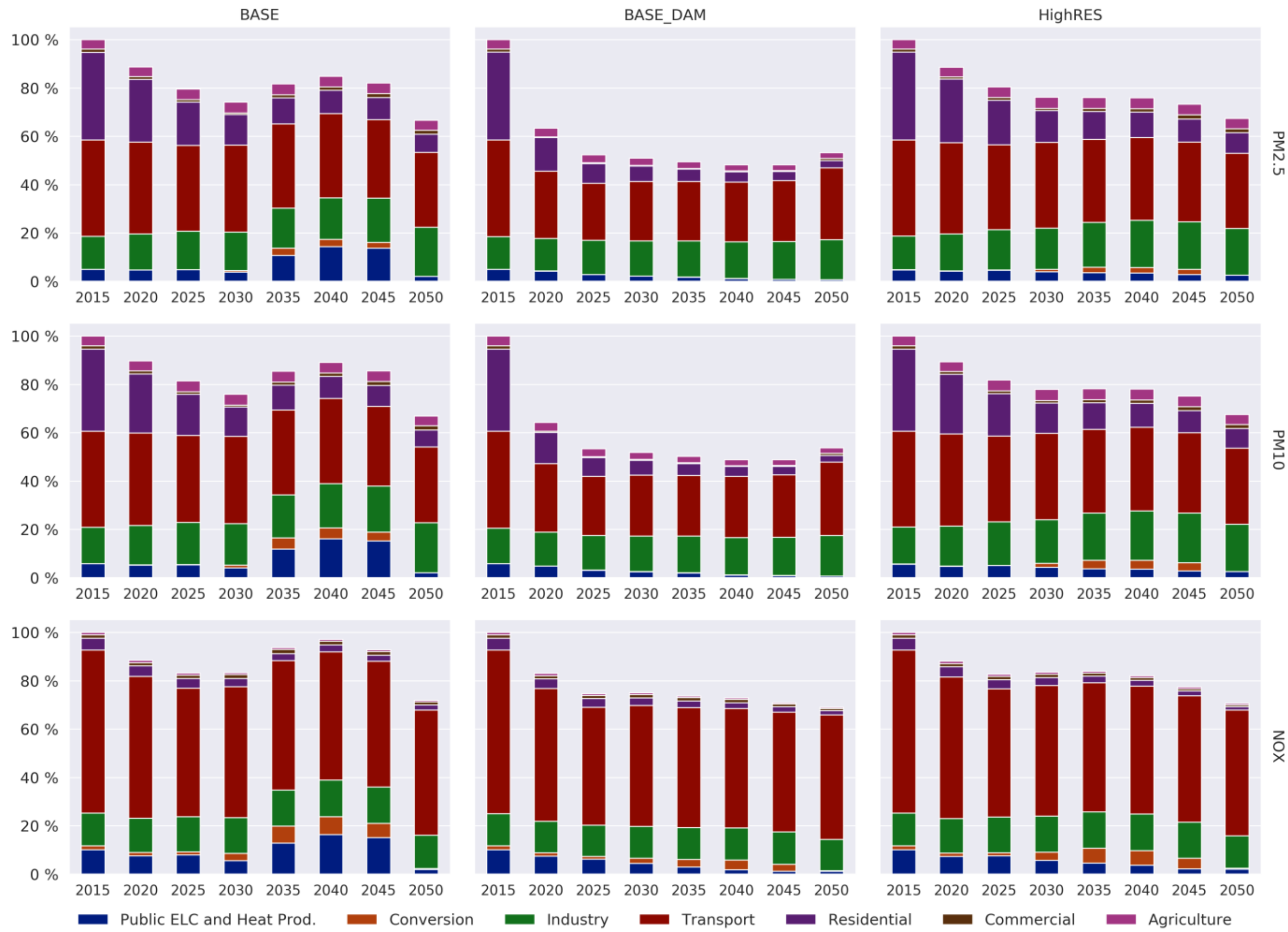

Figure 13: Changes in emissions of particulate matter ($PM_{2.5}$ and PM_{10}) and NO_X relative to 2015 levels split to sectors.

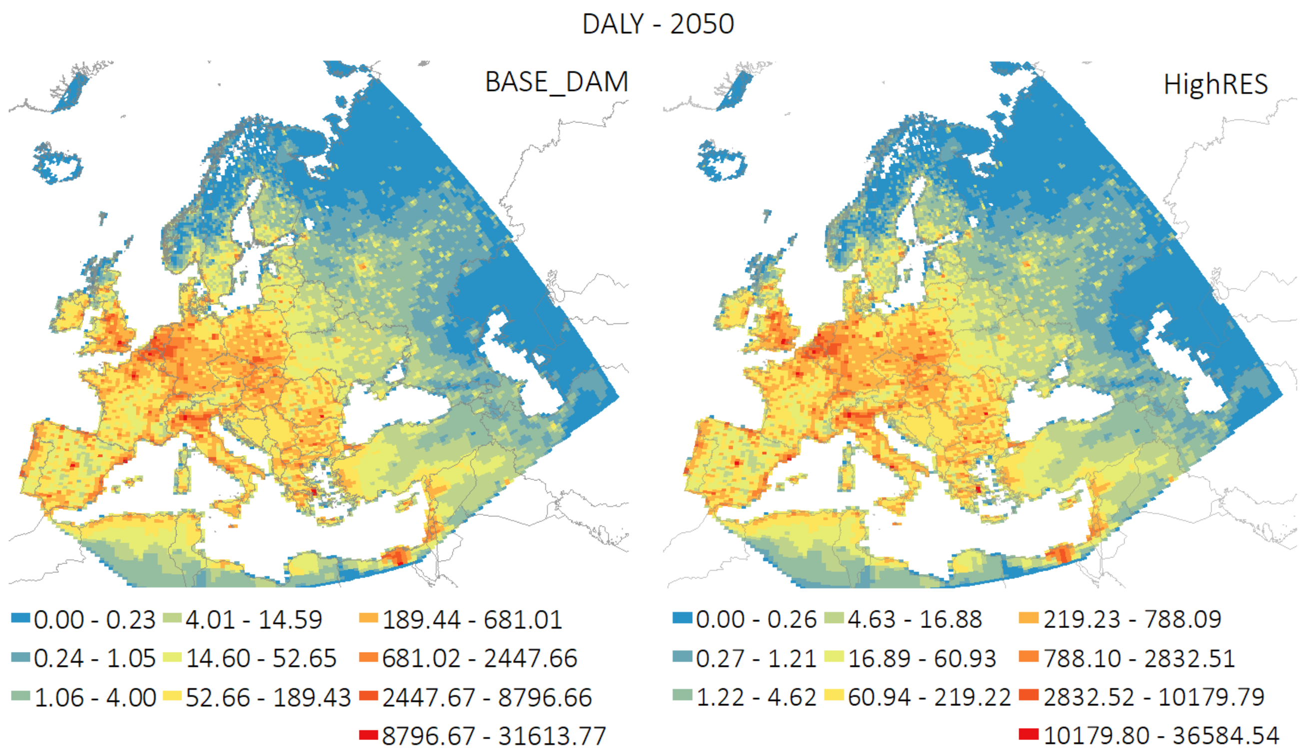

Figure 14: Spatial distribution of DALYs attributable to air pollution from EU28, CH and NO for the BASE_DAM and HighRES pathway in 2050

Figure 15: Total DALYs of morbidity and mortality impacts separated for exposure to $PM_{2.5}$, PM_{10}, NO_2 and ozone (SOMO35).

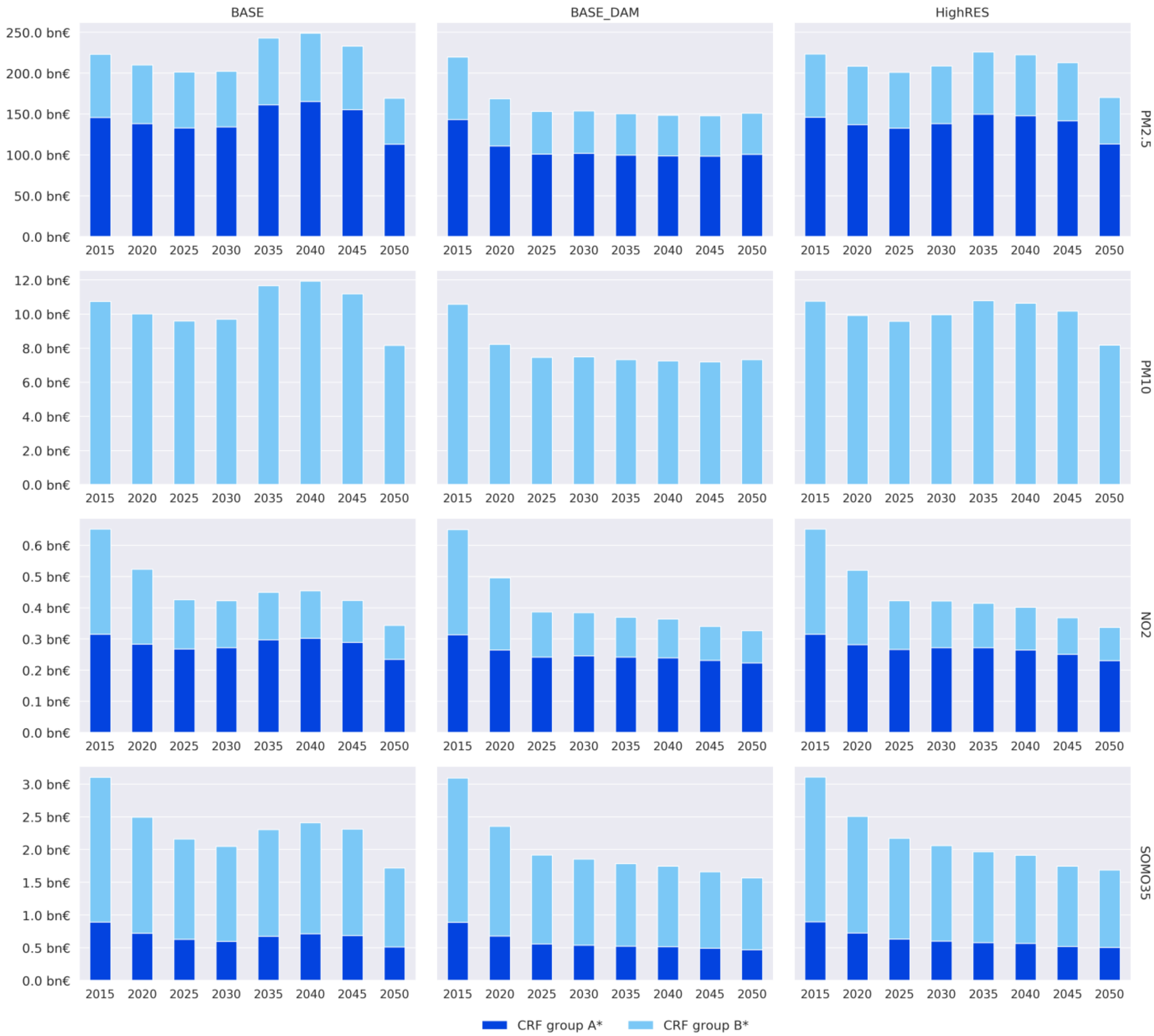

Figure 16: Annual costs of air pollution for EU28 due to exposure to $PM_{2.5}$, PM_{10}, NO_2 and ozone, separated by WHO uncertainty groups.

External costs due to biodiversity losses

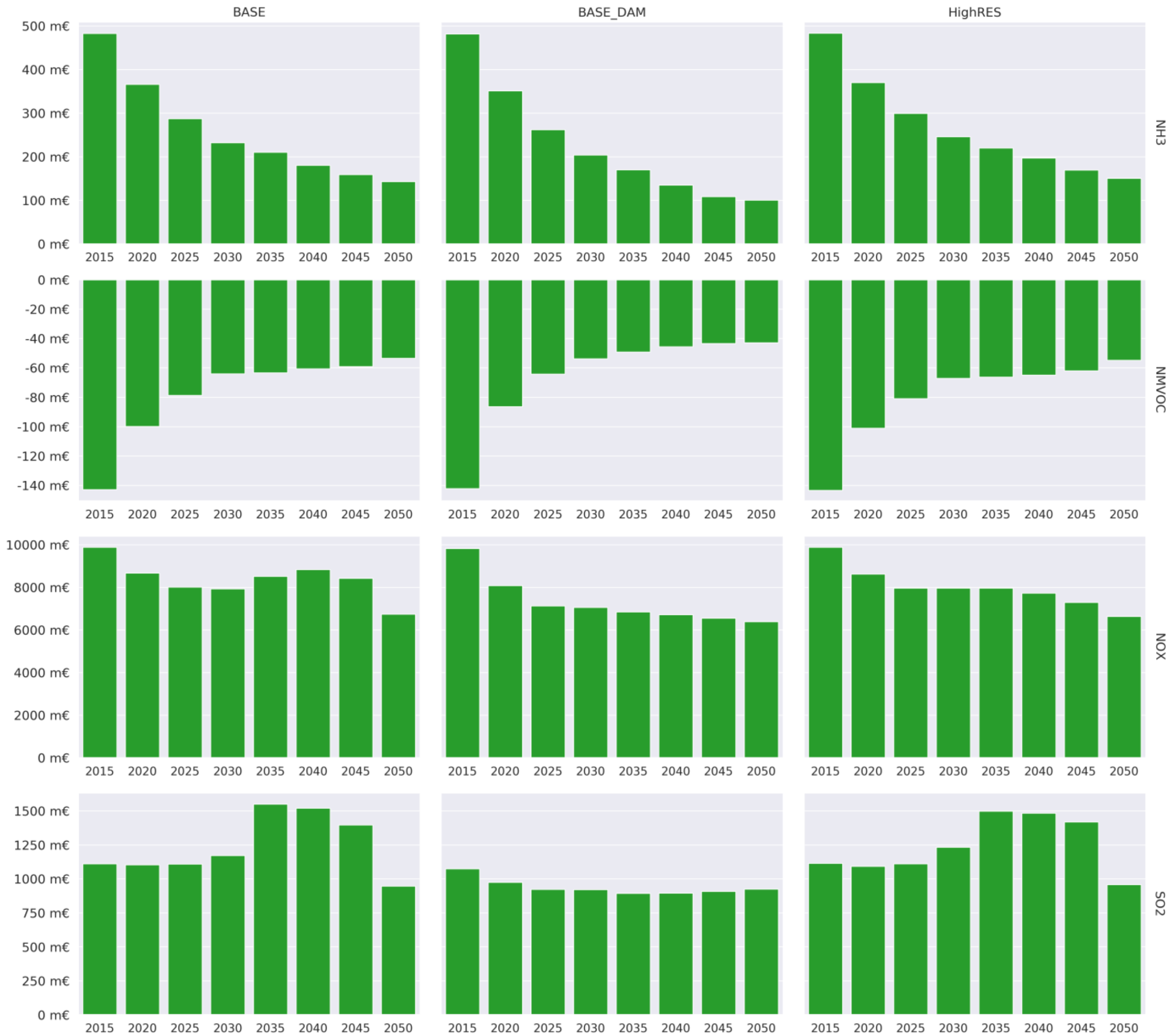

Figure 17: Costs of biodiversity losses due to deposition of sulphur and nitrogen in EU28 split to precursors NH_3, NMVOC, NO_X and SO_2.