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A multiple-uncertainty analysis framework for integrated assessment modelling of several sustainable development goals

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ABSTRACT

This research introduces a two-level integration of climate-economy modelling and portfolio analysis, to simulate technological subsidisation with implications for multiple Sustainable Development Goals (SDGs), across socioeconomic trajectories and considering different levels of uncertainties. We use integrated assessment modelling outputs relevant for progress across three SDGs—namely air pollution-related mortality (SDG3), access to clean energy (SDG7) and greenhouse gas emissions (SDG13)—calculated with the Global Change Assessment Model (GCAM) for different subsidy levels for six sustainable technologies, across three Shared Socioeconomic Pathways (SSPs), feeding them into a portfolio analysis model. Optimal portfolios that are robust in the individual socioeconomic scenarios as well as across the socioeconomic scenarios are identified, by means of an SSP-robustness score. A second link between the two models is established, by feeding portfolio analysis results back into GCAM. Application in a case study for Eastern Africa confirms that most SSP-robust portfolios show smaller output ranges among scenarios.

Software and data availability

Software name Global Change Assessment Model (GCAM)
Developers Joint Global Change Research Institute (JGCRI): http://www.globalchange.umd.edu/
Contact address 5825 University Research Court, Suite 3500, College Park, MD 20740, United States
Year first available 1982
Required software JAVA
Program language C++, XML
Availability Download available at https://github.com/JGCRI/gcam-core/releases/tag/gcam-v4.4.1
Cost Free
Software name AUCMECON 2
Developers Mavrotas, G., & Florios, K. (2013). An improved version of the augmented ε-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. Applied Mathematics and Computation, 219(18), 9652–9669
Contact address Laboratory of Industrial and Energy Economics, School of Chemical Engineering, National Technical University of Athens, Zographou Campus, Athens 15780, Greece
E-mail mavrotas@chemeng.ntua.gr
Year first available 2013
Required software GAM
Program language GAMS language
Availability Download available at https://sites.google.com/site/kflorios/augmecon2
Cost Free

1. Introduction

Integrated Assessment Models (IAMs) are a core element of the scientific processes that comprise the “best available science” (Peters, 2016), when it comes to analysing energy system transitions within the context of climate change mitigation and sustainable socioeconomic development (Nikas et al., 2019; Pietzcker et al., 2017; Schwanitz, 2013; Janssen et al., 2009). These tools are applied to analyse adaptive energy–environment-economy systems in the global scientific and policy

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arena (Ewert et al., 2015; Gidden et al., 2018; Estrada et al., 2019), advance scientific understanding of the potential to combat climate change and underlying dynamics towards robust and sustainable development (Huppmann et al., 2019; Warren et al., 2019), and evaluate the various technologies, initiatives and policy options that ensure clean and sustainable energy transition (Wyrwa, 2015; Shi et al., 2017; Liu et al., 2019).

In particular, these models constitute a well-established scientific tool aimed at understanding feedbacks and influences between different system components, including the social, economic and ecological implications of different natural or anthropogenic factors, especially with regard to interlinkages between the human and the natural system (Calvin and Bond-Lamberty, 2018; Gidden et al., 2018). The core advantage of these complex models is that they provide an integrated system perspective to study the dauntingly complex interactions between energy, economy, land use, water, and climate systems (Scott et al., 1999; Weyant, 2017). Through such an integration, IAMs combine multiple and diverse components across their social, organisational and conceptual boundaries to provide a comprehensive analysis of the problem (Collins et al., 2015; Jakeman and Letcher, 2003). For this purpose, different modules or components are coupled with one other, usually including but not limited to the economy, the environment, the energy system and the climate feedbacks or economic impacts of changes among them (Giupponi et al., 2013). Modelling results are widely used to, inter alia, directly influence decisions and taken stock of towards advising policymakers, as is the case of the assessment reports of the Intergovernmental Panel on Climate Change (IPCC). Recent examples of publications where IAMs contribute to providing background information on possible energy and climate futures, and to scientifically underpinning international climate policy negotiations are the IPCC's special report on the impacts of global warming of 1.5 °C above pre-industrial levels (IPCC, 2018), the World Energy Outlook 2018 (International Energy Agency, 2018), or the European Union (EU) Energy Roadmap 2050 (EC COM, 2016). In this respect, decision makers are based on IAM-driven policy prescriptions to develop policies that contribute to managing environmental resources and assets in a way that delivers acceptable environmental and socioeconomic outcomes. More details on IAMs can be found in Krey (2014), Weyant (2017) and Nikas et al. (2019), which review energy – economic models, including or focusing on IAMs, and provide a categorisation of them based on parameters like their degree of integration and mathematical underpinnings, as well as highlight the challenges associated with these modelling frameworks.

Given their strengths and weaknesses (Hamilton et al., 2015), however, analyses based exclusively on these formalised frameworks alone are usually not sufficient to address the broad spectrum of challenges associated with climate change and policy assessment (Doukas et al., 2018), and recent advances and paradigms call for and/or apply complementing them with other methods and tools (Turnheim et al., 2015; Geels et al., 2016). In this direction, IAMs have recently been coupled with a diversity of tools, towards enhancing scientific processes and leading to more pragmatic policy prescriptions, including but not limited to life cycle analyses (Arvesen et al., 2018), fuzzy cognitive mapping (Nikas et al., 2020; Antosiewicz et al., 2020), and multiple criteria decision aid frameworks (Baležentis and Streimikiene, 2017; Shmelev and van den Bergh, 2016). One of these tools, which has been established in the climate policy domain (Doukas and Nikas, 2020) in diverse applications (Allan et al., 2011; Bistline, 2016; Odeh et al., 2018; Zhang et al., 2018) and long been coupled with IAMs (e.g. Baker and Solak, 2011; Pugh et al., 2011; Forouli et al., 2019a; Forouli et al., 2019b; del Granado et al., 2019), is portfolio theory.

In fact, energy planning decisions are often portfolio building problems, in which the task is to find a viable mix of actions to meet the overall objectives, targets, and constraints. Therefore, today, as many energy-related decisions fall into this category, portfolio decision analysis methods and tools are seen as the next step in energy decision support (Marinoni et al., 2011; Vilkkumaa et al., 2014). Through such tools, decision makers are able to consider a set of actions and create policy incorporating relevant concerns and interests in a balanced way. Typically, decision makers have to consider the overall performance of a portfolio across many relevant dimensions or criteria, such as techno-economic, socio-political and environmental impacts (Huang and Wu, 2008; Muñoz et al., 2009). Portfolio analysis (PA) addresses the need to consider multiple objectives and constraints, and further contributes to identifying promising candidate actions and examining interactions among them.

Portfolio decision models were first applied on risk diversification in financial investments and have their roots to the work of Markowitz (1952). Markowitz proposed a mean-variance model to support investment decisions in light of uncertainty associated with the future returns of financial assets. Today, there is a range of portfolio modelling approaches, which offer modelling and optimisation support to find the most preferred portfolio of actions, and which are applicable to energy and environmental modelling. Lahtinen et al. (2017) provide a detailed, comparative description of portfolio modelling approaches. Among the most common ones are the value–cost (or benefit-cost) approach, where actions are prioritised according to the value–cost ratio until a budget cap is reached (Hajkowicz et al., 2008; Marinoni et al., 2011). The disadvantage of this method is that, in case of synergies or interactions between the actions, optimality is not guaranteed. As interactions play a critical role in energy- and/or climate-economy problems, this approach is often not sufficient. An approach that incorporates the risk parameter into the evaluation is the modern portfolio theory approach where the optimal resource allocation for each risk level is identified (Crowe and Parker, 2008; Paydar and Qureshi, 2012).

From the above, we understand that PA and IAMs are widely used in policy analysis and evaluation of pathways for the transformation of the human and earth systems. The interconnectedness of our world is broadly acknowledged to require integrated rather than piecemeal approaches to resolving complex environmental issues, particularly in view of the increasing speed and pervasiveness of connections associated with globalisation. With the interaction of Sustainable Development Goals (SDGs) with climate change and action gaining increasing prominence at the interface of science and policy, developing computational tools and models that operate across academic disciplines and methodologies becomes ever more important.

In this paper, we use a multi–objective optimisation approach where the result is a set of non–dominated portfolios. Through this approach, interactions among the set of actions and portfolio constraints can be considered. The goal is to generate non-dominated combinations of actions, in terms of comparing between the evaluation criteria. As required by portfolio modelling, and in order to generate the non-dominated portfolios, all candidate actions are simultaneously considered and optimised in the same portfolio optimisation model. The goal is to identify optimal portfolios of actions or a set of non-dominated portfolios that best meet multiple objectives while satisfying the problem constraints. Decision makers can then select a portfolio among the non-dominated ones, tailored to their needs and preferences. To understand the term of portfolio dominance, a portfolio is said to be dominated, if there exists another portfolio of actions that performs better in some attribute (criterion) and at least equally good in all other attributes. The model-based portfolio generation process proposed here supports the consideration of multiple objectives and constraints, and interactions among the actions, while acknowledging the vital role of uncertainty.

In particular, the first goal of this paper is to create an efficient scientific workflow and a two-way technical integration of integrated assessment modelling and portfolio optimisation outcomes. To this end, at first, we simulate future policy under policy-relevant socioeconomic scenarios, such as the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014). The Global Change Assessment Model (GCAM) is used as the implementation integrated assessment model.[1] The outputs from each policy scenario are translated into progress parameters relevant to three SDGs of the United Nations' 2030 Agenda for Sustainable Development and fed into a PA model. These parameters include air pollution-related mortality (SDG3), access to clean energy (SDG7) and greenhouse gas emissions (SDG13). The optimisation problem formulation is run for selecting the optimal combinations of subsidy levels for six technologies, which simultaneously maximise progress in each of the selected SDGs. This is the first step of IAM-PA integration.

Moreover, acknowledging that uncertainty is widely accepted to be pervasive in any attempt to manage and understand environmental problems (Uusitalo et al., 2015), a robustness analysis is incorporated in the proposed framework. Depending on the discipline and context of application, uncertainty of data or model components can be interpreted in different ways, varying from measures of performance, bounds, alternative scenarios (Fuss et al., 2012; Trachanas et al., 2018) or probability distributions (Lin and Beck, 2012). In this approach, the propagation of uncertainties through the integrated models involves determining the effect on the output of changes in the inputs and is expressed stochastically, by means of a probability distribution, and deterministically, with the use of scenarios. Probabilistic uncertainty is incorporated in the portfolio analysis model to find robust Pareto-optimal portfolios of technologies in each of SSPs. Deterministic uncertainty, referring to specific scenarios with clearly determined datasets (Nikas et al., 2019), is used to assess the robustness of the modelling results across different socioeconomic pathways and timescales (Van Groenendaal and Kleijnen, 2002). This is done primarily by using different SSPs, which represent epistemic uncertainty (Hanger-Kopp et al., 2019) but constitute reference single futures of deterministic nature, on which modelling exercises anchor to cover a broad spectrum of possible future socioeconomic states of the world (Van Ruijven et al., 2014). The second goal of this paper is to simulate an "SSP robustness" scenario, by defining SSP-based uncertainty bounds as boundaries for robustness and simulate probabilistic uncertainty among the socioeconomic pathways. Results of the "SSP robustness" scenario are compared with results of the distinct socioeconomic pathways analysis.

The second step of IAM-PA integration is achieved by feeding the PA results back to GCAM. The SSP-robust subsidy portfolios are re-run in the GCAM model with each SSP, to check whether portfolios that are found to be robust to SSP-based uncertainty are also translated to more homogeneity between the SSPs with respect to the portfolio's impact on SDG progress. The identification of technological portfolios that are robust among the different SSPs can be helpful for stakeholders to make decisions and formulate policies that will be optimal, independently of the realisation of different SSPs in the future, providing a useful tool to handle SSP-based uncertainty.

Validation of the methodological framework, which is outlined in Fig. 1, is achieved by means of a case study in Eastern Africa, in Section 3.

[1] The updated GCAM documentation website includes a specific section describing the SSP implementation throughout the model: https://github.com/JGCRI/gcam-doc/blob/gh-pages/ssp.md.

2. Methods

2.1. The Global Change Assessment Model

GCAM is a dynamic-recursive, partial equilibrium model connecting socioeconomics, energy, land use and climate systems, and can be used to investigate the consequences of climate change mitigation policies, including carbon taxes, carbon trading, regulations and accelerated deployment of energy technology (JGCRI, 2017). GCAM and its predecessors have been used in applications investigating future emission scenarios and energy technology pathways (Edmonds et al., 1994; Rao, 2017). GCAM is one of the four models chosen to develop the Representative Concentration Pathways of the IPCC's 5th Assessment Report (Pachauri, 2015) and has been included in almost all major climate/energy assessments over the last few decades. The model covers the entire world, dividing it into 32 regions, and runs in 5-year time steps from 1990 to 2100, simulating future emission paths for 24 greenhouse gases and short-lived species, including CO_2 (from fossil fuel combustion and land use change), CH_4, N_2O, NO_x, SO_2, BC, OC, CO and NMVOC.

For the purposes of this study, GCAM version 4.4 is used as a base. Within this model, the case study region in the model (eastern Africa, see section 3.1) has been adjusted for a more informed reflection of modern, real-world conditions (Van de Ven et al., 2019). In particular, urban energy demand has been separated from rural energy demand (Yu et al., 2014); and specific residential energy demands, such as cooking, lighting, refrigeration and TVs, separated from other residential energy uses. Especially demand for cooking has been modelled in more detail, improving realistic projections into future cooking energy use, and its impacts on indoor and outdoor air quality. These impacts on air quality are quantified by measuring the premature deaths that air pollution (both indoor and outdoor) is projected to cause in future scenarios. Indoor mortality is estimated by extrapolating a historical causal relationship between indoor PM2.5 and mortality measured by the Global Burden of Disease (Forouzanfar et al., 2016). Outdoor mortality is measured through the air quality model TM5-FASST (Van Dingenen et al., 2018). Furthermore, additional costs have been added to the provision of centrally generated electricity to rural areas, representing the required extensions in transmission and distribution networks, while mini-grids have been added as an alternative for rural energy demand. This novelty allows for projecting more realistic future scenarios in terms of household energy access, which has been measured on a household level using the "Tier framework" (World Bank, 2015). See Van de Ven et al. (2019) for all details on how GCAM outputs are translated to SDG progress indicators.

The inputs used to run the GCAM model and the outputs retrieved to be utilised as input in the portfolio analysis (PA) model are presented in Fig. 2. Inputs to GCAM include socioeconomic data for different SSPs, such as population, gross domestic product (GDP), rate of urbanisation, energy demand, food demand, household discount rates, agricultural yields, energy resource productivity and emission factors. Outputs, to be used in the PA model, include energy access tier changes, avoided premature deaths and GHG emission reductions as a result of different subsidy levels for a number of sustainable technologies, per SSP and time point (2020, 2030 and 2040).

2.2. Multi-objective optimisation and portfolio analysis

Multi-objective optimisation refers to the simultaneous optimisation (i.e. minimisation or maximisation) of multiple, usually conflicting, objective functions. Once such a problem is posed, it is of the practitioner's interest to obtain/approximate and view the set of all trade-off, or compromise, solutions of the problem. The set of trade-off solutions is referred to, in the current article, as the Pareto front of the problem. As environmental problems are driven by multiple objectives and criteria, a single optimal solution very rarely exists. Rather, a Pareto set of solutions can be identified, within which no single solution is strictly better

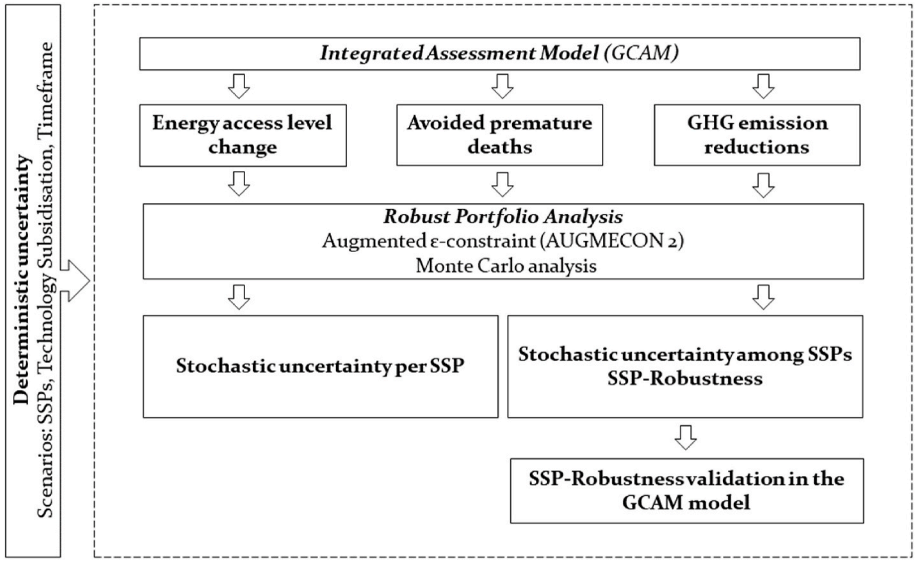

Fig. 1. Methodological framework.

than any other and a trade-off is required between the competing objectives.

If the variables of a multi-objective optimisation problem take values from a continuous set, then we refer to that problem as a multi-objective continuous optimisation problem. On the other hand, if the variables take values from a set of integers, then the problem is referred to as a multi-objective integer programming (MOIP) problem. In this paper we model and solve a MOIP problem.

The most widely used methods concerning the identification of Pareto optimal solutions are the weighting and ε-constraint methods. Especially in cases of integer programming the ε-constraint method has better performance and certain advantages over the weighting generation methods (Steuer, 1989). In the principle of the ε-constraint method lies the optimisation of one of the objective functions (p) using the other objective functions ($p-1$) as constraints. Only portfolios that are non-dominated (i.e. when none of the objective functions can be improved in performance without degrading one or more of the other objective function values) can be considered as portfolios that represent the optimal trade-off between objectives. For the purpose of identifying the non-dominated, or 'Pareto-optimal' solutions to the mathematical optimisation formulation, here the use of an extension of the ε-constraint method, namely the augmented ε-constraint (AUGMECON 2) (Mavrotas and Florios, 2013) algorithm is suggested. The AUGMECON 2 method guarantees the generation of all Pareto optimal solutions, while avoiding the generation of other, non-optimal solutions. The AUGMECON 2 method can deal with multiple objectives simultaneously and has been successful in recent optimisation studies in a variety of fields concerning municipal solid waste management (Mavrotas et al., 2013), energy efficiency policies evaluation (Forouli et al., 2019b), power generation technology portfolio optimisation (Forouli et al., 2019a), equity portfolio construction and selection (Xidonas et al., 2010), biopharmaceutical processes (Vieira et al., 2017), surface mounting devices machines component allocation (Torabi et al., 2013), etc.

In the AUGMECON 2 method the problem to be solved is of the following form:

$$\max\left(f_1(x) + eps * \left(\frac{S_2}{r_2} + 10^{-1} * \frac{S_3}{r_3} + \ldots + 10^{-(p-2)} * \frac{S_p}{r_p}\right)\right) \tag{1}$$

with the following constraints:Subject to:

$$\begin{aligned} &\boldsymbol{X} \in F \\ &f_k(\boldsymbol{X}) - S_k = e_k,\ k = 2 \ldots p \end{aligned} \tag{2}$$

where

$f_k(X)$ is the objective function to be maximized
F is the feasible region
$eps \in [10^{-6}, 10^{-3}]$
e_k is the right-hand side of the corresponding constraint for the objective function k.
r_k is the range of the objective function k.
S_k is a surplus variable for objective function k.

The optimisation process is driven by the parametrical variation in the right-hand side of the constrained objective functions (e_k).

At first, the range r_k of objective functions $2 \ldots p$ that will be used as constraints is calculated, from the payoff table (the table with the results from the individual optimisation of the p objective functions). The AUGMECON 2 method proposes the use of lexicographic optimisation for every objective function in order to construct the payoff table with only Pareto optimal solutions.

The range of the $k-th$ objective function is divided to g_k intervals using $g_k - 1$ intermediate equidistant grid points. Thus, we have in total $g_k + 1$ grid points that are used to vary parametrically the right-hand side (e_k) of the k^{th} objective function. The step for the variation of e_k for objective function $k$will be:

$$step_k = \frac{r_k}{g_k} \tag{3}$$

And the right-hand side of the corresponding constraint in the i^{th} iteration for objective function $k$will be:

$$e_k = fmin_k + i_k * step_k \tag{4}$$

$fmin_k$ is the minimum from the payoff table of objective function k

The optimisation process is solved iteratively for the different e_k, which correspond to the different grid points, and so the number of runs are $(g_2+1)*(g_3+1)*\ldots*(g_p+1)$. Supposing we first begin to optimise by adding $step_2$ to e_2. In each iteration we compare the surplus variable (S_2) of objective function f_2 that corresponds to the innermost objective function (i.e. the first of the p objective functions from which we begin) with $step_2$. When the surplus variable S_2 is larger than $step_2$, it is implied that in the next iteration the same solution will be obtained with the only difference being the surplus variable, which will now have the value $S_2 - step_2$. This makes the iteration redundant and therefore we can bypass it as no new Pareto optimal solution is generated. We then calculate the

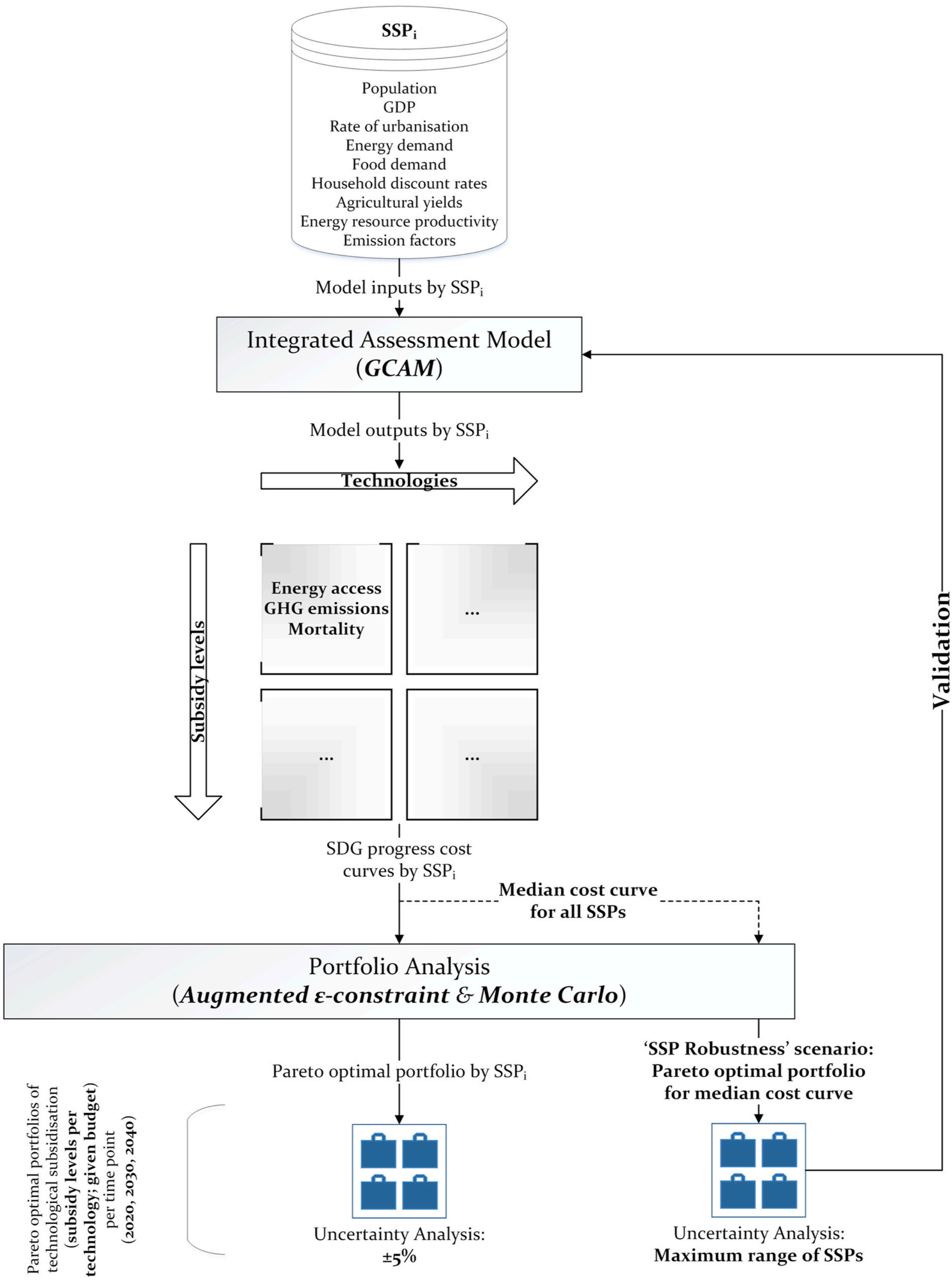

Fig. 2. GCAM - PA model integration (inputs and outputs).

new $e_2^{'}$ by moving forward by $step_2$, until all grid points of f_2 are either assessed or bypassed. Then we repeat the same procedure by varying the right-hand side of f_3, namely e_3, and the iterations are repeated for the p objecting functions. Following the above calculation procedure, we obtain the exact Pareto set of optimal solutions.

For a more in-depth description on finding the exact pareto set in multi-objective integer programming problems with the use of the augmented ε-constraint, the reader is referred to (Mavrotas and Florios, 2013). The portfolio optimisation problem is solved in the General Algebraic Modelling System (GAMS). The portfolio analysis parameters coming from GCAM (Section 2.1) include the three parameters relevant to progress across three different SDGs: energy access tier change, GHG emission cuts, and avoided premature deaths due to air pollution (Fig. 2).

2.3. A cross-scenario framework

To understand the impact of technology subsidies, the GCAM modelling exercise considers subsidies for different energy technology packages, in combination with three different socioeconomic pathways. In the context of the region of the case study focus, i.e. Eastern Africa, SSPs 3 and 5 can be seen as extreme scenarios of respectively low and high development and are expected to represent the margins of uncertainty for policy implementation, drawing from both the narratives associated with the SSP framework (O'Neill et al., 2017) and the GCAM outputs. In a few situations, however, the average conditions as represented in SSP 2, which reflects a possible future following historic patterns, translate to the highest (or lowest, depending on the technology) cost-effectiveness of technological subsidisation. Results for SSP 1 ('Sustainability') and SSP 4 ('Inequality') are assumed to lie in most cases within the margins of the three modelled SSPs, and therefore neither of these two scenarios have been modelled explicitly. The optimisation portfolio analysis problem (Fig. 3) is thus run separately for each of the three SSPs (2, 3, and 5).

We identify three evaluation criteria or objectives to optimise and thus we formulate a tri-objective optimisation problem. The evaluation criteria include the maximisation of GHG emission reductions, the maximisation of energy access tier improvement, and the maximisation of avoided premature deaths; corresponding to SDG13 ('climate action'), SDG7 ('affordable and clean energy'), and SDG 3 ('good health and well-being'), respectively. The three different time points are reflected as differences in the values of the portfolio analysis input data. Last but not least, the model considers a subsidy budget constraint in order to ensure that the overall cost of the approved applications does not exceed a predefined value. Ultimately, nine portfolio optimisation problems are solved: three for each of the different timescales (2020, 2030 and 2040), for each of the three SSPs (SSP2, SSP3 and SPP5).

2.4. Stochastic uncertainty analysis

The proposed approach examines the effects of both deterministic and stochastic (non–deterministic) uncertainty in order to effectively

9 Portfolio Analysis Optimisation Problems
3 SSPs
3 time frames

Optimisation Problem Formulation

6 technologies
20 technology subsidisation options

3 Objective Functions

$$maximise\ Z_1 = \sum_{i=1}^{6}\sum_{j=1}^{20} Energy\ Access\ (i,j) * B(i,j)$$

$Energy\ Access(i,j)$ is the energy access level achieved by the i_{th} technology under subsidisation j

$$maximise\ Z_2 = \sum_{i=1}^{6}\sum_{j=1}^{20} GHGreduction(i,j) * B(i,j)$$

$GHGreduction(i,j)$ is the emissions reduction achieved by the i_{th} technology under subsidisation j

$$maximise\ Z_2 = \sum_{i=1}^{6}\sum_{j=1}^{20} Avoided\ Mortality(i,j) * B(i,j)$$

$Avoided\ Mortality(i,j)$ are the avoided premature deaths achieved by the i_{th} technology under subsidisation j

1 Budget Constraint

$$\sum_{i=1}^{6}\sum_{j=1}^{20} Subsidy\ (i,j) * B(i,j) \leq maxBudget$$

The binary variables Bi,j represent the achievement of subsidisation j for technology i

Fig. 3. The PA optimisation problem formulation.

assess the robustness of the resulting optimal portfolios. Deterministic uncertainty is expressed by means of the above-described scenario analysis: we consider different scenarios in terms of technology performance in each of the three time frames but, more importantly, the optimality of solutions is stress-tested across the three socioeconomic scenarios. Regarding stochastic uncertainty, which is inherent in these parameters, this is incorporated into the model by running a Monte Carlo simulation. The uncertain model parameters, namely the performance of the assumed technologies in terms of maximising emission reductions, energy access and health benefits, are treated as of stochastic nature, by sampling their values using a uniform distribution. At first, we run the model using deterministic values for all the uncertain parameters and the "no uncertainty" Pareto front is determined. Then, Monte Carlo simulation is performed iteratively to sample random values for the uncertain parameters from the uniform distributions, and the model is solved to generate the set of Pareto-optimal portfolios. Eventually, the execution of multiple Monte Carlo iterations results in many differentiated Pareto fronts, which are analysed to draw conclusions over the robustness of the portfolios shaping the Pareto front when no uncertainty is considered. We perform 1000 Monte Carlo iterations.

As discussed above, the GCAM model is run for the three SSP scenarios separately for every subsidy level. The SSPs are seen here as an uncertain set of conditions that affect the performance of every technological subsidy policy. For the three major optimisation problems run to identify the optimal portfolios separately for each of the three considered SSPs, the mean value for the uniform distributions is set equal to the estimated values as obtained from the runs of the GCAM model, and the deviation of the Monte Carlo iterations is set equal to ±5%, as in Forouli et al. (2019a).

2.5. A validation framework

In order to perform a robustness analysis on the modelling results of the individual SSPs, we introduce the "SSP robustness" scenario. The "SSP robustness" scenario is not run in the GCAM model as a new scenario, and there is no intention to introduce a new scenario to "replace" or simulate any of the SSPs. As already mentioned, GCAM is run for the individual SSPs and generates results per SSP, regarding the impact of each technology subsidisation option on the three parameters: energy access change, GHG emissions reductions, and avoided deaths associated to air pollution. This impact is different per SSP. Our purpose is to define robust subsidy portfolios regardless of what SSP our world will resemble in the future. The "SSP robustness" scenario uses the mid-point of the SSP scenario outcomes on the cost effectiveness for progress along these parameters corresponding to the three SDGs and uses the range along the three SSP outcomes to perform a robustness analysis. Uncertainty over which SSP is expected to be realised in the future is therefore incorporated in the portfolio analysis, as a range for the cost-effectiveness of the technologies in achieving progress to each of the SDGs (Van de Ven et al., 2019). In this way, the range of the GCAM SSP simulation outcomes, which are different for each technology, define the ranges of the uniform distribution, which is used for Monte Carlo simulation. Uncertainty ranges differ among the considered technologies: the higher the range of the SSP outcomes is, the broader the range of uncertainty in the uniform distribution is considered. A portfolio analysis problem, in which technologies with narrow uncertainty boundaries are optimised, is thus expected to be more robust among the different SSPs, compared to one with a larger uncertainty range, depicting higher vulnerability to the SSP simulation outcomes. To better clarify this, in the extreme scenario where the resulting performance of a technology is identical among the different SSPs, portfolios resulting from the optimisation will be completely robust, when uncertainty is examined in terms of different SSP realisation. The ranges of the uniform distributions (SSP-based uncertainty boundaries) and an example of calculating the SSP-based uncertainty boundaries based on the mid-point of the performances across the three SSPs are presented in Tables 1 and 2.

Table 1
Uncertainty boundaries (ranges of the uniform distribution) for a timepoint.

Uncertainty boundaries (ranges of the uniform distribution)			
Technology	Indicator #1	Indicator #2	Indicator #3
Technology #1	[0.99,1.01]	[0.98,1.02]	[0.98,1.02]
Technology #2	[0.98, 1.02]	[0.99, 1.01]	[0.95, 1.05]
Technology #3	[0.98, 1.02]	[0.99, 1.01]	[0.89, 1.11]
Technology #4	[0.89, 1.11]	[0.90, 1.10]	[0.90, 1.10]
Technology #5	[0.97, 1.03]	[0.96, 1.04]	[0.91, 1.09]
Technology #6	[0.72, 1.28]	[0.61, 1.39]	[0.93, 1.07]

In order to verify if the robustness of SSP uncertainty bounds leads to more robust solutions among the different SSPs, optimal portfolios of the "SSP robustness" scenario differing in their robustness score are selected and reiterated in the GCAM model. The reiteration is applied across the three different SSPs. New results on the contribution of the technologies to each of the SDGs are retrieved and the goal is to test whether the results of a more robust portfolio are indeed more homogeneous between the different SSPs compared to a less robust one. This is quantified by measuring the ranges of performances across the three SDGs, among the SSPs, and verifying that they are smaller in case of a more robust portfolio.

To summarise the information flow into, between and out of the two models (Fig. 2), the GCAM model is initially fed with socioeconomic data from three SSPs and its outputs are used to calculate avoided premature mortality due to air pollution, GHG emissions cuts and energy access levels associated with different subsidisation levels for a number of sustainable technologies. The latter, along with a given total budget, are fed into the PA model, which calculates the most robust near-optimal technology subsidisation portfolios for three timescales (2020, 2030 and 2040) per SSP, carrying out Monte Carlo analysis within a ±5% uncertainty range for each of the three SDG-relevant parameters. At the same time, an additional subsidy dataset is developed, based on the midpoint of the extreme GCAM-resulting outcomes in terms of cost-effectiveness of technology subsidies for SDG progress (separately for each technology and SDG impact); Monte Carlo analysis for this extra scenario is performed in a different uncertainty range that is defined by the extreme values of each parameter for each subsidy level and technology. Finally, optimal subsidy levels for each technology, from selected portfolios of this scenario of various robustness scores, are fed back into GCAM, in order to validate whether portfolios with higher robustness scores are indeed more robust to the impact of SSP-related modelling inputs on outputs in terms of the cost-effectiveness of SDG progress.

3. Validation and discussion

3.1. Context of the case study

Three different SSP datasets (O'Neill et al., 2014) have been modelled in GCAM for the purposes of a case study focusing on twelve Eastern African countries (Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Rwanda, Somalia, Sudan, South-Sudan and Uganda), aggregated and assessed as one region. These datasets include SSP 2 ('Middle of the Road'), SSP 3 ('Regional Rivalry') and SSP 5 ('Fossil-fuelled Development'). Specifically, the GCAM inputs that have been adapted to each of these SSPs are (global) population, GDP, rate of urbanisation, energy and food demand, household discount rates, agricultural yields, energy resource productivity, and emission factors[2] (Riahi et al., 2017). Table 3 shows the assumed evolution from 2010 to 2040 of the SSP inputs, regionally for Eastern Africa, that have most influence on the GCAM outputs: population, GDP and urbanisation.

[2] https://github.com/JGCRI/gcam-doc/blob/gh-pages/ssp.md.

Table 2
Example of SSP-based uncertainty boundaries for robustness (technology #1) for 2020. Each row represents a different subsidy level.

Mid-point of the performances across three SSPs			Range of performances across the three SSPs			% Range of performances across the three SSPs		
Indicator #1	Indicator #2	Indicator #3	Indicator #1	Indicator #2	Indicator #3	Indicator #1	Indicator #2	Indicator #3
0.000439	62.9566	0.17109	4.2E-06	0.436791	0.001689	0.96%	0.69%	0.99%
0.003189	455.108	1.24059	2.25E-05	2.955247	0.016963	0.71%	0.65%	1.37%
0.00579	825.195	2.25515	3.66E-05	12.78863	0.033728	0.63%	1.55%	1.50%
0.161016	23751.5	59.9151	0.00087	746.8392	1.943537	0.54%	3.14%	3.24%
Uncertainty boundaries (ranges of the uniform distribution) = distance from avg. of the % Range of performances across the 3 SSPs						[0.99,1.01]	[0.98,1.02]	[0.98,1.02]

Table 3
Evolution of key SSP parameters in GCAM.

	2010	2020	2030	2040	2010	2020	2030	2040	2010	2020	2030	2040
	Population (Million inhabitants)				GDP per capita ($(2015) annually)				Urban population share (%)			
	Samir and Lutz (2017)				Dellink et al. (2017)				Jiang and O'Neill (2017)			
SSP2	259	327	399	468	732	965	1438	2173	22.9	27.7	32.6	37.7
SSP3	259	335	425	521	732	951	1248	1547	22.9	24.8	26.7	28.4
SSP5	259	319	373	419	732	980	1833	3893	22.9	31.0	40.0	49.2

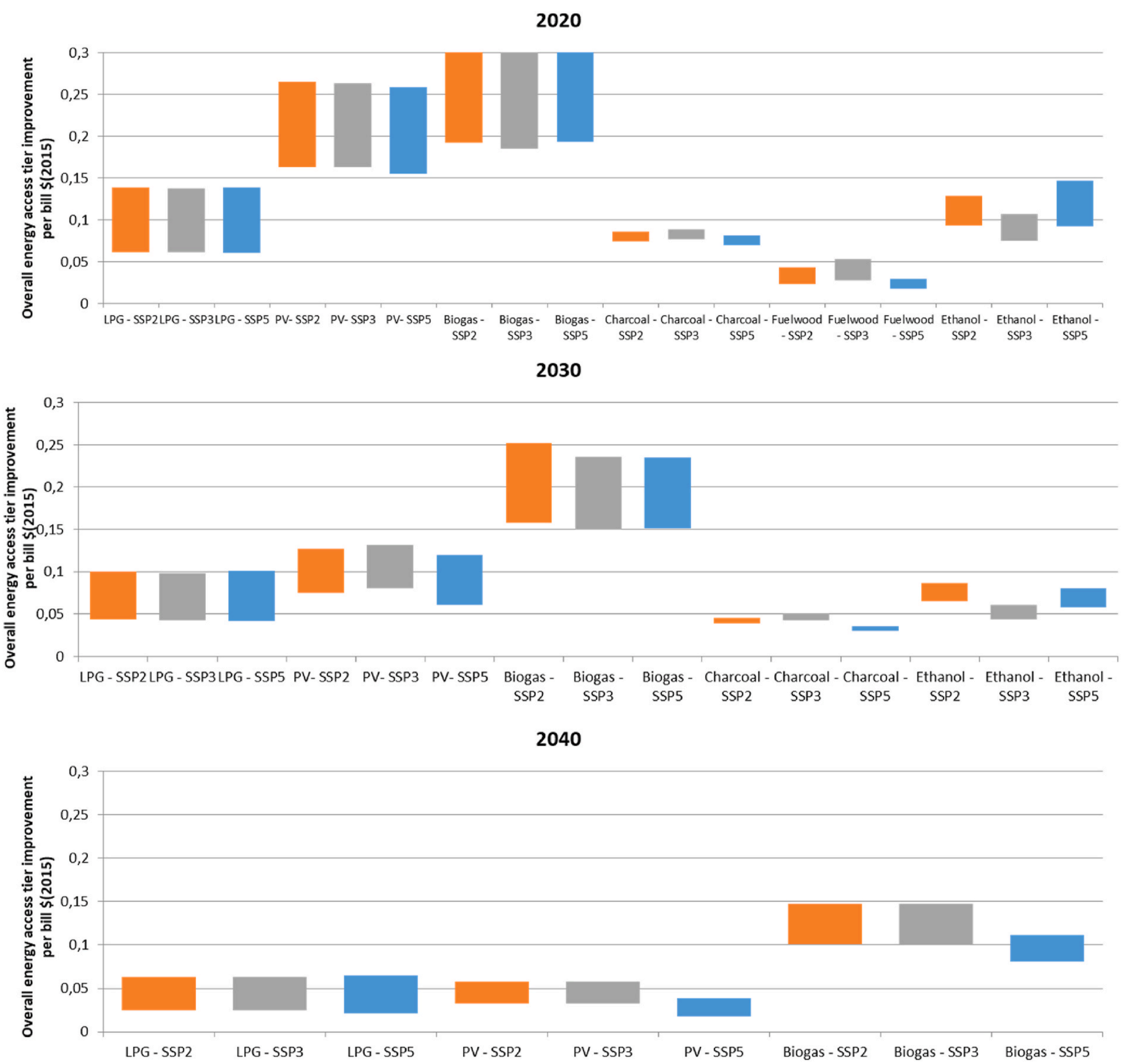

Fig. 4. Impact of energy technology subsidies in terms of **energy access** levels for the different SSPs by 2020, 2030 and 2040.

The candidate actions are six technological subsidisation pathways revolving around liquefied petroleum gas (LPG), photovoltaics (PV), biogas, ethanol, charcoal and fuelwood, i.e. technologies likely to be adopted in the twelve developing countries of Eastern Africa (based on their action pledges, as reflected in their Nationally Determined Contributions), while contributing to the three predefined SDGs. The GCAM-generated parameters for the three SDGs showcase the contribution of each technology pathway to each of the objective functions under twenty subsidy levels. For each of the four major optimisation problems different time frames are applied and results for the years 2020, 2030 and 2040 are extracted.

The budget constraint starts from $3.5 billion (USD at 2015 values) in 2020 and increases by 5% per year until 2030 and 2040.

3.2. Cost-effectiveness of technology subsidies and SDG progress

The first step in the proposed methodological framework is to simulate future socioeconomic scenarios through the GCAM model and translate outputs from each policy scenario into progress parameters relevant to SDGs. This is done by applying six different pathways of technology subsidies, up to 2040, and then measuring the impact of these subsidies on progress towards each of the three SDGs.

Results on the cost-effectiveness of technology subsidies for SDG progress (Figs. 4–6) show that subsidies for biogas systems are the most cost-effective for each of the indicators, scenarios and years. On the contrary, subsidies for fuelwood pathways are only reasonably cost-effective in the short-term. For charcoal pathways, we observe that cost effectiveness is highly dependent on the invested subsidies. When examining progress on the different timescales we see that more subsidies are required for achieving the same impact in the long-term, at least for energy access and premature mortality indicators. In addition, in the medium- and long-term, technologies like fuelwood, charcoal and ethanol show an even negative impact for the examined subsidies. Between the different SSPs, cost-effectiveness remains in the same levels for each technology, with some differences observed in the short-term for biogas and the GHG emissions indicator, as well as on charcoal for reducing GHG emissions in the medium- and long-term. Overall, more subsidies are required to achieve a positive impact in the three SDGs when SSP 5 is realised. Generally, we notice that depending on the scenario and the point in time, some technology pathways are more cost-effective than others for a specific SDG and some result in negative outcomes (and thus not incorporated in Figs. 4–6). Thus, the need to

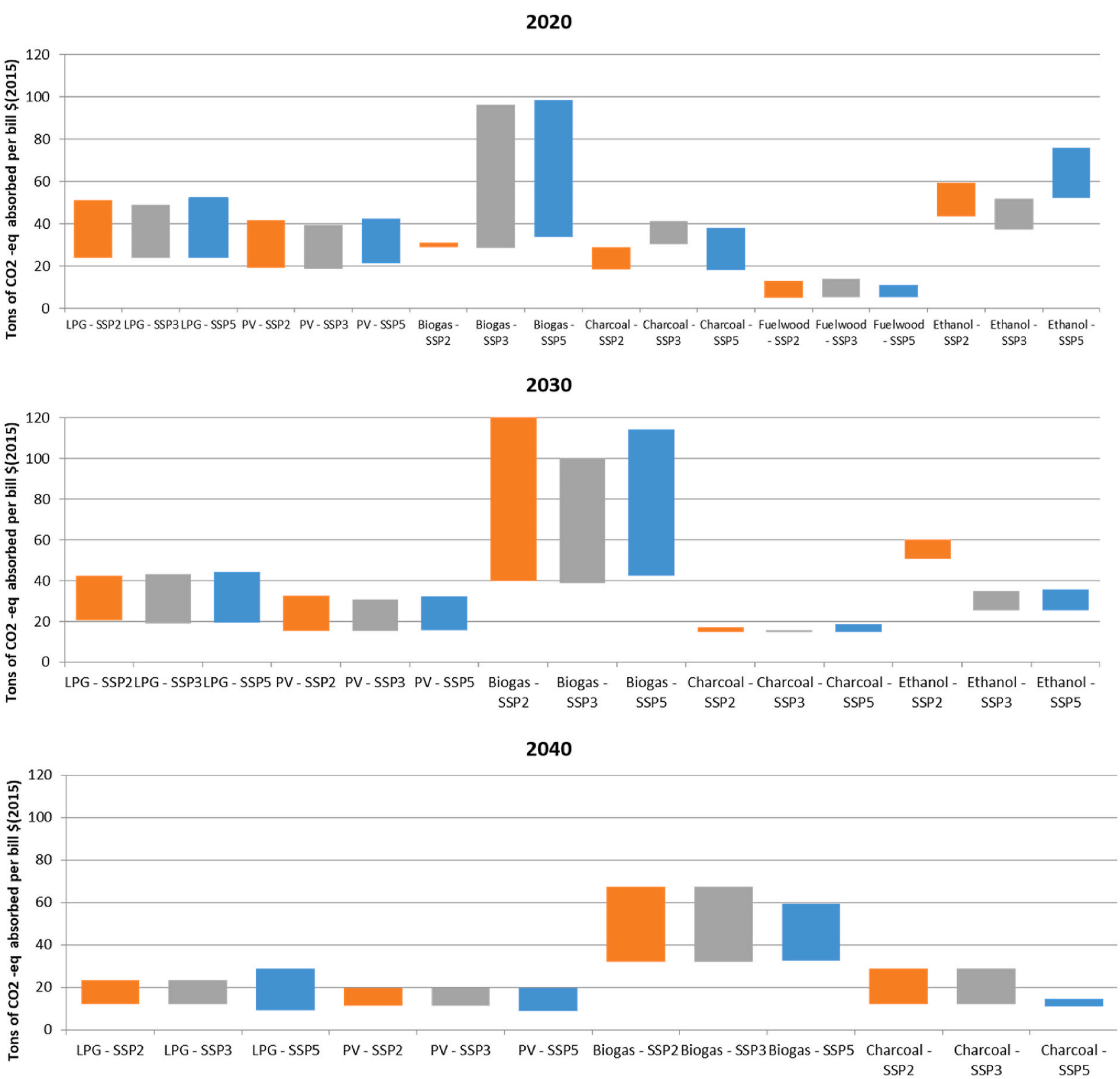

Fig. 5. Impact of energy technology subsidies in terms of **GHG emissions** for the different SSPs by 2020, 2030 and 2040.

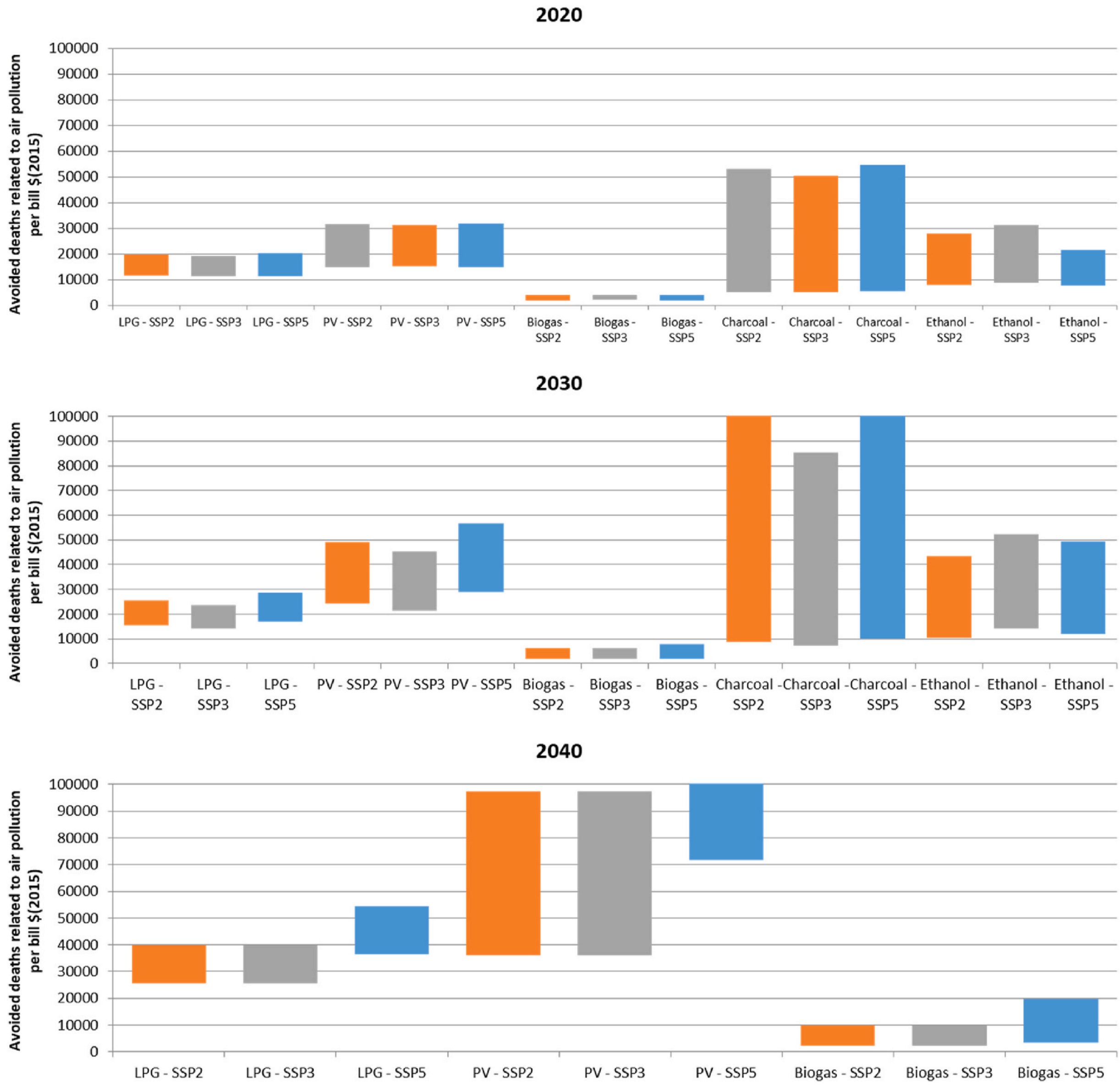

Fig. 6. Impact of energy technology subsidies in terms of **mortality** for the different SSPs, by 2020, 2030 and 2040.

identify technological portfolios that are both Pareto-optimal in terms of contributing simultaneously to the three SDGs and, most importantly, robust among the different scenarios is more than prominent.

3.3. Robust subsidy portfolios in each individual SSP

The second goal of this research is to identify optimal technology portfolios that are robust in each of the different socioeconomic pathways, when probabilistic uncertainty in the model parameters is imposed. The results of the portfolio optimisation, incorporating the robustness information produced by the Monte Carlo runs, are shown per policy scenario in Figs. 7–9, where we can see the set of solutions that represent the best possible trade-offs between the three SDGs. A comparison of results among the different SSPs can be easily retrieved. In each figure, differences on technological performance among the SSPs are mainly observed in SSP 5 for the years 2030 and 2040. In more detail, SSP 2 can prove more progress-friendly in achieving the three SDGs in the short-term, among all different socioeconomic pathways. In the medium- and long-term, SSP 3 leads to better results for the energy access and health criteria, while for the goal of reducing emissions, SSP 2 performs better. SSP 5 features the lowest contribution to the optimisation objectives for all considered time scales, which is fairly consistent with its intended narrative. SSP5 is characterised by higher incomes and urbanisation, which increase access to high-quality energy sources, such as LPG, even without subsidisation. Due to this more "positive" counterfactual, technology subsidisation in SSP5 is found less cost-effective. The reasoning on how policy implications affect the adoption of technologies can be found in Van de Ven et al. (2019).

3.4. Robust subsidy portfolios across all three SSPs

In this section the goal is to define robust subsidy portfolios for any of the three SSPs (2, 3 and 5). To evaluate the robustness of the results, an analysis that applies the ranges of the GCAM simulation outcomes between SSPs as its boundaries for robustness is introduced and carried out. Fig. 10 illustrates the Pareto fronts of the optimal solutions, while giving information on the robustness of the results, which is represented by the size of dots: the bigger the dots, the higher the robustness.

The behaviour of the optimal solutions across the different time-scales shows homogeneity with the analysis provided for the different

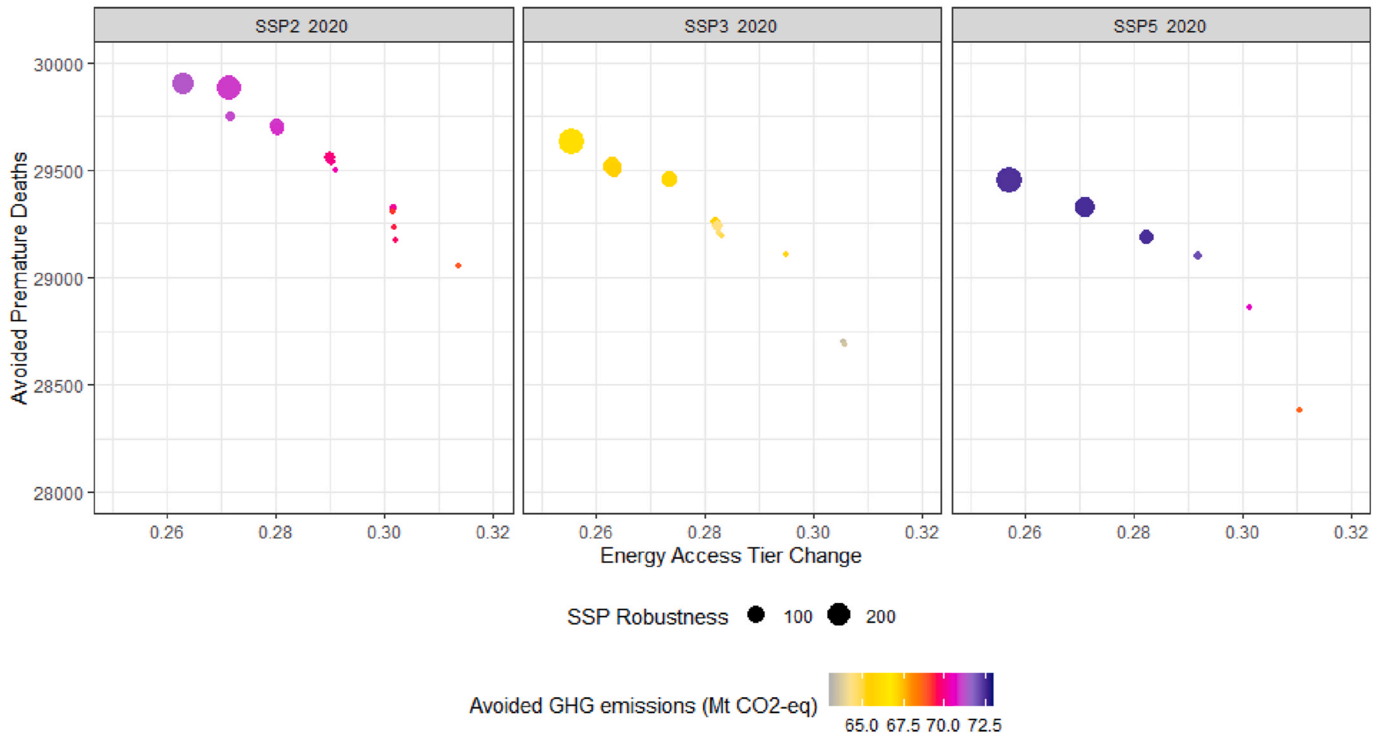

Fig. 7. Technology subsidy portfolios that are Pareto-optimal in terms of simultaneously avoiding GHG emissions, premature deaths and improving energy access per SSP in 2020. Size of dots illustrates robustness against stochastic uncertainty of modelling parameters.

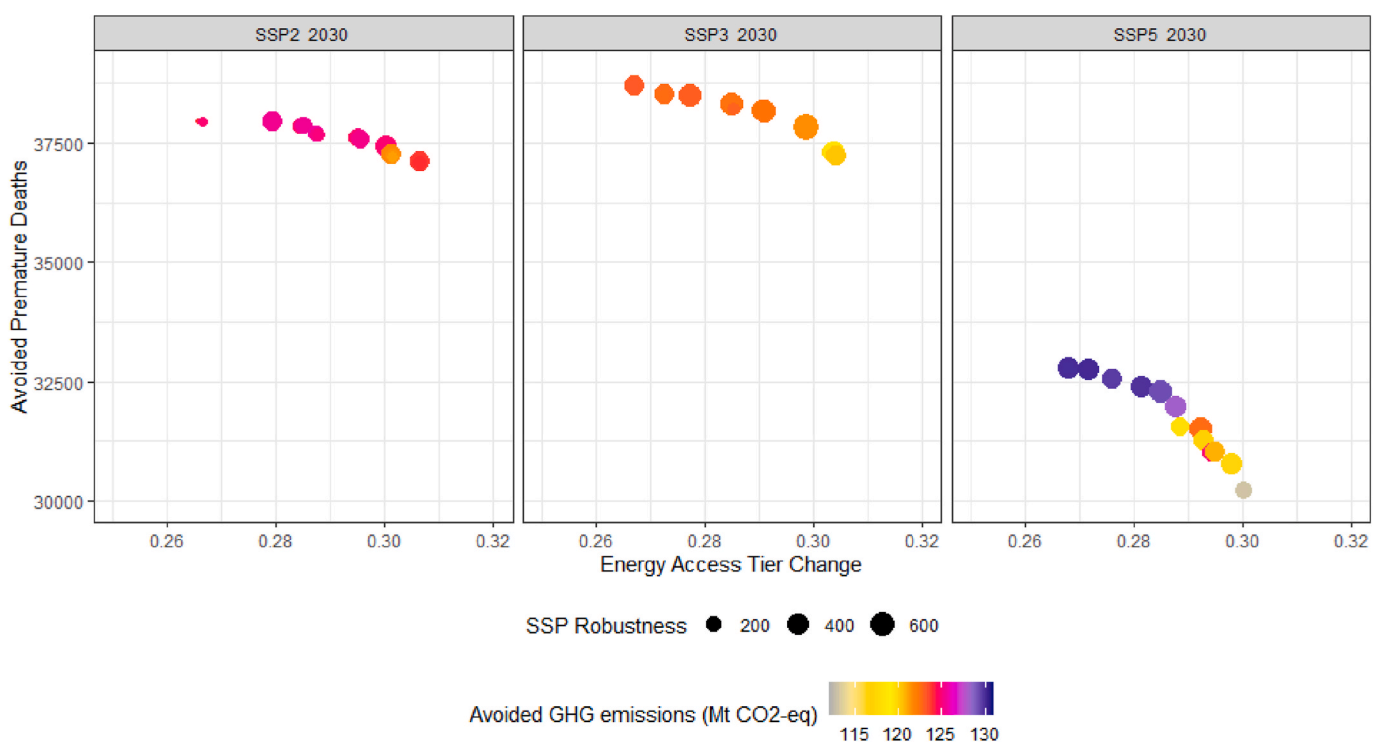

Fig. 8. Technology subsidy portfolios that are Pareto-optimal in terms of simultaneously avoiding GHG emissions, premature deaths and improving energy access per SSP in 2030. Size of dots illustrates robustness against stochastic uncertainty of modelling parameters.

SSPs. What is important is to additionally verify if the robustness of SSP uncertainty bounds leads to more robust solutions among the different SSPs. To achieve that, we select two optimal portfolios for each of the six Pareto curves of Fig. 10, one with a higher robustness score and one with a lower robustness score. The robustness score indicates the number of Monte Carlo iterations within which a portfolio remains optimal. We re-iterate these portfolios in the GCAM model to test whether the results of a more robust portfolio are indeed more homogeneous between the different SSPs, i.e. that the ranges of SDG performances across the SSPs are smaller in case of a more robust portfolio. The results shown in

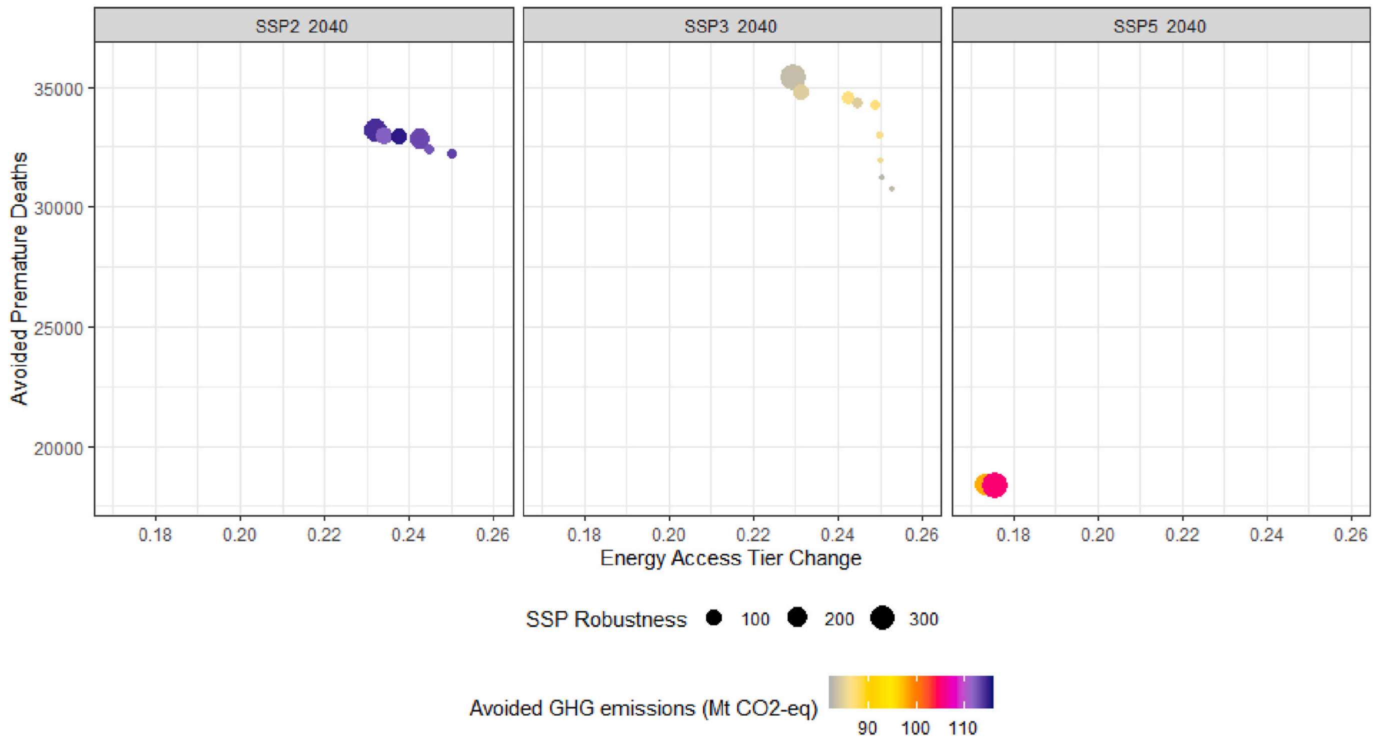

Fig. 9. Technology subsidy portfolios that are Pareto-optimal in terms of simultaneously avoiding GHG emissions, premature deaths and improving energy access per SSP in 2040. Size of dots illustrates robustness against stochastic uncertainty of modelling parameters.

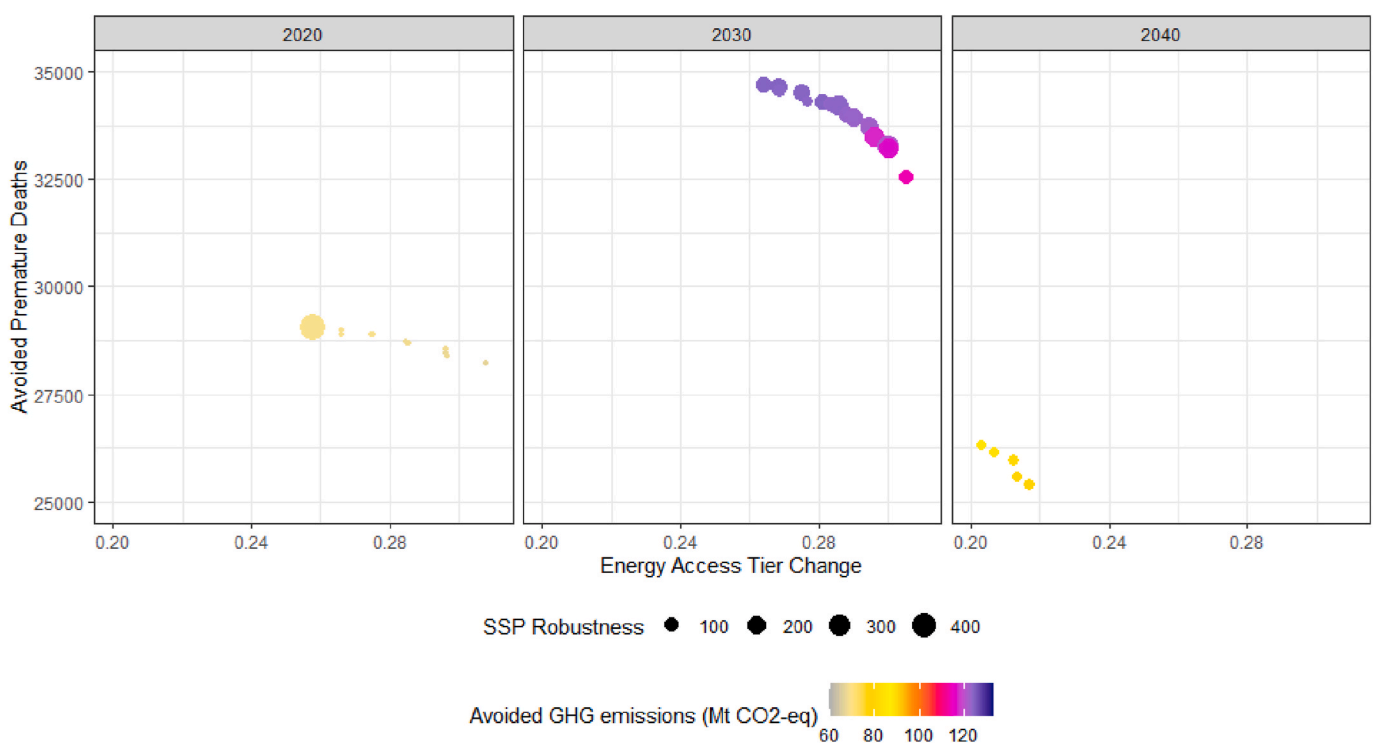

Fig. 10. Technology subsidy portfolios that are Pareto-optimal in terms of simultaneously avoiding GHG emissions, premature deaths and improving energy access in 2020, 2030 and 2040. Size of dots illustrates robustness against SSP uncertainty.

Table 4 suggest that in the majority of the scenarios we can confirm a smaller output range between SSPs, if a portfolio with a higher robustness score is chosen. The range in outcomes decreases by up to 16% for the baseline scenario in 2020.

3.5. Empirical findings, discussion and results

Table 5 shows how the realisation of the different SSPs affects the total impact and contributions per technology for the most robust Pareto-optimal subsidy portfolios. The robustness of the optimisation

Table 4
Decrease in GCAM output ranges between SSPs for each of the three SDGs when selecting a portfolio of higher robustness score.

	Decrease in output ranges between SSPs		
	GHG Emissions	Mortality	Energy Access
Baseline 2020	−1%	−4%	−16%
Baseline 2030	−4%	1%	−1%
Baseline 2040	2%	−1%	−11%

Table 5
Ranges of total impact and contributions per technology for the most robust Pareto optimal subsidy portfolios across SSPs.

SC	Technology	Energy Access	GHG	Mortality	Subsidy
2020	LPG	20–23%	28–34%	15–18%	34–40%
	PV	16–21%	7–8%	3–4%	8–10%
	Biogas	49–53%	50–52%	73–75%	42%
	Charcoal	1–8%	2%	2%	3%
	Fuelwood	0.02–0.2%	0.10%	0%	1%
	Ethanol	3–10%	5–14%	2–7%	4–13%
2030	LPG	10–14%	10–15%	7–10%	13–22%
	PV	18–28%	9–13%	5–7%	18–23%
	Biogas	58–62%	70–72%	78–81%	56%
	Charcoal	1%	1%	1–2%	2–3%
	Ethanol	1–11%	2–10%	1–8%	2–11%
2040	LPG	35–42%	29–51%	24–31%	48–57%
	PV	7–26%	6–20%	3–10%	8–21%
	Biogas	33–55%	29–65%	60–73%	22–43%
	Charcoal	0.00%	0.10%	0%	0%

process is examined for each of the SSPs separately, assuming that the performance of the assumed technologies in terms of maximising emission reductions, energy access and health benefits is stochastically uncertain.

Consistent with the analysis on the cost-effectiveness of the technology subsidies, biogas is the technology with the higher participation in the robust portfolios. This is evident across the different SSPs and timescales. The use of LPG and PV systems also have a high contribution to progress in the three SDGs. Charcoal kilns, and ethanol technologies reach their maximum potential, which though corresponds to a much lower subsidy and impact level compared to LPG, PV and biogas. Fuelwood is the least attractive technology. The policy context on how the different policy scenarios affect subsidisation and effectiveness of the technologies is provided in Van de Ven et al. (2019). Here the SSPs are assumed as an uncertain set of conditions that affect the performance of every technological subsidy policy and we focus on how the realisation of the different SSPs will ultimately affect the participation of technologies in the robust portfolios.

For the year 2020, technologies show a stable share of participation in the robust portfolios. In 2030, a high increase in the contribution of ethanol is observed for SSP 5, where ethanol is subsidised up to 11%, in contrast to SSPs 2 and 3 where subsidisation for ethanol is less than 2%. The realisation of different SSPs has an overall bigger effect on SDG progress in 2040.

4. Conclusions

This research presents a two-level integration of an integrated assessment model, namely GCAM, and a portfolio analysis model, based on AUGMECON 2 and Monte Carlo simulations, with the aim to provide policymakers with a comprehensive tool to address environmental and energy-related issues, facilitating the exchange of input data and model results across different methodologies. The integration is applied to a case study focusing on technological portfolio optimisation among different plausible socioeconomic futures in Eastern Africa. Initially, the GCAM model is run to simulate future socioeconomic scenarios for six relatively sustainable technologies. Outputs from each scenario are translated into progress parameters relevant to SDGs and are fed into a PA model. The portfolio optimisation model leads to the identification of Pareto fronts of optimal portfolios and allows comparison among different SSPs. The results show how resource allocation must be shared among the technologies to achieve optimal trade-offs on the simultaneous achievement of three goals: increase of energy access (SDG7), reduced exposure to air pollution and avoidance of related mortality (SDG3) and mitigation of global warming (SDG13). Biogas is the technology with the higher participation in the robust portfolios, across all SSPs and timescales, while fuelwood is the least attractive technology. A comparison between the SSPs shows that differences in the technological performances among the SSPs are mainly observed in SSP 5 for the years 2030 and 2040.

In order to hedge uncertainty concerning the realisation of different SSPs, an analysis that applies the ranges of the GCAM simulation outcomes between SSPs as its boundaries for robustness is introduced. The second link between the PA and GCAM models is achieved by feeding the GCAM model with the results of the portfolio optimisation analysis, to verify if the robustness of SSP uncertainty boundaries leads to more robust solutions across the different SSPs. We selected for each Pareto front a portfolio of high robustness and a portfolio with lower robustness score and reiterated these portfolios in the GCAM model to retrieve results for the technologies' impact for each SSP. This is to test whether the resulting ranges of SDG performances between the SSPs are smaller in case of a more SSP-robust portfolio. The results confirm that all portfolios show a smaller output range between SSPs, if a portfolio with a higher robustness score is chosen, showcasing the advantage of the proposed methodology.

A limitation of our proposed methodology related to the "SSP robustness" scenario lies on the initial choice of the mid-point between the range of SSP results in terms of the impact of each technology on SDG progress, for identifying the Pareto front of the optimal portfolio. The proposed idea is not to imply that the SSPs have the same probability of occurrence, as no rational assessment of probabilities of various representative scenarios can conclude equal likelihood (Kinzig and Starrett, 2003) hence justifying the use of a mean value; but rather to assess the uncertainty of the results across the entire spectrum of the resulting values, as defined by the individual SSP results. Even though we do apply the full SSP-related uncertainty range when calculating the robustness of the individual portfolios on the Pareto front, it could be that the election of a different point within the SSP outcome range would yield a slightly different Pareto front, and hence alter the portfolio outcome. However, we think that the difficulty to select a justifiable "mid-value" within an SSP-related outcome range poses a limitation that is a necessary evil, which enables the stochastic identification of optimal technology portfolios against all, or most, potential outcomes (Grübler and Nakicenovic, 2001) of technological subsidisation, regardless of our capacity to envisage a future world state that leads to these outcomes, and especially since these outcomes are forecasts of a single model (Allen, 2003).

Nevertheless, acknowledging this limitation and understanding the knowledge gaps reflected in this broad spectrum, against which the resulting technological subsidisation portfolios are assessed, may allow science both to reduce uncertainties in a systematic manner and to convey to policymakers the need to manage and integrate uncertainty into the policymaking process (Schneider, 2003). Along those lines, it is also important to note, that although the policy assumptions of the paper are carefully selected based on published research (Van de Ven et al., 2019), policy-relevance of results is highly dependent on the assumptions applied when modelling the policy scenarios, and these must be carefully considered when interpreting the results. Without overlooking this limitation, the novel methodology introduced in this research can be useful for stakeholders to manage the uncertainty prominent in the future states of the world, according to different adaptation and mitigation challenges. Both core elements of the methodology, namely the

GCAM model and the portfolio analysis model can be extended to include more parameters (i.e. technologies) than the ones represented in the current application. However, we must consider the limitations in terms of time and processing requirements, that the solution of more complex problems i.e. of numerous objective functions, more Monte Carlo simulations may require; this limitation can in the future be overcome, by using an enhanced algorithm for solving the portfolio analysis model, like AUGMECON-R, which is a more advanced version of AUGMECON 2 with significantly faster resolution performance (Nikas et al., 2020). Further prospects towards enriching the proposed methodological framework include the selection of variables with implications for a broader set of SDGs, and the integration of the models with participatory tools, to actively involve stakeholders in the case study; participation of stakeholders in policy analysis has been found to improve system understanding and scoping risks associated with climate policy and technologies (Van Vliet et al., 2020).

Declaration of competing interest

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

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