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Likelihood of climate change pathways under uncertainty on fossil fuel resource availability†

Iñigo Capellán-Pérez,*[a] Iñaki Arto,[b] Josué M. Polanco-Martínez,[bcd] Mikel González-Eguino[b] and Marc B. Neumann[be]

Uncertainties concerning fossil fuel resource availability have traditionally been deemphasized in climate change research as global baseline emission scenarios (*i.e.*, scenarios that do not consider additional climate policies) have been built on the assumption of abundant fossil fuel resources for the 21st century. However, current estimates are subject to critical uncertainties and an emerging body of literature is providing revised estimates. Here we consider the entire range of revised estimates, applying an integrated assessment model to perform a likelihood analysis of climate change pathways. Our results show that, by the end of the century, the two highest emission pathways from the IPCC, the Representative Concentration Pathways RCP6 and RCP8.5, where the baseline scenarios currently lie, have probabilities of being surpassed of 42% and 12%, respectively. In terms of temperature change, the probability of exceeding the 2 °C level by 2100 remains very high (88%), confirming the need for urgent climate action. Coal resource uncertainty determines the uncertainty about the emission and radiative forcing pathways due to the poor quality of data. We also find that the depletion of fossil fuels is likely to occur during the second half of the century accelerating the transition to renewable energy sources in baseline scenarios. Accordingly, more investments may be required to enable the energy transition, while the additional mitigation measures would in turn necessitate a lower effort than currently estimated. Hence, the integrated analysis of resource availability and climate change is essential to obtain internally consistent climate pathways.

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Broader context

The long-established perception of abundant fossil fuel resources has traditionally determined energy and climate policy, with future energy transitions being largely modeled as demand-driven transformations. However, increasing scientific evidence is showing that non-renewable energy resources availability is subject to high uncertainty. We show that the consideration of robust and transparent estimates of fossil fuel resources reduces the expected climate response in relation to current baseline scenarios (*i.e.* scenarios without additional climate policies). Still, the need for an urgent action against climate change is confirmed. We also find that the depletion of fossil fuels is likely to occur during the second half of the century, accelerating the transition to renewable energy sources in baseline scenarios. Hence, the integrated analysis of resource availability and climate change emerges as an essential feature to obtain internally consistent climate pathways.

1. Introduction

Research to date on climate change related uncertainties has primarily focused on technological, economic, political and climatic factors.[1–9] Although future emissions critically depend on the availability of fossil fuel resources (fossil fuels were responsible for 65% of total greenhouse gas (GHG) emissions in 2010[3]), their global resource base is commonly considered to be large enough to cover the bulk of the energy demands through the 21st century in current baseline scenarios, according to the resource estimates assumed by the Intergovernmental Panel on Climate Change (IPCC).[3,10–14] As the Special Report on

[a] *Low Carbon Programme, Instituto de Economía Pública, University of Basque Country, Avd. Lehendakari Aguirre, 48015 Bilbao, Spain. E-mail: inigo.capellan@ehu.es, inigocapelll@gmail.com*
[b] *Basque Centre for Climate Change, BC3, Alameda Urquijo 4-4a, 48008 Bilbao, Spain. E-mail: inaki.arto@bc3research.org*
[c] *EPHE, PSL Research University, Laboratoire Paléoclimatologie et Paléoenvironnements Marins, 3615 Pessac, France*
[d] *Univ. Bordeaux. UMR CNRS 5805 EPOC, 33615 Pessac, France*
[e] *IKERBASQUE, Basque Foundation for Science, Bilbao, Spain*

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Emissions Scenarios (SRES) concluded, "It is evident that, in the absence of climate policies, none of the SRES scenarios [ending in 2100] depicts a premature end to the fossil fuel age".[10] Accordingly, fossil fuel resource abundance, understood as the vast geological availability accessible at an affordable price, is a default assumption in most of the prominent integrated assessment models (IAMs) used for climate policy analysis. Future energy transitions are thus largely modelled as demand-driven transformations.[11–13,15]

The consensus on the abundant availability of fossil energy was pointed out as a shortcoming in the IPCC 5th Assessment Report (IPCC-AR5)[3] following the review of the full range of baseline scenarios in the literature. According to the report, although some assumptions vary considerably (*e.g.*, future income, energy demand, and carbon intensity), there is less diversity in others: "the scenario literature does not systematically explore the full range of uncertainty surrounding development pathways and possible evolution of key drivers such as population, technology, and resources".[3] In fact, a fraction of unconventional fuels has only recently become economically profitable and the existing estimates for these are sparse and with a tendency to overestimate.[13,16–21] Although in-place (*i.e. in situ*) resources of unconventional hydrocarbons are vast, the proportion that can be recovered economically and at a net energy profit is much smaller.[12,19,22] For coal, usually seen as a vast abundant resource, there are large uncertainties related to the available resource base due to the lack of robust global estimates. Recent studies are pointing to potentially large overestimates in coal resource assessments as geologists uncover restrictions on the coal that is extractable.[17,23–25] This phenomenon is especially relevant in some regions that contain a substantial share of the global resource, such as the USA (30% of the world's reported reserves) where the National Academy of Sciences recently concluded that existing coal reserve data are insufficient for long-term planning.[26,27]

In the light of these facts, we have analysed the sensitivity of the climate response to the availability of fossil fuel energy resources considering the peer-reviewed estimates of the total amount of resources that could ever be recovered, *i.e.*, the ultimately recoverable resources (URR). We apply the URR approach which aims to provide a "best estimate" using the most robust, transparent and up-to-date information available; this approach has been successfully applied to explore future fossil fuel extraction at regional and global levels.[13,16–19,28] We focus our study on the implications for baseline scenarios (*i.e.* scenarios with no additional climate policy). Since the baseline scenarios are the counterfactuals against which policy scenarios are developed and tested, substantial changes in their energy system (*e.g.* in terms of the cost of technologies, energy mix, *etc.*) would entail profound implications for mitigation scenarios.

Although previous studies have estimated future emission paths applying an URR approach,[13,15–18,29–35] we make four main contributions to the literature by: (1) using a probabilistic approach to account for the uncertainty in up-to-date peer reviewed estimates on recoverable energy resources; (2) using an integrated assessment model of climate change (GCAM-MAGICC[36]), enabling us to capture the complexity of energy substitutions, technology improvements, economic interactions and trade-offs with land-use changes; (3) integrating the uncertainty in the response of global temperature to a doubling of atmospheric GHG concentrations (equilibrium climate sensitivity, ECS), allowing us to (4) analyse the relative importance of uncertainty in resources *vs.* uncertainty in the climate system with respect to total radiative forcing and global surface temperature change.

Therefore, the proposed framework combines the uncertainties in future emission pathways with the uncertainty in equilibrium climate sensitivity (ECS), two factors that have been identified to contribute most to uncertainties in the projection of the global temperature change.[2,4,7,37] Although research to better characterize ECS has been conducted for several decades, little progress in narrowing its uncertainty has been achieved, with particular difficulties in ruling out higher values. Current overall understanding of ECS indicates a 68% confidence range between 2 and 4.5 °C.[7]

In our study we integrate the approaches of two different research communities: geologists and geological engineers, who have focused on estimating recoverable energy resources robustly and transparently, and the climate integrated assessment community, which has centred its efforts on exploring the technological and socioeconomic dimensions assuming the energy-abundance paradigm. By applying an ECS consistent with IPCC-AR5,[37,38] and the GCAM-MAGICC integrated assessment model of climate change which has been used in all IPCC reports to date, we ensure a robust comparison with the reported IPCC-AR5 results.[3]

The paper is organized as follows: Section 2 reviews the methods and metrics to assess the availability of fossil fuel resources; in particular, Section 2.3 describes the URR approach. Section 3 describes the literature review of inputs and methods applied for the uncertainty and sensitivity analyses. Section 4 presents and discusses the results, while Section 5 covers the limitations of the study and provides recommendations for further analyses. Policy implications and conclusions are drawn in Section 6.

2. Assessment of the availability of fossil fuel resources

Non-renewable fuels occur mostly as underground resources. Thus, the methods to assess their availability such as sampling, simulation and extrapolation are inherently subject to uncertainty. Additionally, their future availability critically depends on factors such as technological progress, economic development and socio-political circumstances.

2.1. Reserves and resources

A variety of metrics is used to describe the future availability of fossil fuels. The most common type of classification distinguishes between different categories of "resources" and "reserves". Generally, the term "resources" is used to represent the amount of energy resources (proven or geologically possible), which cannot currently be exploited for technical and/or economic reasons but may be exploitable in the future. "Reserves" refer to the fraction of the resource base estimated to be economically extractable at the time of determination and are commonly quoted to three levels of confidence (1P, 2P and 3P).‡ A supplementary category named "additional occurrences" is also sometimes considered to include additional low-grade quantities with unknown degrees of assurance.[12,16,40–42] These uncertainties can be represented in a McKelvey box (see Fig. S1, ESI†), which presents resource categories as a function of geological assurance and economic feasibility of extraction.§ These are the most widely used metrics by governments and international agencies such as the International Energy Agency (IEA), World Energy Council (WEC), International Monetary Fund (IMF) and IPCC.

Depending on the study, the term "resources" may refer to in-place or to recoverable amounts. Recoverability factors represent the fact that due to physical/chemical constraints, all the resource in-place will never be recovered. Additionally, these factors try to capture the future evolution of two opposing forces: the diminishing returns of the resource-base (smaller deposits in harsher environments, increasing exploration and production costs, diminishing energy ratios, *etc.*) and the rate of technology improvement through innovation. For example, the average recovery from conventional petroleum reservoirs around the world is estimated to be approximately 35%. Applying enhanced oil recovery techniques typically increases recovery factors by 5–15% whereas the high costs and technological requirements reduce their large-scale deployment.[43,44] Typical recovery rates are even lower for coal (~20%[12,27]), while for conventional natural gas they are in the range of 80–90%.[45]

2.2. Limitations of the current reserve and resource estimates

Resource and reserve estimates are subject to critical inconsistencies and uncertainties due to: (1) a lack of methodological standardisation (definitions, assessment of future recoverability from known fields or undiscovered volumes, probabilistic methods, *etc.*) at national and/or regional levels, which implies inconsistencies in the global aggregates;¶ (2) a lack of transparency in the reporting of reserve estimates in many countries with significant shares of world resources, such as Russia, Saudi Arabia and China (*e.g.*, "political reserves"); (3) confusion in the use of terminology for classifying different types of resources (*e.g.*, conventional and unconventional fuels); and (4) the scarcity of reports providing reliable estimates of unconventional resources due to their recent commercial exploitation.[13,16,17,20,23–28,39,44,47–51]

The lack of updated, transparent and robust estimates at the global level is particularly problematic in the case of coal. In fact, only two original datasets exist at the global level: the Federal Institute for Geosciences and Natural Resources (BGR)[52] and the World Energy Council (WEC)[53] assessments. The BGR assessment reports the total coal in-place rather than an estimate of the resources that can be recovered, and the WEC estimates of resources and reserves are mainly data collected from its member countries, and hence do not address the limitations outlined above. Actually, recent studies have pointed out that coal reserve/resource estimates suffer from a combination of weaknesses such as outdated data and methods and a considerable heterogeneity in methods applied across different regions hampering robust global aggregations,[23–25,47–49] suggesting that common coal reserve/resource estimates might be substantial overestimates, especially in some key regions.‖ The widespread perception of coal abundance might be partly explained by these inconsistencies. For example, in the USA (which holds 30% of reported world reserves and 40% of resources[52]), two recent assessments from the United States Geological Survey (USGS) and the National Academy of Sciences concluded that the reported coal reserve estimates for the country are out of date ("Present estimates of coal reserves [···] are based upon methods that have not been updated since their inception in 1974, and much of the input data were compiled in the early 1970s"[26]) and of poor quality ("However, it is not possible to confirm the often quoted assertion that there is a sufficient supply of coal for the next 250 years"[27]). The implied downgrading may be significant, since the results of the USGS assessment indicate that, in most cases, less than 20% of the original coal is expected to be economically recoverable.[27] Furthermore, many countries have not reassessed their coal reserves for a long time, and when they have, revisions have mostly been downwards,[23,24,47,50,54] contrary to what would be expected from the energy abundance paradigm.[12,55]

The inadequate treatment of these ambiguities and uncertainties by most studies leads to considerable uncertainty as well as fluctuations over time. These two aspects are particularly problematic for long-term assessments such as those required for climate change research. In the case of the IPCC, currently considered estimates[12] show notable differences in relation to the previous estimates by Rogner (1997).[42] Whereas coal and unconventional oil reserve estimates approximately halved, the resource estimates substantially increased for unconventional gas (2- to 5-fold) and coal (3- to 4-fold) due to upgrading of large stocks previously identified with unknown degrees of geological assurance (see Table S7, ESI†). In fact, it is generally assumed that in the long-term, resource scarcity will drive up prices, spurring technical improvements and exploration activities provided that adequate investments are forthcoming. These technical improvements are expected to continuously allow new discoveries and upgrading of abundant

‡ 1P, 2P and 3P reserve estimates are commonly expressed as P90, P50 and P10 respectively (referring to the percentiles): P1 thus refers to quantities recoverable with at least 90% probability (P90) under existing economic and political conditions and using existing technology.[12,39]

§ Moreover, the advances in exploration and production technologies blur the borders that distinguish reserves from resources and resources from occurrences.[12,41]

¶ For example, while reserves reporting in the United States require a 90% (1P) probability of recovery under existing economic, technological, and political conditions, other reporting bodies typically declare reserves at a median, 50% (2P), probability.[12] The latter is the case, for example, of the five major Middle East oil exporters from 1984.[46]

‖ In fact, just six countries dominate coal globally: according to the BGR (2013)[52] estimates, the combined reserves of the USA, China, India, Russia, Australia and South Africa represent almost 85% of the world's total.

resources and occurrences to offset the cumulative extraction of reserves.[12,55]

2.3. The ultimately recoverable resources approach

To overcome the aforementioned limitations, the ''ultimately recoverable resources'' (URR) approach has been proposed as an alternative to explicitly address the uncertainties and aiming to provide robust estimates of the total amount of resources that can ever be recovered and produced from a region/country in the light of the best available transparent information.[16,17,40] Thus, it includes future reserve growth at known fields/mines as well as the fuel estimated to be economically recoverable from expected discoveries of new fields/mines. In this approach, resource prices are viewed as weak scarcity indicators since energy markets are far from functioning under perfect conditions.[56,57] Instead, the focus is shifted to the physical components of energy resources (*e.g.* resource discoveries, field size, depletion rates, energy return on energy invested (EROEI), *etc.*). Diverse methodological approaches are usually combined to estimate the URR of fossil fuels; they include: standardisation;[16,20,39,48] discarding of ''political reserves'';[28] global bottom-up aggregation from a field-by-field analysis;[25,47,58,59] and the generation of original, alternative URR estimates combining statistical methods with geological modelling.[24,25,28,60]

The URR metric includes the sum of all historic and future production. The remaining URR in a given time t ($RURR_t$) is defined as the difference between the URR and cumulative extraction that has occurred by time t (see eqn (1)).

$$RURR_t = URR - \text{cumulative extraction}_t \quad (1)$$

The RURR metric can be related to the conventional definitions of reserve and resource if: (1) official reserve and resource estimates are revised to take into account potential inconsistencies and reduce uncertainties (*e.g.* political reserves, erroneous aggregations, *etc.*); (2) resources refer to the recoverable portion of the amount in-place; and (3) there is no double counting of reserves and resources. Under these conditions, the RURR can be estimated as the sum of reserves and recoverable resources (*e.g.* the estimated ultimate recovery of oil and gas from the BGR[52]).[40,61]

The URR approach has been successfully applied to forecast oil extraction. For example, global conventional oil production reached its peak in the mid-2000s and has already entered the phase of geologic decline,[62,63] as forecasted by Campbell & Laherrère (1998)[28] (in the line with the original Hubbert (1956)[64] projection). More recently, in 2011, the US EIA estimated that California's Monterey Shale had 15.4 billion barrels of recoverable tight oil, *i.e.* 64% of all reserves in the contiguous United States** at that time.[65] However, in May 2014, the US EIA downgraded their previous estimates by 96%, a result anticipated by an URR-based analysis.[19,22]

** The contiguous United States consists of 48 adjoining U.S. states plus Washington, D.C. on the continent of North America. The term excludes the non-contiguous states of Alaska and Hawaii and all off-shore United States territories and possessions.

3. Uncertainty analysis

In this section we describe the materials and methods applied to perform the uncertainty and sensitivity analyses in relation to the likelihood of climate change pathways under uncertainty on fossil fuel resource availability and equilibrium climate sensitivity.

All depletable resources are modelled in GCAM by cumulative supply curves, *i.e.*, upward-sloping supply–cost curves where the marginal monetary cost of resource extraction increases with cumulative extraction. Thus, it is assumed that the first deposits exploited are the most accessible and thus the most economically profitable.†† Thus, the availability of a non-renewable resource depends on the accessible amounts of the resource and the corresponding extraction cost.

We designed a probabilistic analysis considering uncertainties in the following inputs: (a) the RURR estimates of non-renewable energy resources and the associated supply–cost curve shapes; and (b) the equilibrium climate sensitivity (ECS). The CO_2 emissions arising from energy and land use changes are computed in GCAM. These emissions are then passed on to the climate model emulator MAGICC together with an input value for the ECS where the total radiative forcing (TRF) and global mean surface temperature change (ΔT) are computed. The GCAM-MAGICC model is run in baseline mode (*i.e.* scenarios with no additional climate policy) for the period 2005–2100. The entire process for a single simulation is illustrated in Fig. 1.

The probabilistic analysis was performed in four steps, which are detailed in the following sections:

(1) Literature review on uncertainty of inputs (Section 3.1),

(2) Propagation of uncertainty of inputs through GCAM-MAGICC (Section 3.2) for the period 2005–2100 using Monte Carlo simulation ($n = 1000$),

(3) Analysis of the uncertainty of outputs: total cumulative CO_2 emissions, total radiative forcing and global surface temperature change (Section 3.3),

(4) Identification of the inputs that explain most of the uncertainty in the outputs (global sensitivity analysis, see Section 3.3).

3.1. Literature review on the uncertainty of inputs

In this section we document the literature review on the uncertainty of inputs: RURR of non-renewable energy resources (Section 3.1.1), the shape of the cumulative supply–cost curves (Section 3.1.2) and the ECS (Section 3.1.3). Fig. S2 (ESI†) shows the empirical cumulative distribution functions (ECDFs) of the input distributions applied in the analysis.

3.1.1. Non-renewable energy resources RURRs. Non-renewable energy resources are divided into two broad groups: fossil fuels (Section 3.1.1.1) and uranium (Section 3.1.1.3). Probability distributions (see ESI†) are developed for each fuel on the basis of the literature review. This section also contains a comparison

†† Supply–cost curves are thus a model of efficient resource extraction, whose validity has been confronted by the ''Mayflower problem'',[66] *i.e.* the best resources are not always extracted first.

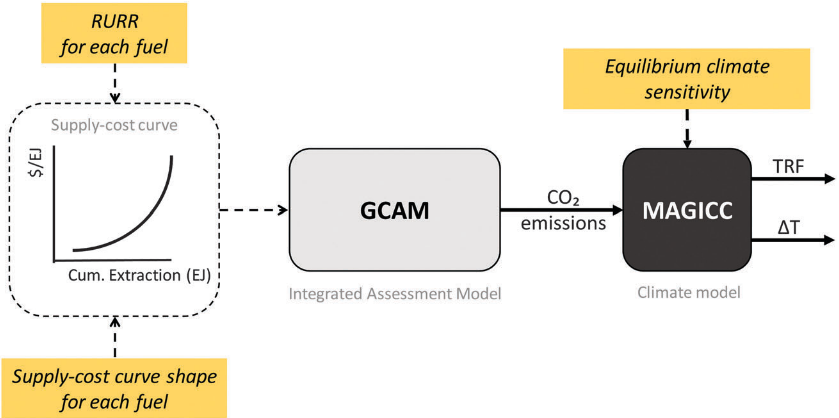

Fig. 1 Methodology of GCAM-MAGICC simulation. The yellow boxes (RURR, supply–cost curves, ECS) refer to the uncertain inputs that need to be supplied for a simulation.

with the updated range given by the IPCC-AR5 in terms of carbon endowment of fossil fuels (Section 3.1.1.2).[3]

3.1.1.1. Fossil fuel RURRs. We performed a comprehensive literature review of the URR for all fossil fuels in order to identify the probability distributions for the inputs. RURRs for the year 2005 were computed applying eqn (1).

For conventional fuels (coal – including bituminous, sub-bituminous and lignite-, conventional oil and conventional gas), due to their extensive exploitation over recent decades, large numbers of estimates have been published. Thus, we used Dale's (2012)[40] dataset, which is the result from a meta-analysis covering estimates made up to 2012. This dataset collates estimates of recoverable resources from diverse sources such as national and international agencies (*e.g.* USGS, WEC, BGR, IEA, and IIASA), independent associations (*e.g.* ASPO and EWG), industry (*e.g.* ESSO, Shell, and International Gas Union) and scientific peer-reviewed studies. The meta-analysis was performed as follows:‡‡ compilation of original estimates (avoiding double-counting) through a literature review; updates counted as different estimates; if an estimate was provided by a high–low span, the mean was taken; if an estimate was characterised using a high–middle–low range, the middle value was taken; where estimates for subtypes were provided (*e.g.* sub-bituminous, bituminous and lignite for coal), these were aggregated based on heating values. The objective of the meta-analysis was to determine the distribution in estimates, not to provide an in-depth analysis of the differences in assumptions leading to the discrepancy in estimates. Thus, no estimates were discarded for the construction of the original dataset. For our analysis we eliminated URR estimates with values less than the current cumulative production. The number of estimates that needed to be removed was less than 5% of the estimates from the original dataset for each of the fuels. The final dataset contains a total of 39 estimates for coal, 191 for conventional oil and 68 for conventional gas. Hence, since we have a large set of studies with no preference of any particular one, we consider the estimates to be equally probable. Therefore, in the Monte Carlo analysis we randomly sample an entry from the dataset, which is equivalent to random sampling from the corresponding empirical cumulative distribution function (ECDF). The resulting ECDF for coal, conventional oil and conventional gas is in agreement with a recent review of the RURR of fossil fuels performed by Mohr *et al.*, (2015)[17] (see Table S2, ESI†).

The situation is very different for unconventional oil and gas, since a fraction of these fuels has only recently become economically profitable (*e.g.* shale oil and gas) and extraction techniques for some resources are still under research & development (R&D) (*e.g.* methane hydrates). As a result, few published estimates exist with large associated uncertainties.[12,17,19,20,39,40] This implies that the existing sample of RURR estimates is too small and cannot be properly used for an uncertainty analysis.[40] Thus, in this case, we considered the results of Mohr *et al.* (2015),[17] who performed an exhaustive literature review providing three estimates for each resource: "low case", "best guess" and "high case". We applied a discrete triangular distribution assigning the probabilities of 0.2, 0.6 and 0.2 to these three cases. Unconventional gas includes coal bed methane, hydrates, shale and tight gas, and unconventional oil includes extra-heavy, kerogen, natural bitumen and tight oil.

The mean and standard deviation of the resulting ECDF of the fossil fuel distributions applied in the analysis are listed in Table S2 (ESI†).

3.1.1.2. Comparison of the carbon endowment with the IPCC-AR5. The carbon endowment associated with these RURR estimates is depicted in Fig. 2 and compared to the updated range of "reserves" plus "resources" given by the IPCC-AR5,[3] which stems from the Global Energy Assessment (GEA, chapter 7).[12] As shown by previous model comparison exercises, the sum of "reserves" plus "resources" is used to represent the long-term future availability of fossil fuel resources in most IAMs of climate change.[11] An examination of the IPCC estimates reveals that the abundance paradigm of fossil fuel resources is mainly related to coal (the most carbon intensive fossil fuel) and unconventional gas. In both cases, these high estimates have wider ranges of

‡‡ Personal communication from M. Carbajales-Dale (May 2016).

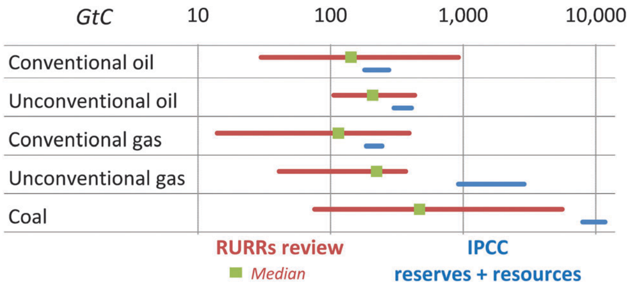

Fig. 2 Ranges of remaining carbon content estimates of fossil fuels in 2005 from the IPCC-AR5[3,12] (blue bars) and from our literature review of RURRs (red bars) in gigatonnes of carbon (GtC). IPCC estimates include the carbon content of reserves and resources (in the case of coal they are in-place amounts); the carbon-content of the RURR values is obtained by multiplying the RURR energy content estimates from the literature review with the carbon factors derived from Table 7.2 from the IPCC-AR5[3] (see also Table S2, ESI†). For conventional oil, conventional gas and coal RURRs, the ranges of the interval represent the minimum and the maximum estimate of the ECDF derived from Dale (2012)'s dataset.[40] For unconventional gas and unconventional oil RURRs the interval is bounded by the "low" and "high" estimate from Mohr *et al.* (2015),[17] while the median is represented by their "best guess" estimate. For comparison, the total cumulative carbon emissions from fossil fuel combustion to date are around 350 GtC. Fig. S2 (ESI†) shows the empirical cumulative distribution function by fuel obtained in the RURR literature review.

uncertainty than oil or conventional gas. In the case of coal, which has been extensively extracted for decades and currently represents the second-largest primary energy source globally after oil, the IPCC lowest bound estimate is 45-fold its cumulated past extraction.

A comparison between the two sets of estimates shows that the energy resource base of the IPCC is in the top of the range (for oil and conventional gas) or above the range (for unconventional gas and coal) obtained with the URR methodology.§§ An analysis of the unconventional gas resources by type in the GEA reveals that the discrepancy mainly derives from the assumption of the future availability of a very large reserve (47 000 EJ) and resource (81 700 EJ) potential for natural gas hydrates, which is around one order of magnitude higher than other resource estimates provided in the literature which range from 0 to 7000 EJ,[52,67] and clearly above the "high" RURR estimate of 12 500 EJ from Mohr *et al.*, (2015).[17] However, the GEA does not explain how these estimates are obtained. The reporting of reserves is disputable since methane hydrates have not yet been commercially produced. As a result, the GEA estimate for total unconventional gas appears to be one order of magnitude higher in relation to the literature (Table S2, ESI†).

In the case of coal, the reported definition in the IPCC-AR5 is not accurate. Rather than recoverable amounts,¶¶ the GEA reports in-place resources: "*resources are shown as in situ amounts,*" pointing out that "*the eventually extractable quantities will be significantly lower*".[12] Since RURR estimates focus on the recoverable fraction, this difference explains most of the discrepancy with the GEA and also with other sources such as BGR and IEA (Fig. 2 and Table S2, ESI†).

If we estimate the recoverable coal from the GEA values of reserve and *in situ* resources (see eqn (1)) by assuming a conventional recovery factor of 20%,[12,27] we would obtain the range 75 500–108 000 EJ that would roughly translate into 1950–2800 GtC of emissions, which is in the range of our RURR estimates (see Fig. 2 and Table S2, ESI†). The potential of future discoveries to increase the extractable resource base is challenged by the fact that, as revealed by the literature review of coal assessments (*cf.* Section 2), they are relatively out-of-date and that recent reassessments have led to downward revisions of coal reserves.[23–25,47–49]

It is important to remark that, for both IPCC and URR-based estimates, the remaining total carbon content is much greater than the identified "carbon budget" for having a likely chance of limiting temperature increases to 2 °C (260–410 GtC).[3,68]

3.1.1.3. RURR of uranium. The level of uranium deployment has indirect repercussions in terms of CO_2 emissions due to substitution effects in the energy mix (*e.g.* avoiding emissions from fossil fuels). Uranium availability is particularly prone to uncertainties and lack of transparency due to its geopolitical importance.[40,69] Four RURR levels for 2005 were constructed from the different degrees of assurance of the reported resource categories including undiscovered resources from the Nuclear Energy Agency estimates[69] (see Table S6, ESI†). Linearly decreasing probabilities were assigned to each RURR level from the most to the least likely categories. The uranium resources considered include conventional resources (from which uranium is recoverable as a primary product, a co-product or an important by-product) and unconventional resources (reliant on currently unexploited techniques in which uranium might only be recoverable as a minor by-product, mainly from phosphate rocks). Uranium from seawater was not considered since its industrial processing would not be possible during this century without a major technological breakthrough.[70]

3.1.2. Shape of the cumulative supply–cost curves. The cumulative supply curves are upward sloping cost-curves assuming that the first deposits exploited are the most accessible and thus the most economically profitable. The increasing demand would imply a continuous shift towards deposits that are less accessible and/or of lower grade and thus more expensive. This effect is somewhat compensated for by technological improvements (GCAM includes an exogenous extraction cost reduction to account for this). Depending on the evolution of these factors over time, the supply–cost curve can follow different paths, *i.e.*, the curve can have different shapes.

Depending on the shape, the future technology competition will evolve differently. With a greater steepness (*e.g.* logistic shape), substitution processes by other fuels and/or technologies will be boosted. A review of the literature has revealed that there is a great level of uncertainty about which of the potential shapes is ultimately likely to occur for all depletable resources.[11,16,42,69,71–73] Specifically, three main patterns were identified and integrated

§§ Similar conclusions are extracted when comparing with the RURR data from other references such as BGR[52] or IEA[67] (see Table S2, ESI†).

¶¶ The IPCC-AR5[3] reports GEA estimates under the following definitions: "Reserves are those quantities able to be recovered under existing economic and operating conditions; resources are those where economic extraction is potentially feasible" (see Table 7.2).

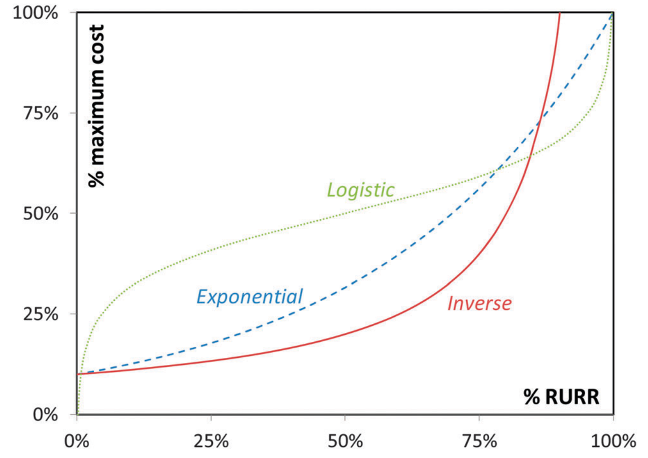

Fig. 3 Three main supply–cost curve shapes identified in the literature review as a function of RURR and the maximum cost.

into our study: inverse, exponential and logistic (Fig. 3, see ESI† for the equations). Due to the uncertainty in the assessment of the actual shape for the depletable resources, we assigned an equal probability of 1/3 to each shape considered.

Each cumulative supply-curve is dependent on three parameters: the cost of the last (most expensive) grade, the RURR and the shape of the curve. We kept the cost of the last grade available from the GCAM model as the maximum cost, focusing on the uncertainty on the RURR and the shape of the curve. The continuous curves were discretised by grades to correspond with the requirements of GCAM. One shape is considered for natural gas since the GCAM model aggregates conventional and unconventional gas in a single supply–cost curve. In the case of uranium, preliminary analyses revealed that the outputs were insensitive to the uranium cost-curve shape leading to the removal of this parameter for further analysis.

3.1.3. Equilibrium climate sensitivity (ECS). This parameter characterizes the global surface temperature response to a doubling of GHG concentration[7,74] and is recognized as one of the key uncertain parameters in climate change projections beyond a few decades.[2,4,7,37] However, there are different types of ECS depending on the feedbacks considered. ''Fast'' ECS includes the feedbacks occurring at the time-scale of decade(s) that scale with temperature (water vapour, lapse rate, clouds and surface albedo); accordingly, it is usually applied in integrated assessment modelling of climate change, typically focusing on projections up to 2100.[3,75,76] In this way, surface albedo feedbacks associated with changes in land ice (*e.g.* continental ice sheets and mountain glaciers) and vegetation are either not considered or are part of the forcing, which may ultimately result in an underestimation of the climate response.[74]

In this study, we apply the ECS probability distribution function estimated by Rogelj *et al.* (2014)[38] that is consistent with the overall consensus understanding of ECS of the IPCC-AR5, which stated that ECS is: likely (>66%) in the range of 1.5–4.5 °C, extremely likely (>95%) larger than 1 °C, and very unlikely (<10%) larger than 6 °C (see Fig. S2, ESI† for the ECDF).[37] At present, these values seem to be rather robust estimates as they have not changed much in the last few decades and are supported by recent studies.[7,75] In relation to this, the applied ECS estimate[38] is actually very close to the estimate fitting the IPCC-AR4 consensus that was applied in the IPCC-AR5 to homogenize the climate response of the emissions delivered by all the reviewed scenarios.[3,75] Thus, the implementation of this ECS estimate in the same modelling framework (MAGICC) allows us to robustly compare the results of our study with the IPCC-AR5 review of scenarios.

3.1.4. Summary of probability distribution of model inputs. Table 1 compiles the methods and references applied to develop the probability distribution of the 11 inputs. Fig. S2 (ESI†) shows the empirical cumulative distribution functions (ECDFs) of the input distributions applied in the analysis. The ECDFs of the non-renewable RURRs considered in the analysis are available as ESI.†

3.2. GCAM-MAGICC model and baseline scenario

The Global Change Assessment Model (GCAM) is a global IAM available under the terms of the ECL open source license version 2.0.[36,77–79] In this paper, we use the standard release of GCAM 3.2 with the non-renewable energy supply–cost curves and ECS values specifically modified in each scenario. GCAM is an optimization partial equilibrium (dynamic-recursively solved for every 5 years in the period 2005–2100) global model, integrating the global economy with energy, agriculture and land use systems. Although the model is regionally disaggregated, we apply global supply–cost curves for each resource since this version of the model assumes global energy markets. It includes a representation of the climate system, the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC) 5.3[80,81] which is similar to version 6 applied in the IPCC-AR5 review of baseline scenarios.[76] The MAGICC total radiative forcing output has been adjusted to the RCP definition excluding mineral dust, nitrate and the effect of land albedo.[82] The general structure is unidirectional: the exogenous socioeconomic inputs drive the energy extraction and the associated GHG that subsequently induce the temperature increase (with no damage function).

The exogenous socioeconomic inputs of the baseline scenario from the standard GCAM 3.2 release were slightly modified in order to produce a climate response in the middle of the range of the IPCC-AR5 review of baseline scenarios‖ to reach 7.5 W m^{-2} and 4 °C by 2100. The applied scenario considers the following conventional baseline scenario assumptions: global population peaks at almost 10 billion people in 2070 and then slowly declines in line with the median scenario from the UN World Population Prospects,[84] and global gross domestic product increases at an average rate of +2.4% between 2005 and 2100. The ESI† provides more details on the applied baseline scenario.

‖ 1184 scenarios from 31 models were assembled,[3,83] around 300 of them were identified as baseline scenarios.

Table 1 Information source for the probability distributions of model inputs

Input		Probability distribution
Remaining ultimately recoverable resources (RURR)	• Conventional oil • Conventional gas • Coal	ECDF of estimates from Dale (2012)[40] removing URR estimates less than current cumulative production
	• Unconventional oil • Unconventional gas	Discrete triangular distribution with probabilities of 0.2, 0.6, and 0.2 for low, best guess and high estimates from Mohr *et al.*, (2015)[17]
	• Uranium	Linearly decreasing probabilities for four RURR levels from NEA (2012)[69] (see Table S6, ESI)
Shape of the cumulative supply-cost curves	• Conventional oil • Unconventional oil • Natural gas • Coal	Equal probability (1/3) to each shape considered (inverse, exponential and logistic, see Section 3.1.2)
Climate sensitivity	• Equilibrium climate sensitivity (ECS)	ECDF from Rogelj *et al.*, (2014)[38]

Fig. S2 (ESI) shows the empirical cumulative distribution functions (ECDFs) of the input distributions applied in the analysis. The ECDFs of the non-renewable RURRs considered in the analysis are available as ESI.

3.3. Uncertainty propagation and sensitivity analysis

Monte Carlo simulation is performed to obtain the probability distributions of three outputs Y: cumulative CO_2 emissions, radiative forcing and temperature change. GCAM is run with 1000 scenarios that are obtained by random sampling from the probability distributions of the 11 inputs X_i (conventional oil RURR, unconventional oil RURR, conventional gas RURR, unconventional gas RURR, coal RURR, uranium RURR, conventional oil shape, unconventional oil shape, gas shape, coal shape and equilibrium climate sensitivity).

To determine which of the uncertain inputs (X) are responsible for producing uncertainty in the outputs (Y), we calculated the squared standardized regression coefficients (SRC^2).[85] These are obtained by first applying a multivariate linear regression to the results of the Monte Carlo simulation (eqn (2)) and then normalising the slopes b using the standard deviations of inputs σ_{X_i} and outputs σ_Y (eqn (3)). Since the GCAM model does not distinguish between the conventional and unconventional gas resource, total natural gas RURR (the addition of conventional and unconventional gas RURRs) is considered as a single input for the sensitivity analysis.

$$Y = \sum b_i \cdot X_i + a \tag{2}$$

$$\mathrm{SRC}_i^2 = \left(b_i \cdot \frac{\sigma_{X_i}}{\sigma_Y}\right)^2 \tag{3}$$

$$R^2 = \sum_i \left(\mathrm{SRC}_i^2\right) \tag{4}$$

The resulting SRC^2 approximate the first-order contributions of the inputs to the output variance. R^2 represents the coefficient of determination of the multivariate regression (eqn (4)). All computations for the uncertainty and sensitivity analysis were performed using R version 3.1.2.[86]

In fact, more parameters than those considered in the analysis are uncertain in the model, such as future population evolution, technology costs or GDP growth.[87,88] However, in this study we are interested in the role of resource-related uncertainties. For a review of methods and some applications of uncertainty and sensitivity analysis applied to IAMs of climate change, see Van Vuuren *et al.* (2008)[6] and Anderson *et al.* (2014).[89]

4. Results and discussion

4.1. Probabilistic climate pathways

We summarise the 1000 Monte Carlo simulations with interquartile and 5–95th percentile ranges as well as the minimum and maximum pathways obtained in terms of total cumulative CO_2 emissions (Fig. 4A), total radiative forcing (Fig. 4B) and temperature change since the pre-industrial period (Fig. 4C). The outputs are compared with the results from the IPCC-AR5 review of baseline scenarios,*** *i.e.* scenarios that ultimately serve as the reference for developing climate policies. The report's review and statistical analysis of outputs characterize the current state-of-the-art of the integrated assessment modelling of climate change, providing a benchmark for comparison.

4.1.1. CO_2 emissions. Our results show that the median cumulative emissions by 2100 reach a 30% lower level than the median of current baseline scenarios; the interquartile range of emission is 970–1470 gigatonnes of carbon (GtC) compared to the IPCC's 1370–1700 GtC (Fig. 4A). The inflection point of the median cumulative emissions around the middle of the century indicates that most fossil fuel resources are by then entering the depletion phase, driving the transition to renewable energies. By 2100, this leads to a median value that roughly coincides with the 10% percentile of the IPCC-AR5 review of baseline scenarios (1150 GtC). In fact, the probability that annual emissions exceed current levels at the end of the century is less than 25% even though the total median primary energy consumption doubles over the same period. Although our results show that the high emission levels are less probable, we also observe that the lowest cumulative CO_2 emissions path obtained in the Monte Carlo simulation exceeds the ''carbon budget'' to limit warming to below 2 °C by the year 2100 (Fig. 4A).[3]

*** The IPCC-AR5 reviewed 1184 scenarios from 31 models,[3,83] around 300 of them were identified as baseline scenarios.

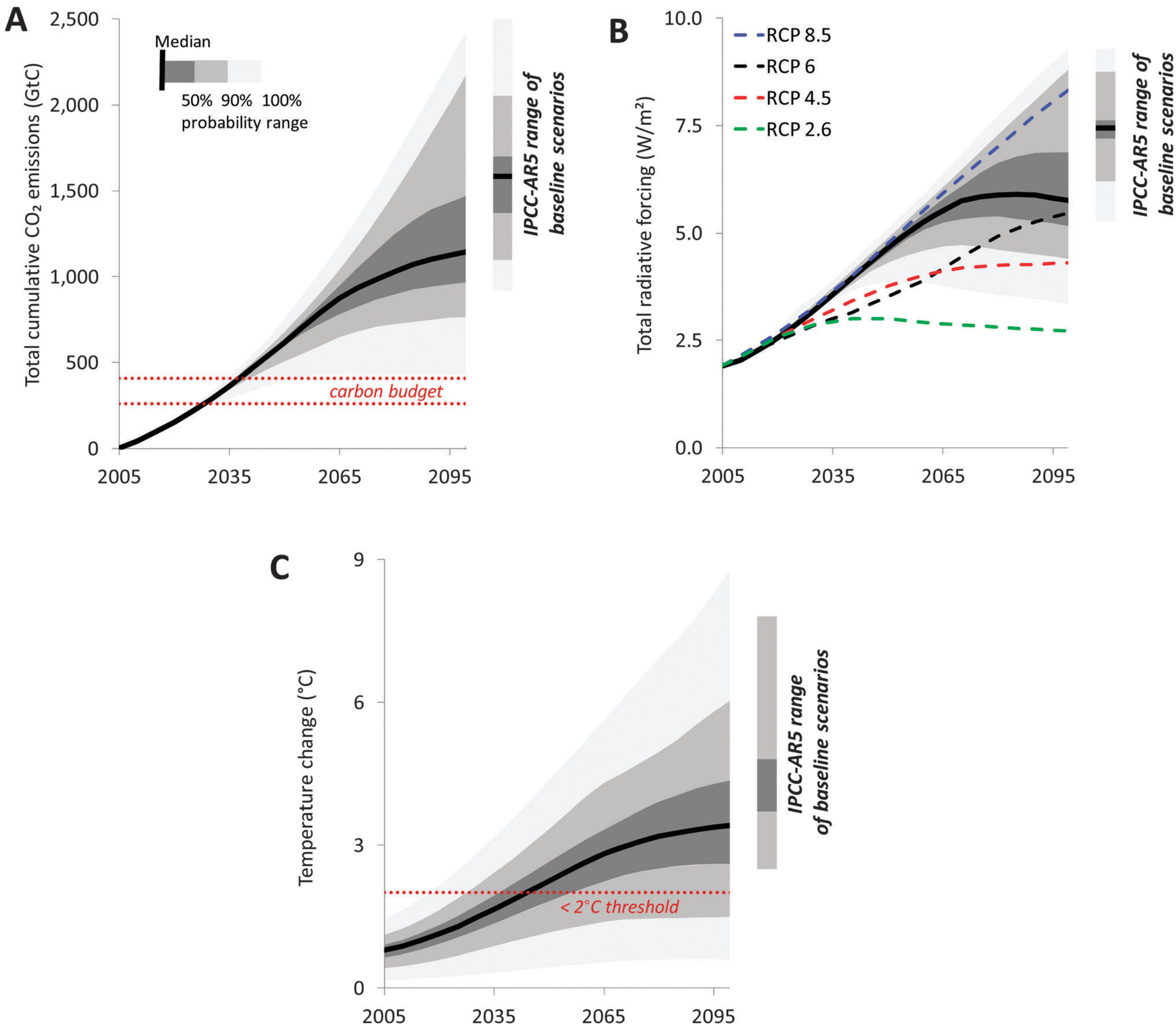

Fig. 4 Pathways of total cumulative CO_2 emissions, total radiative forcing and the temperature change (2005–2100) and comparison with the IPCC-AR5[3] range of baseline scenarios for 2100. Shaded areas depict the uncertainty ranges (whole range, 5–95%, 25–75%), the black line represents the median. Numeric values are provided in Table S3 (ESI†). (A) Total cumulative CO_2 emissions from industrial processes, fossil fuel combustion and land-use change. The dotted lines depict the "carbon budget" range estimated by the IPCC-AR5;[3] (B) total radiative forcing (TRF). For comparison, the four Representative Concentration Pathways (RCPs)[14] are indicated by blue, black, red and green dashed lines. (C) Global surface temperature change since the pre-industrial period. The dotted-line indicates the 2 °C threshold.

4.1.2. Total radiative forcing. Using total radiative forcing (TRF) enables us to compare our results with the Representative Concentration Pathways (RCPs), which constitute the new common set of scenarios developed as a standard basis for near and long-term climate modelling experiments. Four reference pathways (with no associated probabilities) have been defined by the climate research community spanning the range of 2100 radiative forcing values found in the literature: 2.6, 4.5, 6 and 8.5 W m^{-2}.[14] ††† Comparing our simulations to the RCPs', we observe that the median TRF values of the 1000 Monte Carlo simulations closely follow the RCP8.5 path during the first half of the century (Fig. 4B). However, during the second half, the increase in TRF slows down rapidly and then levels off, diminishing slightly at the end of the century and ending up close to the RCP6 level in 2100. By the end of the century, the two highest emissions pathways RCP6 and RCP8.5, where the baseline scenarios currently lie, have probabilities of being surpassed of 42% and 12% respectively, due to the likely depletion of fossil fuels during the second half of the 21st century (Fig. 4B and 5B). However, at the same time, our simulations show that it is also unlikely to end up at low levels of radiative forcing: by 2100, the interquartile range of 5.0–6.8 W m^{-2} is well above the safe thresholds to avoid

††† Note that the name of the RCP scenarios does not necessarily correspond to the TRF value for 2100 (*e.g.*, RCP6 "only" reaches 5.5 W m^{-2} that year).[14]

dangerous effects (*i.e.*, 2.6 W m^{-2}). Similar conclusions are obtained by comparing our results in terms of cumulative CO_2 emissions with the previous set of emission scenarios SRES[10] from the IPCC (see Fig. S5, ESI†).‡‡‡

4.1.3. Temperature change. In terms of the temperature change, we find an 88% probability of surpassing 2 °C and a 63% probability of surpassing 3 °C by 2100 (Fig. 4C and 5C). Moreover, there is a 50% probability of the 2 °C level being reached between 2035 and 2055.[92] These results are in accordance with the implications of burning all currently proven fossil fuel reserves.[5,16] The interquartile range for the temperature change by the end of the century is 2.6–4.4 °C; this result extends below the lower bound of the corresponding range of baseline scenarios in the literature reviewed by the IPCC-AR5 (3.7–4.8 °C).[3] However, as a consequence of the "fat tail" in the ECS distribution, we find a 15% probability that the temperature change will be more than 5 °C by the end of the century. Thus, despite the fossil fuel depletion provoking an earlier than expected transition to renewables, the increase in global temperature would still be well over the 2 °C threshold.§§§

4.2. Probabilistic distributions in 2100

Fig. 5 depicts the ECDF of the climate outputs for the year 2100, together with the interquartile range of the IPCC-AR5 review of baseline scenarios. The cumulative probability of emissions and TRF for the year 2100 depicts a bimodal distribution with a relative maximum at high levels between the RCP6 and RCP8.5 pathways by the end of the century (Fig. 5A and B). Thus, there is a relatively low, but significant, probability of reaching high emission and associated TRF pathways by the end of the 21st century, *i.e.* that fossil fuels do not deplete before the end of the century. In other words, the combined upper range of our RURR distributions contains the current consensus on abundant availability implemented in the baseline scenarios of current IAMs of climate change.

4.3. Sensitivity analysis

The global sensitivity analysis reveals that the coal RURR uncertainty is, by far, the most determinant factor among the fossil fuel resources considered in the uncertainty of emissions and TRF by the end of the century (Table 2). This indicates that the simulations leading to high emission pathways are being ultimately driven by the high values in the coal RURR estimates. As evidenced by inter-comparison analyses,[3,11] most models use harmonized default assumptions about coal estimates that lie in the higher regions of our coal URR review (Fig. 2). The importance of the coal resource uncertainty is somewhat lessened when

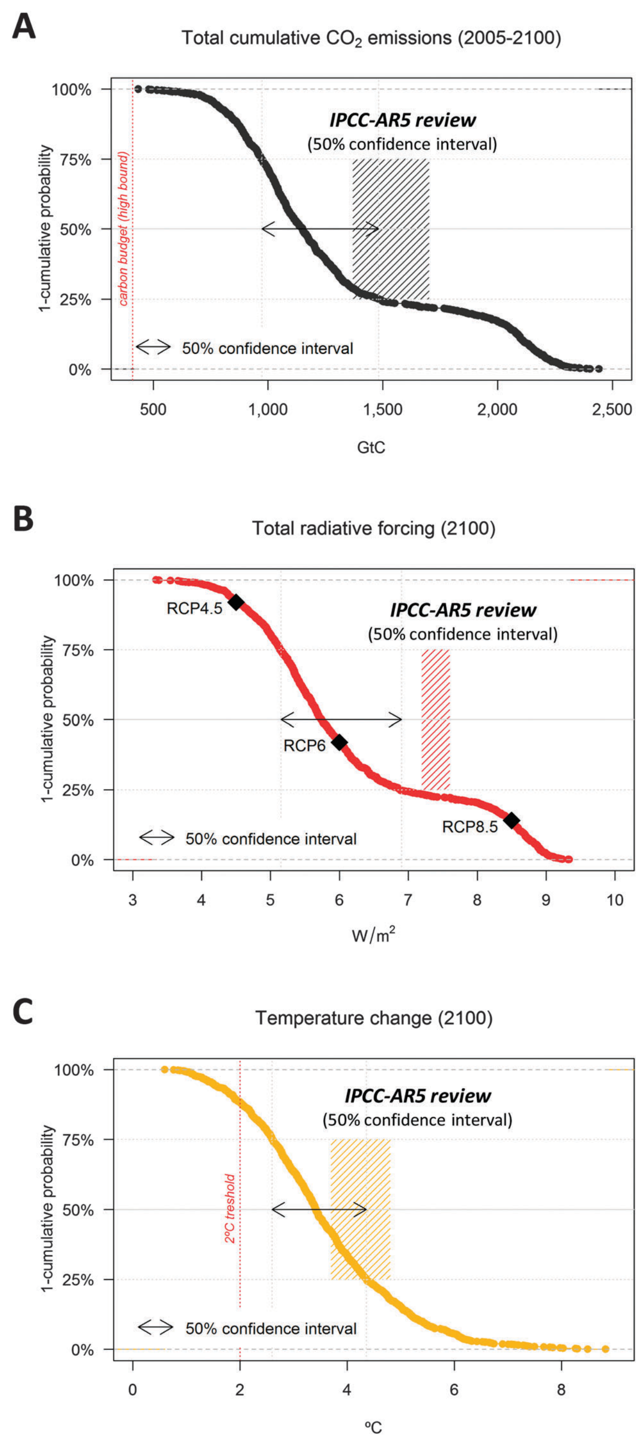

Fig. 5 Likelihood of climate outcomes in 2100 and comparison with the 50% confidence interval from the IPCC-AR5 review of baseline scenarios.[3] Cumulative distributions of outputs: (A) total cumulative CO_2 emissions 2005–2100 (GtC), the dotted line depicts the high bound of the carbon budget; (B) total radiative forcing (W m^{-2}), the likelihood of exceeding each RCP level by 2100 is 100% (RCP2.6), 92% (RCP4.5), 42% (RCP6) and 12% (RCP8.5); and (C) the temperature change in relation to preindustrial levels (°C), the dotted line indicates the 2 °C threshold. The shaded area shows the IPCC-AR5 50% confidence interval, the arrow shows our 50% confidence interval. The evolution of the cumulative distributions over time is shown in Fig. S3 (ESI†).

‡‡‡ By the end of the century, the high emission scenarios A1, A2 and A1G, where the baseline scenarios used to lie at the time, have probabilities of being surpassed of 29%, 22% and 13%, respectively. For the rest of the scenarios, B2, A1T and B1, implicitly entailing increasing levels of policy intervention,[90,91] the probabilities of being surpassed are 64%, 79% and 90%, respectively. In this sense, the RCPs represent a continuation of the SRES scenarios.

§§§ Confidence is increasing that even such a temperature change may pose significant risks.[92–95] In this sense, we find a 95% probability of surpassing 1.5 °C by 2100.

Table 2 Fraction of variance in climate outcomes for the year 2100 explained by the main inputs (squared standardized regression coefficients, SRC^2)

	Total cumulative CO_2 emissions	Total radiative forcing	Temperature change
Conventional oil RURR	0.014	0.020	0.003
Unconventional oil RURR	0.003	0.007	0.002
Natural gas RURR	0.022	0.043	0.012
Coal RURR	**0.730**	**0.676**	**0.138**
ECS	—	0.017	**0.702**
Other inputs	0.004	0.005	0.001
Total (R^2)	0.774	0.766	0.857

For total cumulative CO_2 emissions and total radiative forcing, the coal RURR explains 73% and 68% of the uncertainty respectively, whereas for the temperature change, coal RURR explains only 14%, with equilibrium climate sensitivity (ECS) explaining 70%. Total (R^2) represents the coefficient of determination of the total multivariate regression.

analysing the temperature change, which is mainly driven by the uncertainty in ECS (Table 2 and Fig. S4, ESI†).

The evolution over time reveals that the conventional oil resource uncertainty is also especially relevant to total cumulative CO_2 emissions and TRF during the first half of the 21st century. On the other hand, the shape parameter of the supply–cost curves has a weak influence on the uncertainty of the outputs in comparison with the RURR (see Fig. S4, ESI†). For the evolution of SRC^2 over time and the individual contributions of other inputs, see Fig. S4 (ESI†).

The majority of previous URR studies applied a deterministic approach focusing solely on fossil-fuel related emissions, finding levels of cumulative CO_2 emissions by 2100 below the RCP6 scenarios.[13,15,17,18,29–35] Hence, their conclusions were limited to indicate that the highest IPCC emission scenarios were incompatible with fossil fuel resource endowments. In contrast, we find a 42% probability of total radiative forcing being above 6 W m^{-2}, which indicates that these previous studies by following a deterministic approach were not accounting for values in the upper ranges of fossil fuel availability estimates from the literature.¶¶¶

4.4. Transition to renewable energy sources

The obtained results indicate that a transition to renewable energies driven by fossil fuel depletion would likely take place from the middle of the century onwards. For example, in a scenario applying the median values of our RURR estimates, renewable energy sources would represent 36% of the cumulative primary energy consumption of the period 2005–2100 (50% in 2050–2100), reaching 80% by the end of the 21st century. The transition to renewable energy sources translates into higher costs for the energy system: comparing the energy costs of this with a scenario considering the energy endowments consistent with the IPCC-AR5,‖‖‖ the end-user electricity price is found to almost double (+80%) and the refined liquids price to increase more than 3-fold by 2100 (results not shown). However, the feasibility and timing of the likely transition to renewable energy sources could not be analysed in detail since constraints on the diffusion of emergent technologies[96] as well as geological limitations to the extraction rate of non-renewable fuels[15,44,97] are not implemented in the standard version of the GCAM model. In fact, accounting for the first factor would hamper the deployment of renewable energy technologies, whereas considering the second would imply that the alternative sources of energy should be ready to replace fossil fuels earlier than obtained in this analysis.****

5. Limitations and recommendations for further analyses

Uncertainty and sensitivity analyses are dependent on the quality of the input distributions. In this sense, Dale (2012)'s dataset,[40] from which the data for conventional oil, conventional gas and coal are taken, is a compilation of all the historic RURR estimates found in the literature. It does not include a comparative review of the quality, confidence and trustworthiness of the different estimates. Although the obtained ECDFs are found to be in broad agreement with a recent review of the RURR of fossil fuels (see Table S2, ESI†),[17] further work might be directed to improve the dataset's quality. Additionally, it was found that the shape parameter of the supply–cost curves has a weak influence on the uncertainty of the outputs in comparison to the RURR (see Fig. S4, ESI†). In fact, the examination of individual scenarios from the Monte Carlo analysis reveals that most fossil-based technologies are not substituted by renewable energy technologies until fossil fuels are depleted. However, this result depends on model exogenous assumptions of future renewables technology costs, which were beyond the scope of this study.

Despite the vast uncertainties related to uranium availability due to its geopolitical relevance, the sensitivity of the climate outputs to the uranium RURR is found to be negligible (see Table 2 and Fig. S4, ESI†). However, as only the Nuclear Energy Agency reports uranium estimates for some regions of the world without any likelihood metric, the derived input distribution in this work is doubtful. Still, since baseline scenarios in GCAM do not generally depict a higher share of the nuclear technology along the century, our findings with regard to climate change pathways would remain unchanged. Though, a larger

¶¶¶ Similar conclusions are obtained in relation to the assessment of the SRES scenarios by previous URR studies.[10] In fact, many of these studies, carried out in the 2000s, compared their outcomes with this set of scenarios finding that the highest SRES emission scenarios A1, A2 and A1G were incompatible with fossil fuel resource endowments (see Fig. S5, ESI†).

‖‖‖ For more details about this scenario see the section "GCAM baseline scenario" in the ESI.†

**** The GCAM framework assumes that renewable energy sources (together with efficiency improvements) compensate for fossil fuel depletion optimally fulfilling the energy demand of each scenario in each 5 year period. Since in this model the exogenous socioeconomic inputs are not affected by potential energy availability shocks, eventual "crisis" or "collapse" scenarios that may reduce the future demand (and thus the extraction) of fossil fuels are not considered in this analysis.

uranium availability may eventually affect the findings in relation to the transition to renewable energies within the electricity sector.

Thus, future work could address these limitations by exploring ways to improve the RURR dataset of non-renewable fossil fuels. Especially in the case of coal, due to the sensitivity of the climate outputs to the assumption on its availability and the evident limitations of current data, an effort to estimate transparent and robust values of coal recoverable resources at global level is of critical importance. This uncertainty could be reduced by a coordinated international effort devoted to evaluating coal availability at a global scale, as has already been proposed for the case of the USA.[26] Resource availability should be continuously reassessed in the light of updated information such as new geologic knowledge, progress in science and technology, and shifts in economic and political conditions. The latter is especially relevant for unconventional fuels that have only recently started to be extracted or are still under R&D; it is likely that as the experience about their extraction increases, better data might be available. Accordingly, it would be recommendable to update on a regular basis the assumptions on recoverable resources of IAMs and to test the sensitivity of the climate change pathways to the uncertainty on these inputs.

Additionally, the analysis of baseline scenarios might be extended to study the interaction with other relevant sources of uncertainty such as socioeconomic drivers (*e.g.* population or economic activity) and the costs of alternative technologies. Furthermore, considering policy scenarios (*i.e.* introducing carbon taxes) would allow us to analyse in more detail the implications for climate policies. The detailed investigation of the energy transition feasibility and dynamics would require the integration of constraints on the diffusion of emergent technologies as well as geological limitations on the extraction rate of non-renewable fuels.

The transition to renewable energies would actually take place in a context of more expensive energy inputs. This reduced availability of energy inputs would include a monetary but also an energetic dimension. In fact, fossil fuel supply in the second half of the 21st century would be dominated by low grade and unconventional fuels, whose extraction requires comparatively higher energy investments than conventional fuels (*i.e.* are characterised by lower EROEI).[12,22] Moreover, most renewables are characterised by low EROEI levels and require substantial levels of overcapacity and/or storage to tackle intermittence and variability at high penetration levels. Thus, current integrated assessment modelling of climate change would benefit from the adoption of a net energy analysis approach.[98]

6. Policy implications and conclusions

Fossil fuel resource availability is a key driver of emission pathways. However, the uncertainty in this parameter has not been sufficiently analysed in baseline emission scenarios. The current integrated assessment models of climate change apply very high endowments of fossil resources, assuming that future discoveries and technological improvements will make available the energy resources demanded by the economy at an affordable cost. In turn, the application of the URR approach we used in our study suggests that the exploitation of fossil fuel resources during the 21st century will likely decline globally, even in the absence of policies promoting the transition towards renewables. In particular, our results show that more investments may be required to enable the energy transition, while the additional mitigation measures would in turn necessitate a lower effort than currently estimated (around a 30% lower mitigation cost to stabilise below 2 °C by 2100, results not shown). Thus, although an effective policy to mitigate emissions to safe levels would certainly require more rapid reductions in fossil fuel use than their likely geological depletion rates, the mitigation policies would actually take place in a context of "higher than expected" penetration of renewables.

Timely and adequate R&D investments for renewable energies and related technologies (*e.g.* storage) are critical to successfully achieve the energy transition.[99] Our results suggest that renewable energies, that have traditionally received a minority share of funds for R&D in relation to other technologies and fuels,[100] should be prioritized in relation to other fossil-based low carbon technologies such as CCS. Anticipatory strategies to address fossil fuel depletion (*e.g.* efficiency improvements, fiscal measures and quotas to increment the share of renewable energies, *etc.*) combined with a proactive climate policy could accelerate the learning curves of the renewable technologies, eventually contributing to reduce the overall transition costs.

Our results confirm the need for urgent global coordinated action to avoid dangerous climate change (we obtain an 88% probability of surpassing 2 °C by 2100). Additionally, our analysis constitutes an opportunity to revisit the likelihood controversy concerning future climate change that arose after the publication of the SRES in 2000,[10] when the approach shifted to consider emission scenarios as being "equally sound", with no associated probabilities. At the time, this shift was questioned, pointing out the difficulty of effectively orientating decision-making in such a framework since climate change mitigation and adaption is ultimately a risk management challenge.[4,6,9,101,102] However, the calls to provide a subjective probability assessment for the set of scenarios based on expert opinion collided with the divergent views of participants in the scenario design process.[101] Since no likelihood or preference is attached to any of the RCPs,[14] the assignment of probabilities to scenarios remains an open debate in the design and application of climate scenarios. In fact, the process of estimating absolute probabilities for different scenarios necessitates the comprehensive integration of all relevant sources of uncertainty, many of which remain extremely difficult to estimate, due to the existence of unknowns such as future societal processes. In this sense, our approach constitutes a workable alternative by focusing on the compatibility of emission pathways with physical resource restrictions. Thus, the obtained results could assist the climate policy making process in cases where the equal probability assumption may act as an obstacle.

In relation to the likelihood of climate change pathways, we find that the highest emission pathways from the IPCC where the baseline scenarios historically lie have probabilities of being reached of below 50%. Hence, the integrated analysis of the resource availability and climate change emerges as an essential condition to obtain internally consistent climate pathways and might contribute to the future development of standard sets of climate scenarios.

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