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The implications of uncertain renewable resource potentials for global wind and solar electricity projections

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Supplementary material for this article is available online

Abstract

Studies exploring long-term energy system transitions rely on resource cost-supply curves derived from estimates of renewable energy (RE) potentials to generate wind and solar power projections. However, estimates of RE potentials are characterized by large uncertainties stemming from methodological assumptions that vary across studies, including factors such as the suitability of land and the performance and configuration of technology. Based on a synthesis of modeling approaches and parameter values used in prior studies, we explore the implications of these uncertain assumptions for onshore wind and solar photovoltaic electricity generation projections globally using the Global Change Analysis Model. We show that variability in parametric assumptions related to land use (e.g. land suitability) are responsible for the most substantial uncertainty in both wind and solar generation projections. Additionally, assumptions about the average turbine installation density and turbine technology are responsible for substantial uncertainty in wind generation projections. Under scenarios that account for climate impacts on wind and solar energy, we find that these parametric uncertainties are far more significant than those emerging from differences in climate models and scenarios in a global assessment, but uncertainty surrounding climate impacts (across models and scenarios) have significant effects regionally, especially for wind. Our analysis suggests the need for studies focusing on long-term energy system transitions to account for this uncertainty.

1. Introduction

Studies exploring long-term energy system transitions suggest that renewable energy (RE) is expected to play an increasingly prominent role in the future, particularly driven by increasing demand for, and plummeting costs of, intermittent renewables [1]. As the interest for a deeper understanding of the future role of intermittent RE in global and regional energy systems increases, investigations aiming to support energy-sector decision-making have largely relied on quantitative modeling tools with representations of the energy system and its key processes (e.g. energy production, transformation, distribution, and use). However, model-based projections of RE deployment are characterized by significant uncertainty stemming from different sources. Among these sources, two relevant factors can be cited. First, the parametric uncertainty associated with alternative approaches to quantifying RE potentials globally. Second, likely climate change impacts on intermittent renewables. In this context, recent model-based investigations on climate change impacts on the energy sector have just started to account for climate change impacts on intermittent renewables using the uncertain global RE potentials as model inputs [2, 3]. This creates new challenges to the understanding of the future evolution of the energy system.

To date, few model-based projections of RE have accounted for climate impacts on wind and solar energy [2–4]. Among them, the recent study by Gernaat *et al* [2] proposes a novel approach. The authors incorporate climate impacts on wind and solar energy into their modeling framework by building global gridded estimates of RE potentials produced from climate projections data. RE potentials, defined as the potentially available wind or solar power generation over a geographical area [5], are used in the Gernaat *et al* [2] methodology to modify resource supply-cost curves (or simply 'supply curves') in models with the goal of assessing climate impacts on RE. As mentioned later, wind and solar supply curves are critical inputs to many models that generate projections of intermittent electricity production.

The Gernaat *et al* study [2] accounts for the uncertainty associated with climate change model projections. However, it computes RE potentials based on a fixed pool of assumptions about uncertain factors such as the suitability of land for the deployment of RE, density of wind turbines and solar panels installed and choice of technology. This means that the uncertainty associated with these factors, which we refer to as 'parametric assumptions' henceforth, remains unaccounted for. Although some prior studies [5–8] have examined the effect of specific parametric assumptions when computing wind or solar potentials, no past work has investigated their implications for electricity generation projections. Previous studies have also not examined how uncertainties in RE potentials could interact with climate impacts on intermittent renewable resources, influencing our understanding of future energy system transitions.

In this study, we fill the above gaps by addressing the following question: *What are the implications of parametric uncertainties in the computation of RE potentials for projections of future wind and solar power generation regionally and globally?* For the purposes of this study, we first calculate the global onshore wind (henceforth 'wind') and solar photovoltaic (PV) technical potentials under a range of assumptions about the suitability of land, the performance and configuration of technology, rotor height, average wind turbine installation and the future evolution of the climate. Our parameter values are obtained from a synthesis of modeling approaches in prior studies. We then evaluate the impact of the uncertainties on future electricity generation projections by incorporating supply curves produced from the RE technical potentials calculated above into the Global Change Analysis Model (GCAM), a state-of-the art model with a long history of long-term energy systems transition analyses [9–11]. GCAM links representations of the energy, land, water, climate, and economic systems in 32 geopolitical regions [12] (see supplementary note 1 for details about GCAM available online at stacks.iop.org/ERL/16/124060/mmedia). A core contribution of this study is to synthesize approaches to estimate wind and solar PV energy potentials and parameter values used in prior studies, and to demonstrate their influence on RE deployment projections. This synthesis can help to guide future RE potential assessments and the definition of sampling ranges for formal sensitivity analyses. For example, future RE potential assessments could use the ranges for the key parameters identified in our study to account for this source of uncertainty.

We note that this study aims to examine the implications of a subset of uncertainties in RE potentials for renewable electricity generation projections. Nevertheless, future renewable electricity generation will also depend on a variety of socioeconomic, technological, political, and institutional factors including but not limited to population and economic growth, technological advancement, and grid integration limitations. Also, future feed-in tariffs systems and other subsidies for RE sources are uncertain and impact the future deployment of renewable technologies like wind and solar. We reserve a detailed exploration of such factors for future studies. In addition, this study does not seek to conduct a formal sensitivity analysis to assess the relative variance contributions of numerous higher-order interactions of parameter values [13–15]. Rather, this study seeks to provide an initial assessment of the scale of uncertainty and to identify a subset of candidate parameters for the research community to potentially focus on in efforts to reduce uncertainty moving forward.

2. Methods

2.1. Overview

Figure 1 summarizes our approach. Prior studies have computed intermittent RE potentials (blue boxes in figure 1) using a common approach that assesses the theoretical, geographical, technical, and economic potentials [2, 5–8, 16–20]. This process is discussed in more detail in section 2.2. We implement that same approach here, but we explore parametric uncertainty by surveying the literature (orange box in figure 1) to identify a range of candidate parameters that influence geographical and technical potentials (see supplementary note 2 for details on the literature search approach and the full list of articles reviewed). Ultimately, we construct RE supply curves (a representation of the economic potential)

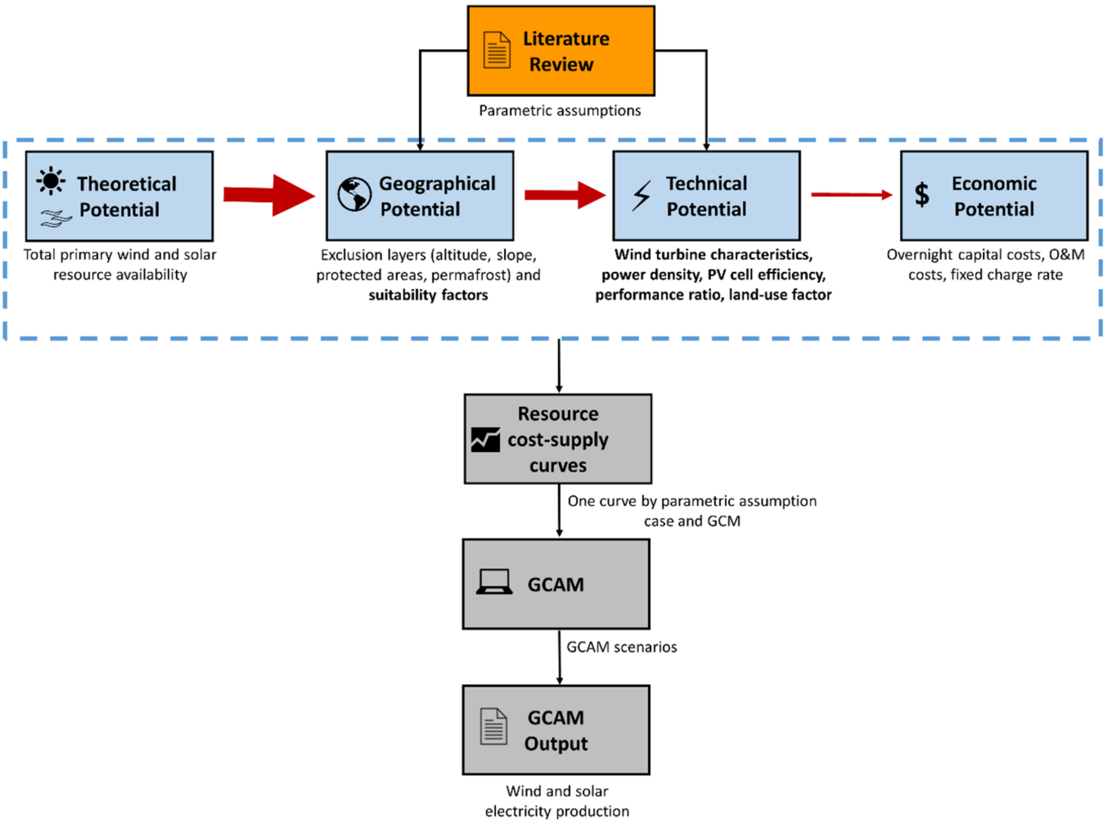

Figure 1. Methodological schematic describing the analytical approach employed here to evaluate the implications of parametric uncertainty on wind and solar resource potentials and projected deployment. The left-most red arrow represents the theoretical upper bound of RE availability (theoretical potential), which is reduced in each subsequent step of the calculation of the intermittent renewable potentials. Colors denote specific steps: literature survey (orange boxes), computation of renewable potentials as conducted by various prior studies (blue boxes inside the dashed blue rectangle), and derivation and implementation of resource cost-supply curves in GCAM (gray boxes). Bold text below the blue boxes represents parameters that are accounted for in this study.

used by GCAM in projecting the future evolution of the energy system under scenarios described later on in section 2.4 (gray boxes in figure 1). Supply curves are essential assumptions within the economic framework of integrated models such as GCAM because they represent the increasing costs of generating electricity from renewable sources as locations with the best (cheapest) resources are used first.

2.2. Assessing renewable energy potentials

Following the Gernaat *et al* methodology [2], we compute the global wind and solar PV technical potentials for historical and future periods. To do so, we have used the climate data from the four ISIMIP2b general circulation models (GCMs) [21] (supplementary note 3 provides information on these GCMs) as an estimation of the theoretical potential, and have determined the geographical potential. While the GCM outputs provide the spatial distribution and temporal evolution of the primary natural resource, the geographical potential accounts for land use restrictions to identify suitable locations for renewable electricity generation. As in many prior studies, the geographical potential is determined by combining the climate dataset with global geospatial datasets of key terrain characteristics (e.g. elevation, slope, land-use/land cover, protected areas, permafrost). Starting with the total world surface area and working at the grid cell resolution of the climate data ($0.5^\circ \times 0.5^\circ$), we [1] apply certain exclusion criteria (using the geospatial datasets as filters) to exclude land areas considered unsuitable for the given renewable technology (wind or solar PV), and [2] assig suitability factors to the non-excluded grid cells based on the land categories of the land-use/land cover dataset. Suitability factors represent the fraction of the grid cell that is suitable or available for RE deployment, and are assigned on the 0–1 range. A suitability factor value of 0 indicates a totally unsuitable grid cell, whereas a value of 1 indicates that 100% of the land within a grid cell is suitable [17].

Following the assessment of the geographical potential, technical potential is next assessed by accounting for factors such as limitations to the conversion from primary to secondary energy and overall losses due to technical and/or operational factors [2, 8, 17]. Finally, the production costs of electricity are estimated by accounting for factors such as capital and operations and maintenance costs as well as

Table 1. Parametric assumptions for all technical potential cases (corresponding to the blue boxes in figure 1) analyzed for the onshore wind technology. (Supplementary notes 3–9 provides details on how these assumptions affect the computation of the RE potentials.)

Parameter assumption	Case label	Reference	Value
Power output estimate[a]	Central	Rinne *et al* [5]	Turbine technology Vestas V136-3.45; hub height = 125 m
	E101_3.05	Höltinger *et al* [22]	Turbine technology Enercon E101-3.05; hub height = 135 m
	GE_2.5–100	Lu *et al* [23]	Turbine technology General Electric GE 2.5–100; hub height = 100 m
	V90_2.0	Bosch *et al* [20]	Turbine technology Vestas V90-2.0; hub height = 100 m
Suitability factors	Central	Eurek *et al* [18]	See supplementary note 4
	S_low (low suitability I)	Zhou *et al* [6]	
	S_low_II (low suitability II)	Deng *et al* [24]	
	S_high (high suitability)	Lu *et al* [23]	
Power density[b]	Central	Rinne *et al* [5]	5.3 MW Km^{-2}
	Pdens_1	Adams and Keith [25]	1.0 MW Km^{-2}
	Pdens_9	Lu *et al* [23]	9.0 MW Km^{-2}
	Pdens_13	Rinne *et al* [5][c]	13.0 MW Km^{-2}
Hub height[d]	Central	Rinne *et al* [5]	125 m
	Hub_75	Rinne *et al* [5]	75 m
	Hub_100	Rinne *et al* [5]	100 m
	Hub_150	Rinne *et al* [5]	150 m

[a] Refers to the methodology to compute wind power conducted in prior studies. See supplementary note 5 for details, in particular supplementary figure 3, which shows the power curve for the wind turbine model Vestas V136-3.45 (central assumption), and supplementary figure 4, which compares all turbine models analyzed in this study.
[b] Refers to the average wind turbine installation density.
[c] The high power density case is set to 13.0 MW Km^{-2}. The upper bound limit for this parameter in the literature has been shown to be in the 12–15 MW Km^{-2} range [5].
[d] The hub height refers to the height of the rotor above the ground. This term is also referred to as rotor height. Many previous assessments have assumed hub heights within the 70–100 m range [5].

financing costs. This means that only part of the technical potential can be cost-competitive depending on production costs, which defines the economic potential [6, 8, 16]. (supplementary notes 3–9 provide more details, including the equations used to calculate RE potentials, and the supply curves implementation in GCAM.)

2.3. Characterizing parametric uncertainty

This study seeks to assemble the range of parametric assumptions made in published global assessments of wind and solar energy potentials, and to explore the implications of this parametric uncertainty for wind and solar deployment projections from GCAM. We surveyed the literature (orange box in figure 1) to define defensible parameter ranges for a set of 'Central' and key 'sensitivity' cases. Note that although this is not a formal sensitivity analysis, we use the term 'sensitivity' cases to refer to the technical potential cases analyzed in this study. The parameter values for the *Central* cases are taken from the Eurek *et al* [18] and Rinne *et al* [5] studies in the case of wind potential, and from Gernaat *et al* [2] in the case of solar potential. Central case values do not necessarily reflect the mid-range values across the literature. Rather, they are intended to serve as a benchmark for comparison against a diverse set of sensitivity cases, which represent a wide range of parameter assumptions that have been employed in the literature.

Assessing the variability in wind and solar potentials and deployments that emerge from differences in parametric assumptions across studies achieves two purposes. First, assessing the magnitude of variability in key outcomes that emerges from variability in parameter assumptions helps to characterize the magnitude of the challenge facing the modeling community, providing context around how to prioritize future studies. Second, identifying which parameters may be more significant contributors to uncertainty can help the research community identify priorities for reducing uncertainty. Although a rigorous sensitivity analysis is beyond the scope of the present study, our results provide valuable inputs to future sensitivity analyses in the form of parameter categories and value ranges.

Using the methodology detailed in supplementary notes 3–9, the wind and solar PV technical potentials (see blue boxes in figure 1) are calculated for the cases listed in tables 1 and 2. Specifically,

Table 2. Parametric assumptions for all technical potential cases (see blue boxes in figure 1) analyzed for the solar PV[a] technology. (Supplementary notes 3–9 provides details on how these assumptions affect the computation of the RE potentials.)

Parameter assumption	Case label	Reference	Value
Performance ratio (PR) [b]	Central	Gernaat *et al* [2]	0.85
	PR_75	Deng *et al* [24]	0.75
	PR_90	Used to understand implications from higher assumptions[c]	0.90
Suitability factors	Central	Gernaat *et al* [2]	See supplementary note 4
	S_low (low suitability I)	Deng *et al* [24](low case)	
	S_low_II (low suitability II)	Deng *et al* [24](medium case)	
	S_high (high suitability)	Dupont *et al* [19]	
Land use factor (η_{LPV}) [d]	Central	Gernaat *et al* [2]	0.47
	Nlpv_20	Deng *et al* [24]	0.20
	Nlpv_30	Deng *et al* [24]	0.30
	Nlpv_100	Hoogwijk [7]	1.0

[a] The solar PV technology that this study focuses on refers to utility-scale systems, i.e. large-scale power plants.
[b] Expresses the ratio between the actual output of the PV system and the performance under standard test conditions (i.e. standardized set of conditions under which solar panels are tested) to account for the overall efficiency losses within any PV system.
[c] No reference found for a value higher than the Central case.
[d] Refers to the fraction of the suitable grid cell area actually covered by PV panels (for example, η_{LPV} accounts for the spacing between the panels).

tables 1 and 2 define for wind and solar PV, respectively: the cases explored for each parameter assumption, the values that define each case, and the literature consulted to identify the values. Supplementary note 4 provides more details about land suitability factor assumptions in particular, which affect the geographical potential. For the 'Suitability factors' cases, the subsequent technical potentials are computed using *Central* assumptions. Supplementary note 7 shows that the technical potentials computed under the *Central* case are within the range of results obtained by prior global studies.

2.4. Scenarios

The effects of the implementation of supply curves produced from the distinct technical potential estimates are analyzed in the context of the forward-looking scenarios constructed using GCAM described in table 3.

3. Results and discussion

3.1. Land suitability and wind power density assumptions create substantial uncertainty in global RE technical potential estimates

Figures 2(a)–(c) summarize the strong effect of distinct parameter assumptions on the quantification of wind and solar PV technical potentials, respectively, by comparing the changes associated with each case with the *Central* cases. Land-use parameters (i.e. suitability and solar PV land-use factors) play critical roles in these changes. The wind potential is also strongly influenced by the choice of the average turbine installation density, with the high power density case (13 MW Km^{-2}) showing the largest deviation from the central assumption. The wind power computation approach is also important. Our results contrast the effect of the combination of a modern turbine (Vestas V136-3.45—a 2015 technology according to 'The Wind Power' database—www.thewindpower.net) and a taller hub height (125 m), as assumed in the *Central* case, against a past (2004) technology (V90-2.0 MW) placed at a lower hub height (75 m). The latter leads to ∼30% reduction relative to the *Central* case. The other assumptions show considerably lower relative changes than land-related parameters. However, the low hub height assumption (75 m) leads to non-trivial reductions in wind potential of ∼17%.

3.2. Uncertainty in RE potential estimates are reflected in the projected global wind and solar PV electricity generation

When supply curves produced from all technical potential cases are implemented in GCAM, the corresponding changes in the 2100 global wind and solar PV electricity generation reproduce the patterns of change in the input potentials (figures 2(b)–(d)). As one might expect, technical potential cases with the largest deviations from *Central* assumptions result in the largest changes in generation, which can be very pronounced depending on the case. For example, one of the low suitability cases of wind (*low suitability II*) results in very large reductions in generation ranging from 58% to 73% depending on the GCM input and scenario. Additionally, negative changes in

Table 3. Scenarios explored in this study.

Scenario	Description [a,b]
Reference_NoCI	This reference scenario assumes a 'reference' set of socioeconomic and technological assumptions. It is constructed as a 'middle-of-the-road' scenario to compare scenarios constructed with alternative assumptions. Broadly, our reference scenario captures inertia in various systems in the near-term; however, in the long term, outcomes are largely driven by economic forces. This scenario assumes no climate impacts on wind and solar, utilizing supply curves derived from technical potentials calculated using climate forcing data taken from a historical time period, defined here as the 1971–2000 period, throughout the entire simulation.
Reference_CI	This scenario is similar to Reference_NoCI, but it includes climate impacts on wind and solar, utilizing supply curves derived from technical potentials calculated using climate forcing data[c] from the RCP8.5.
RCP2.6_NoCI	In this scenario, the end-of-century radiative forcing reaches 2.6 W m^{-2} (consistent with a 2 °C scenario). This scenario explores a low carbon future in which intermittent renewable energy—along with other low carbon technologies such as nuclear, and carbon capture and storage (CCS)—is deployed at larger scale compared to the above two scenarios. To achieve the target, the model iteratively solves for the global carbon price pathway needed. This scenario assumes no climate impacts on wind and solar, utilizing supply curves derived from technical potentials calculated using climate forcing data taken from a historical time period, defined here as the 1971–2000 period, throughout the entire simulation.
RCP2.6_CI	This scenario is similar to RCP2.6_NoCI, except that it includes climate impacts on wind and solar, utilizing supply curves derived from technical potentials calculated using climate forcing data[c] from the RCP2.6.

[a] The supply curves (varying by climate impact assumptions) are implemented individually by renewable technology. This means that when a supply curve is implemented for wind, the GCAM default assumptions are kept for solar and vice-versa.
[b] The scenarios do not account for climate impacts on other renewable sources such as biomass and hydropower or in water availability. This is an illustrative scenario framework that aims to help understand the effects of the uncertain supply curves on the GCAM assessment of climate impacts on wind and solar power generation.
[c] For the climate impacts (CI) scenarios, supply curve assumptions change over time and are implemented for the periods 2011–2040, 2041–2070 and 2071–2099 based on the 30 yr average potentials of each period. This is in line with the Gernaat *et al* methodology [2].

electricity generation are more prominent than positive changes, even for a very large increase in potential like in the high suitability case of solar PV. This is because GCAM imposes limitations to the deployment of wind and solar capacities to account for the added cost of managing the inherent intermittency of these resources (see Santos da Silva *et al* [3] for details on these 'intermittency' cost assumptions).

3.3. Parametric assumptions play a larger role in compounding the uncertainty in the projected global wind and solar PV electricity generation than climate data and scenarios

An examination of figure 2 shows that the general sensitivity patterns reported there are robust across RCPs, climate forcings and scenarios. This is corroborated by supplementary figure 10, which presents technical potential and electricity generation change results for the historical period (1971–2000) and the no climate impacts '*NoCI*' scenarios, respectively. This figure unveils similar patterns of sensitivity to the ones reported in figure 2. These results suggest that parametric uncertainty in mathematical formulations used to estimate RE potentials are more critical to understand than those emerging from climate models and scenarios. Also, they indicate the issue of uncertain RE potentials as a focus of attention for future efforts aiming to strategically minimize uncertainties in long-term RE projections.

3.4. Sensitivity of regional RE technical potentials to parametric uncertainty is consistent with global patterns with land suitability cases showing strong regional variation

Here we focus on results for the historical period of the GFDL-ESM2M model since the qualitative insights of this discussion are not affected by the choice of climate data. (supplementary figures 11–18 provide the technical potential case results for the four ISIMIP2b GCMs, two RCPs, and two periods (1971–2000 and 2071–2099), demonstrating no major effects on the patterns of sensitivity presented).

Overall, the regional patterns of changes in technical potentials (relative to the *Central* case) are consistent with the global results (figures 3(a) and 4(a)). While changes in certain parameters affect the computation of technical potentials equally in all regions (e.g. power density, performance ratio and solar PV land use factor), effects from other sensitivity cases vary regionally with some of them displaying strong variation (notably the suitability cases).

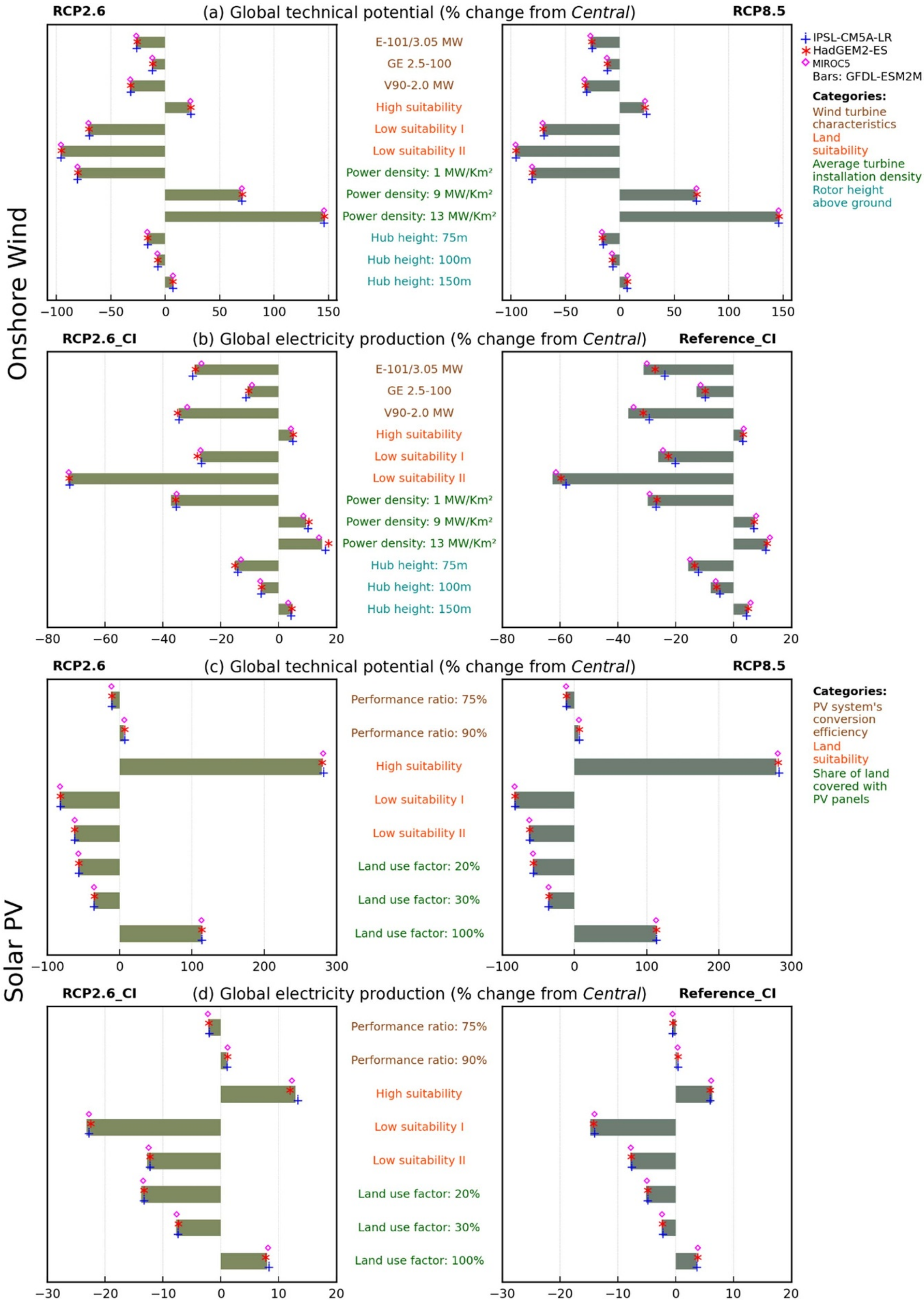

Figure 2. (a) Changes in the global onshore wind technical potential relative to the *Central* case. Technical potentials are computed for the 2071–2099 period under RCP2.6 and RCP8.5 forcing scenarios. (b) Changes in the global wind power generation in 2100 under the climate impact *'CI'* scenarios described in table 3. Changes are relative to a GCAM simulation using supply curves produced from the *Central* technical potential case. (c) As in (a) but for the global solar PV technical potential. (d) As in (b) but for the global solar PV power. See supplementary figure 10 for similar technical potential and electricity generation results for the historical period (1971–2000) and under the *'NoCI'* scenarios, respectively.

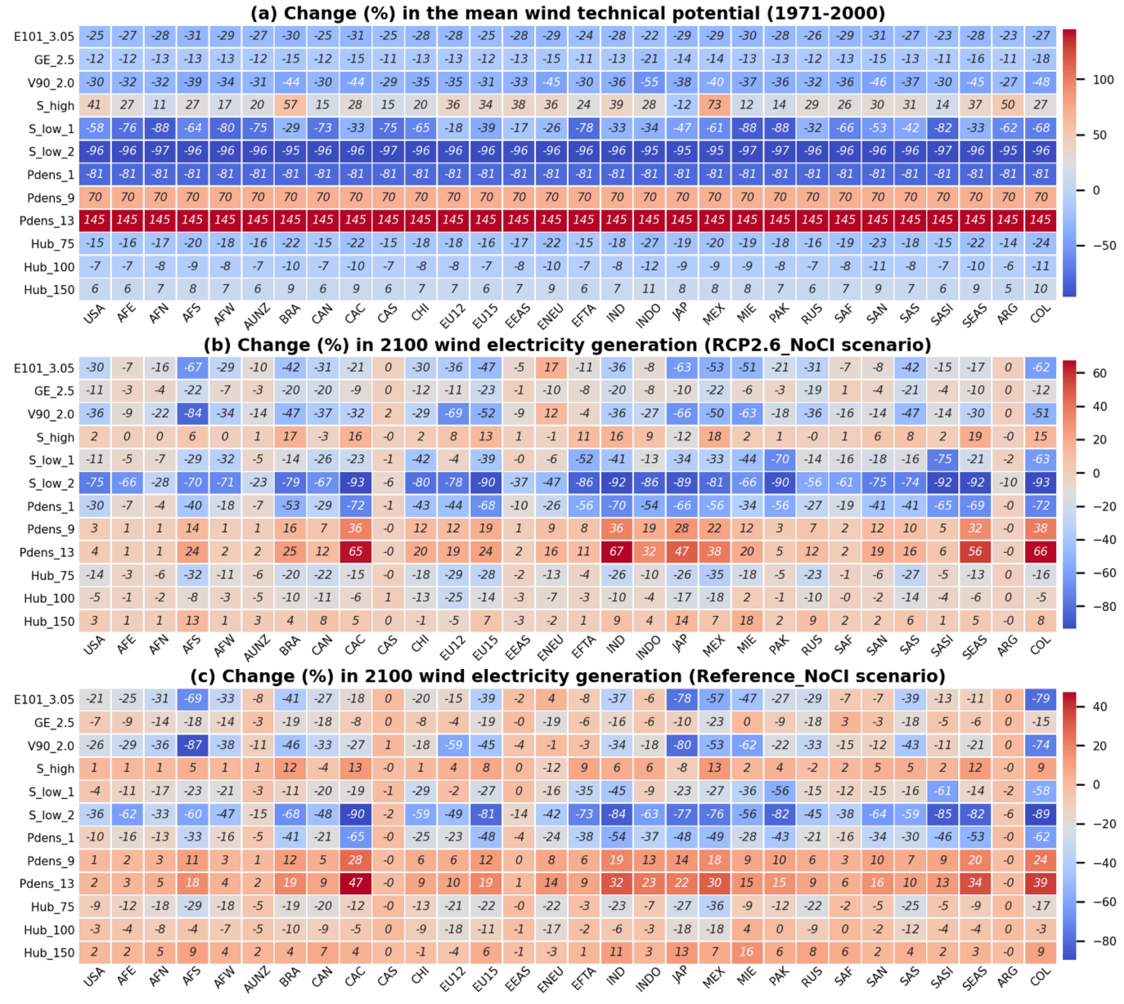

Figure 3. (a) Relative changes in onshore wind technical potential from *Central* assumption by GCAM region (input data: GFDL-ESM2M model—1971-2000). (b) Relative changes from the *Central* case in onshore wind electricity production in 2100 (*RCP2.6_NoCI* scenario). (c) As in (b) but for the *Reference_NoCI* scenario. See supplementary table 13 for the definition of each GCAM region abbreviation presented on the *x*-axis. *Y*-axis corresponds to the case labels presented in table 1. (Note that this study excludes two GCAM regions: Taiwan and South Korea. In these regions, the spatial resolution of this analysis (0.5 degree) does not allow for a sufficiently large number of data points to produce a supply curve in all technical potential cases.)

3.5. As in the global situation, sensitivity of regional electricity production to parametric uncertainty is large and scenario-independent, but displays strong regional variation

As in the global results, the sensitivity of the regional onshore wind and solar PV power to the parametric assumptions is large and scenario-independent, but the resulting changes from the *Central* case vary substantially by region (figures 3 and 4(b) and (c)). This marked regional variation is determined by two factors: (a) the ratio between electricity demands and the technical potentials embedded in the supply curves, and (b) the effect of the shifting supply curves on regional power-sector market competition. The first factor means that in regions where electricity demand is high compared with the available technical potential, differences among the distinct supply curves are more pronounced, which contributes toward larger differences in electricity generation. Conversely, with low ratios between electricity demands and technical potentials, the effects from the shifting supply curves originate from the lower ends of the curves where differences among the curves are smaller. The second factor relates to how the supply curves associated with distinct RE potentials affect competition across electricity generation technologies. Higher/lower availability of the intermittent renewable resource represented in the supply curves affect the total cost of the renewable technology in GCAM. This in turn affects the economic competitiveness of wind and solar relative to other power-sector technologies (See supplementary note 8 and Santos da Silva *et al* [3] for further details).

3.6. Wind and solar PV can gain or lose importance compared to other technologies due to parametric uncertainty

A key insight from figures 3 and 4 is that the role of intermittent renewable generation in scenarios could

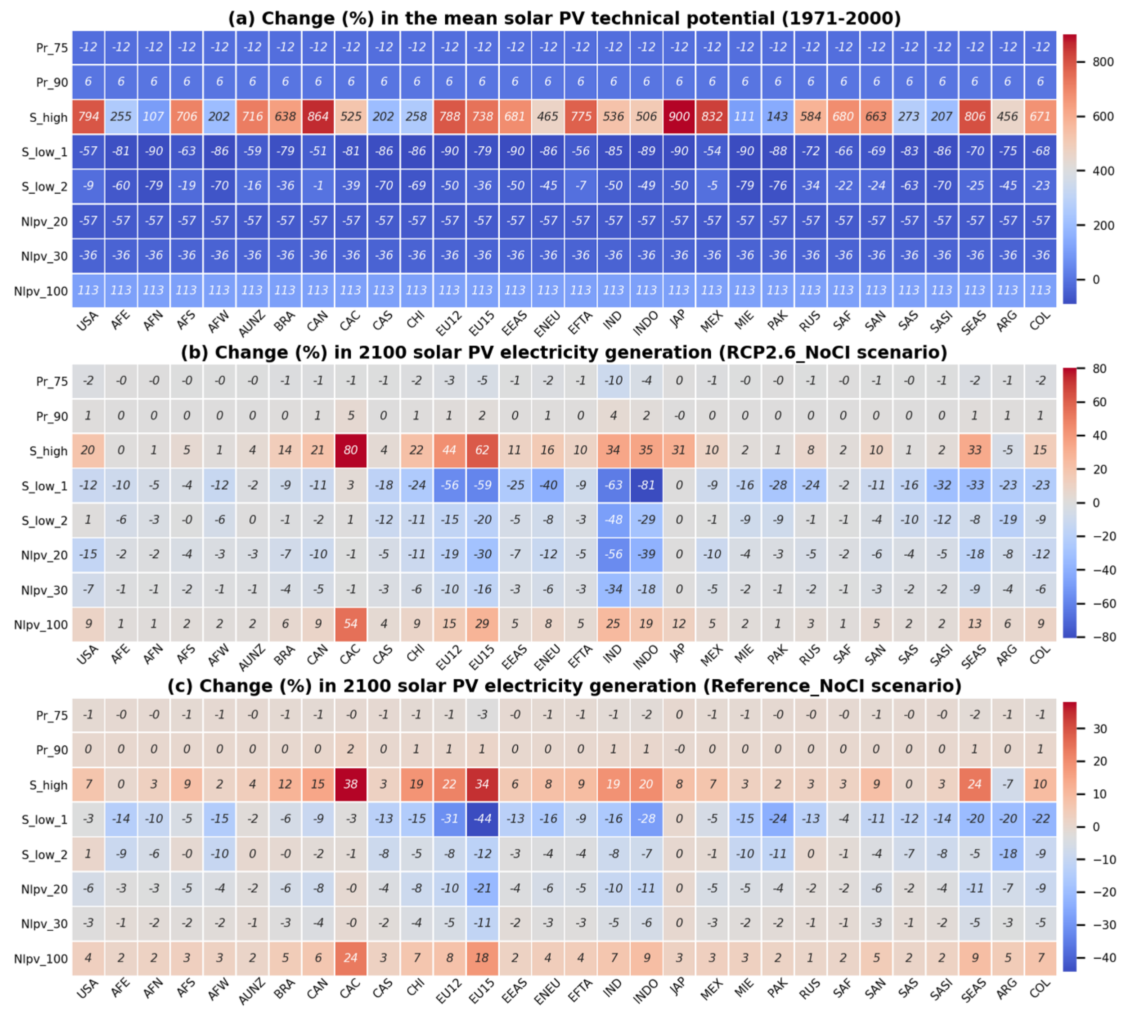

Figure 4. (a) Relative changes in solar PV technical potential from *Central* assumption by GCAM region (input data: GFDL-ESM2M model—1971-2000). (b) Relative changes from the *Central* case in solar PV electricity production in 2100 (*RCP2.6_NoCI* scenario). (c) As in (b) but for the *Reference_NoCI* scenario. See supplementary table 13 for the definition of each GCAM region abbreviation presented on the *x*-axis. *Y*-axis corresponds to the case labels presented in table 2.

be considerably under- or over-estimated relative to other technologies in some regions depending on the technical potential case. Thus, this is an important uncertainty to consider in studies exploring the future evolution of the power sector and its interactions with other systems. As GCAM balances electricity supplies and demands, reduced intermittent renewable generation results in increased deployment of other technologies, whereas the upscaling of wind and solar capacities diminishes the market share of other technologies. In other words, wind and solar can lose or gain importance in GCAM scenarios. This is further illustrated in supplementary note 10, which reports the changes in the mix of power-sector technologies under some selected wind and solar PV sensitivity cases and scenarios that differ with respect to the low-carbon strategy. Independently of the scenario's low-carbon strategy, any gains or losses in wind/solar PV generation due to the parametric uncertainty affects the projected mix of power-sector technologies. For scenarios that consider reductions in greenhouse gas emissions, such as the *RCP2.6* scenarios, this affects, in particular, the mix of low-carbon technologies, whereas for scenarios in which greenhouse gas emissions are unconstrained, like the *Reference* scenarios, there are important effects on the mix of fossil fuel technologies. For example, for the *Reference* scenario, supplementary note 10 shows that lower wind power generation forces the model to place higher emphasis on carbon-intensive technologies (typically less capital intensive than low-carbon technologies). Hence, our results suggest challenges for the decision-making on questions such as the definition of robust long-term energy strategies or the planning of power sector infrastructure investment needs that depend on power generation projections.

3.7. Implications for the analyses of climate impacts on intermittent renewable generation: effects of parametric uncertainty in RE potential estimates are more significant than uncertainties associated with climate model projections

Our assessment of the projected multi-model mean (%) changes in the end-of-century (2071–2099)

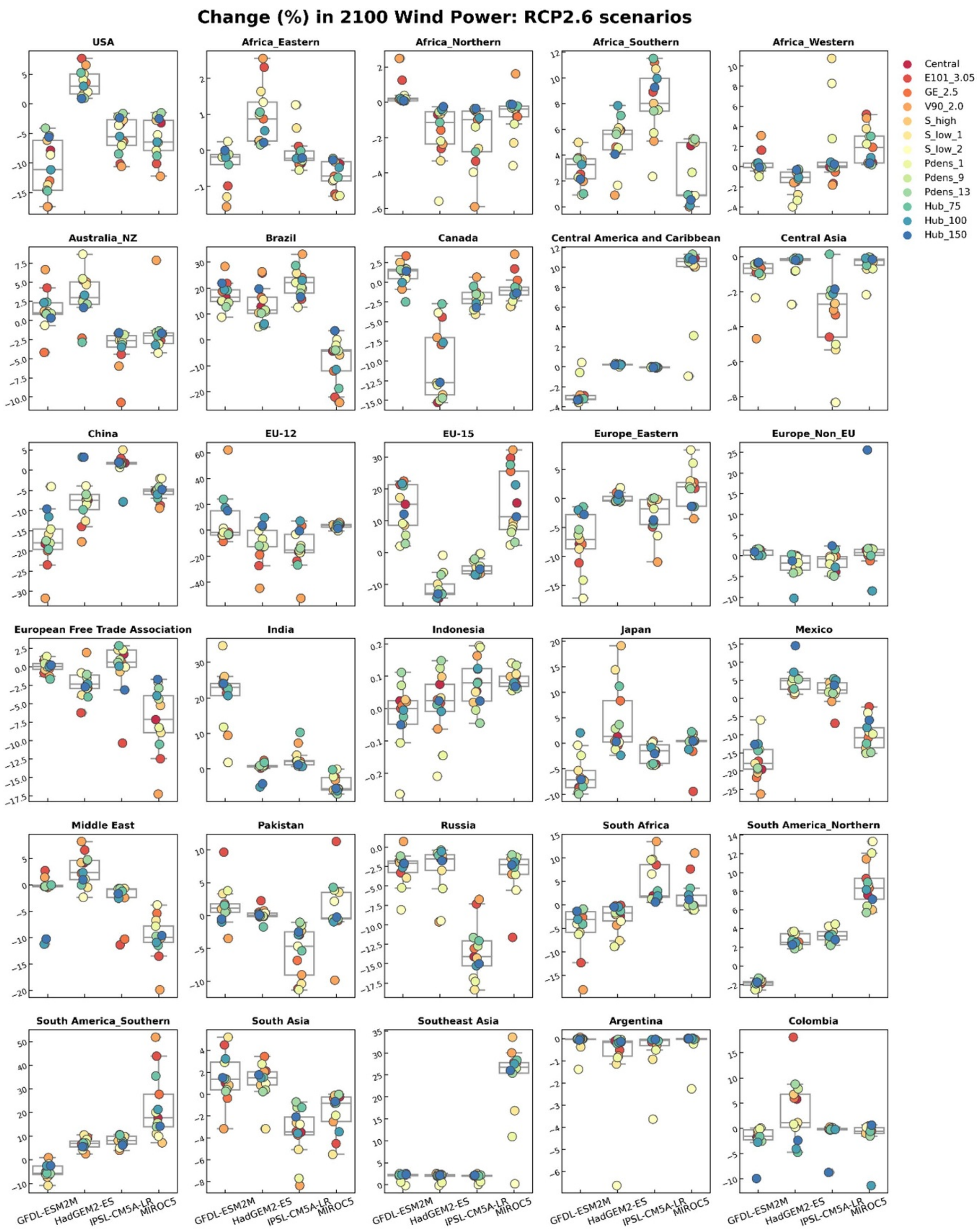

Figure 5. Regional changes (%) in 2100 wind power generation: *RCP2.6_CI* scenario relative to the *RCP2.6_NoCI* scenario (y-axis) by GCM forcing (x-axis). See supplementary figure 21 for similar results under the *Reference* scenarios. Note that the legend uses the sensitivity case labels presented in table 1.

wind, and solar PV technical potentials from the historical period indicates modest climate impacts at the global scale, which corroborates prior literature [2, 26] (supplementary tables 14 and 15). At the regional scale, we found that the projected changes in the wind resource are in general more pronounced than changes in solar PV energy (supplementary figures 19 and 20), which agrees with the recent analysis by Gernaat *et al* [2] (also based on ISIMIP2b GCMs) and with prior studies [27–29]. Figures 5 and 6 provide insights into the issue of how the uncertain RE potential estimates may interfere with model-based assessments of climate impacts on intermittent RE production. Specifically, these figures report relative changes (%) in wind and solar PV electricity generation, respectively, by sensitivity case and GCM forcing for the climate impacts scenario (*RCP2.6_CI*) relative to the no climate impacts situation, i.e. *RCP2.6_NoCI* scenario in 2100 (supplementary figures 21 and 22 provide the results for the *Reference* scenarios, demonstrating similar qualitative insights as figures 5 and 6). It can be noted that

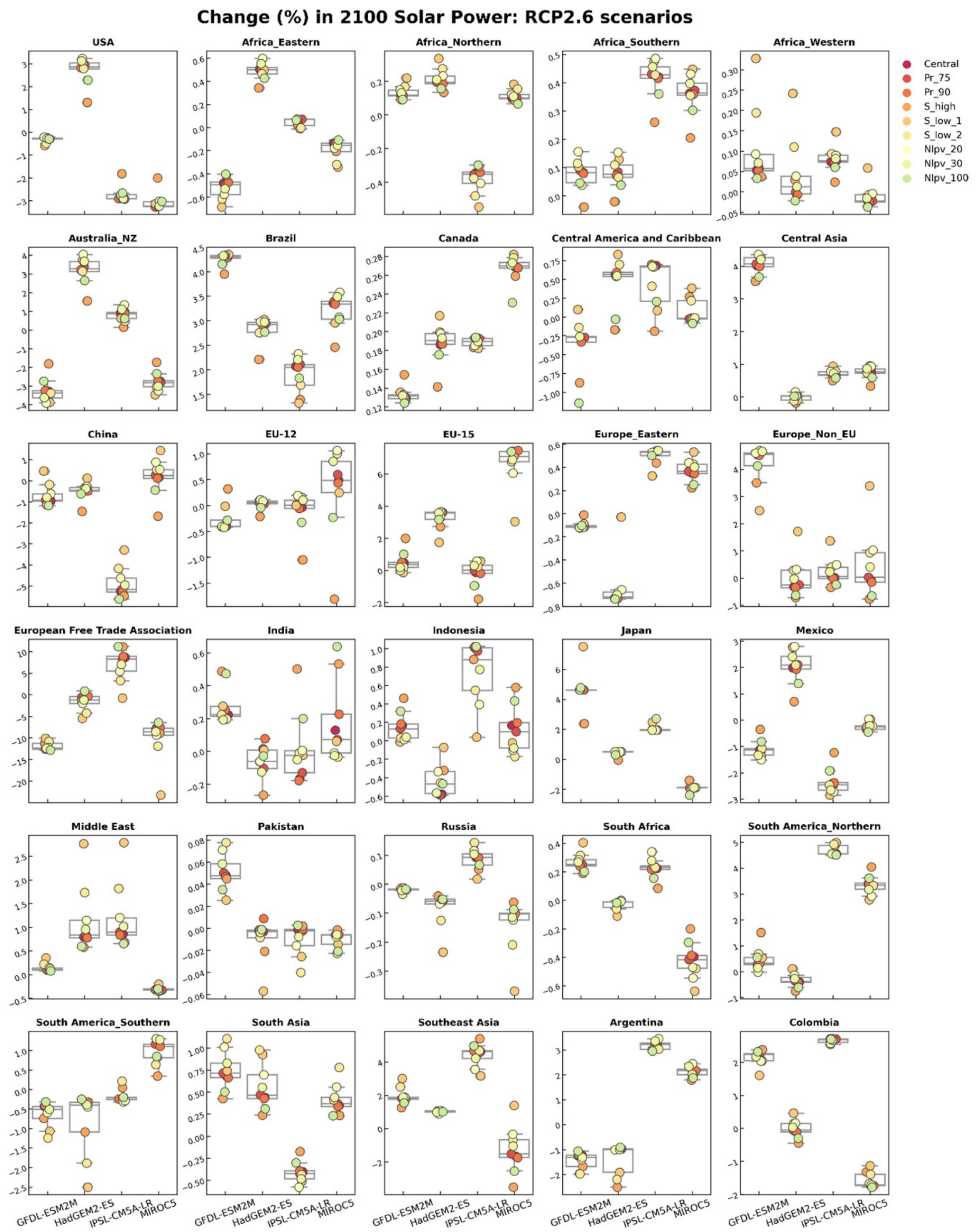

Figure 6. Regional changes (%) in 2100 solar power generation: *RCP2.6_CI* scenario relative to the *RCP2.6_NoCI* scenario (y-axis) by GCM forcing (x-axis). See supplementary figure 22 for similar results under the *Reference* scenarios. Note that the legend uses the sensitivity case labels presented in table 2.

the resulting changes in GCAM electricity generation vary largely for similar GCM forcings due to the parametric uncertainty. However, these effects vary substantially from region to region. For wind power, relevant effects are seen in certain regions such as the USA, in which changes range between ∼−3% and −20% considering the GFDL-ESM2M model, or in the EU-15 region with changes ranging between ∼0% and 35% for the MIROC5 (figure 5). On the other hand, effects from the uncertain supply curves are not relevant in regions such as Indonesia.

The overall changes in 2100 solar electricity production tend to be lower than those in wind power because of the less pronounced climate impacts on solar mentioned above (figure 6). Hence, the effects from the varying supply curves, although evident in figure 6 and supplementary figure 22, tend to be less impactful than in wind. For example, in the USA, the changes in solar power considering the GFDL-ESM2M model and *RCP2.6_CI* scenarios range between ∼0% and −1% considering all cases, which is considerably narrower than the range found for wind (figure 6). However, in some regions where the overall changes associated with the GCM forcings are more pronounced (e.g. European Free Trade Association), there are important changes in generation due to the parametric effect.

Figures 5 and 6 (and supplementary figures 21 and 22) also contrast the effects from uncertainties due to GCM projections against those from the supply curves. There are large differences in the projected changes in generation due to the GCM choice. This can be illustrated with the case of the EU-15 region for wind (figure 5). It is seen that the GCM choice markedly shifts the distributions with two GCMs projecting positive effects whereas the other two indicate negative impacts. This lack of agreement creates ambiguity with respect to the direction of the climate change impact. As with the effects associated with GCM uncertainty, parametric uncertainty remains similarly significant. As noted above these effects are large for some regions, particularly for wind power. This is the case for India in the *RCP2.6* scenarios (figure 5). In this region, the wind power change projections from GFDL-ESM2M reveal a wide range of outcomes associated with the technical potential cases (∼0% to 35%), which is larger than the differences across all GCMs.

Our results then suggest that the uncertainty issue in RE potential estimates incorporated in energy-sector climate impact assessments translates into a range of potential gains and losses in wind/solar PV electricity generation for the same climate forcing. As a consequence, for any given region, GCAM will have to balance these changes in generation by addition or retirement of generation capacity although this pattern will depend on the scenario's low-carbon strategy (since carbon prices affect the costs of power-sector technologies). In the case of negative climate impacts, for example, there may be challenges to assess the future climate adaptation effort needed in the energy sector depending on the range of potential losses in generation.

4. Conclusions

This study demonstrates that onshore wind and solar PV power projections from an integrated global model of the coupled human-earth system (GCAM) are markedly affected by the uncertain assumptions about parameter values used to quantify the wind and solar technical potentials. Specifically, we have developed a framework to produce distinct estimates of onshore wind and solar PV global technical potentials using varying key parametric assumptions collected from the literature to compute these potentials. These various technical potential cases were used to produce supply curves that were implemented in GCAM to assess the consequences for intermittent renewable electricity generation. Overall, we find that the choice of parameters related to land-use largely influences technical potential estimates and electricity generation projections. In the case of wind, the average turbine installation density and turbine technology are highly influential as well. We also highlight important implications for analyses of climate change impacts on wind and solar energy. In general, we find that the extent to which uncertainties in resource estimates may interfere with the analyses of climate impacts on intermittent renewables relates to the severity of the climate impact. In our study, scenarios that account for climate impacts on wind (as opposed to solar) are more affected. We also find that the effects of parametric uncertainties in technical potential estimates on RE electricity generation are far more significant than the uncertainties associated with climate model projections. Hence, future model-based investigations of climate impacts on intermittent RE relying on the implementation of climate-impacted supply curves in their methodology will need to consider the uncertainty coming from the RE potential estimates embedded in the supply curves apart from the well-known uncertainty from climate models.

Concerning our results, we acknowledge that the technical potential estimates produced in this study may be underestimated because of the temporal resolution (daily data) of our input climate data (ISIMIP2b), which cannot resolve the high-frequency hourly wind speed variations. However, this possible underestimation has no implications for the main qualitative insights of the study, i.e. the large effect of the parametric uncertainty on wind and solar PV projections, which are independent of the climate dataset used. Similarly, the key insights of the paper are independent of the selection of parameters for the *Central* case. A different set of assumptions for the *Central* case would have modified the magnitudes of RE potentials for the *Central* case as well as the magnitudes of differences relative to the other sensitivity cases, but not the qualitative insights. Lastly, we note that, although produced from GCAM, our results have broader implications for similar models that rely on supply curves to model wind and solar resource availability and production costs.

The ensemble of technical potential cases investigated in this analysis were produced based on a literature review, which identified a list of main parametric assumptions used to compute wind and solar PV technical potentials in prior studies. This survey by itself constitutes an important contribution to the scientific community since it can help to guide future formal sensitivity, uncertainty, and scenario discovery analyses (e.g. Lamontagne *et al* [30]). Our results can feed directly into these large ensemble exercises through the supply curves as an additional form of uncertainty. Rather than considering all of the parameters that affect wind and solar technical potential estimates, we have narrowed down the list of parameters to the most important ones.

However, we acknowledge that the list of parametric assumptions considered in this study is by no means exhaustive and could be expanded in future studies. Examples of parameters not considered include array availability, array efficiency and the power-law exponent in the case of wind and panel efficiency in the case of solar PV (supplementary notes 5–6 show how these parameters affect the computation of wind and solar PV technical potentials). Future studies could also expand this analysis to other generation technologies not covered here such as solar CSP, solar rooftop PV and offshore wind. Moreover, the methodology to assess land suitability could be further refined by accounting for the access to transmission lines, which was not considered in this study. This is of particular relevance for those remote and/or desert areas away from the transmission lines. Another methodological improvement that can be made in future work is to consider the fact that many of the parameter values assumed in our study are expected to evolve over time (e.g. solar PV panel, turbine technologies) since we have assumed static values only. The climate impacts dimension of the scenarios analyzed in this study focuses on wind and solar for a specific analysis of the interplays between climate impact assumptions on these sources and the uncertainty stemming from the supply curves. Future work could include climate impacts on the other renewables, i.e. agricultural crop yields that affect biomass availability and water supply that affects hydropower production. This will help to understand if, within a context of multiple and simultaneous impacts, the effects from the parametric uncertainty on wind and solar projections might be dampened or exacerbated. Future research could also compare the relative impacts on wind and solar production from parametric uncertainty related to resource potentials with technology cost improvements or policy incentives (including feed-in tariffs or other subsidies) that are not accounted for in our approach.

Our results underscore the need of careful consideration of the parametric choice in RE potential estimates. However, narrowing this type of uncertainty is a difficult undertaking. Prior studies [5, 20, 24] have emphasized the quality of the datasets used, pointing out the need of high-resolution datasets and analyses. In this regard, we acknowledge that this study is conducted at relatively low spatial resolution (0.5° spatial resolution), which is sufficient to support the points raised in this article.

Even with the use of high-resolution/high-quality datasets, certain assumptions will continue to be highly uncertain, such as the land suitability factors. As seen in the results, the assumptions concerning suitability factors are highly influential, but there is no methodology to derive them. These factors have been derived based on authors' judgement. Indeed, even recent analyses [2, 18, 20] use suitability factors from studies published in the 2000s highlighting the difficulty to develop more precise approaches. To try to improve upon this uncertainty issue, recent RE technical potential estimates [5, 24] have defined distinct land-use scenarios. This could be considered the path forward for the other influential parameters. However, a deeper understanding of the implications of this uncertainty issue for global assessments of electricity system projections will require sampling of a broader range of technical potential cases than those explored in this study within a formal sensitivity analysis. The results then suggest the need for a dialogue within the research community that might result, for example, in a subsequent intercomparison exercise using models with varied representations of energy systems since the methodology employed in this study can be implemented in other models.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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