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Uncertainty analysis of the future cost of wind energy on climate change mitigation

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Abstract
We conduct uncertainty analysis on the impacts of the future cost of wind energy on global electricity generation and the value of wind energy to climate change mitigation. We integrate data on global onshore and offshore wind energy cost and resources into the Global Climate Assessment Model (GCAM), and then propagate uncertainty based on distributions derived from an expert elicitation study on the future cost of onshore and offshore wind energy. The share of wind energy electricity generation in 2035, without a global policy on CO2 emissions, ranges between 4% and more than triple the 2019 share of 5.3%. Under a 1.5°C cap, this range is wider, with shares up to 34%. This range of uncertainty implies the need for flexible systems and policies, allowing large amounts to be deployed if needed. We explore whether a breakthrough in wind energy could prevent the demand for natural gas as a bridge technology to a low carbon economy, and find that uncertainty in wind energy is only pertinent for medium-stringency policies, such as a $60/t carbon tax. Under this scenario, there is a 95% chance that the cost of wind energy will be low enough to lead to an immediate reduction in the share of natural gas. In contrast, under a business-as-usual scenario without a breakthrough in cost, natural gas is highly likely to continue increasing in share of electricity generation. Under a 1.5°C cap, natural gas will decrease in share regardless of wind energy cost.

Keywords Wind energy · Climate change mitigation · Uncertainty · Cost · IAM

1 Introduction

In the 2015 Paris Climate Agreement, the power sector was identified for emission reduction by nearly all countries (UNFCCC 2015). Policymakers faced with the challenge of

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decarbonizing the sector in the face of climate change, and rising demand for electricity, must manage significant uncertainty about the future cost of low carbon energy technologies, deployment of new technologies, and global climate policy.

Wind energy has emerged as one of the fastest-growing electricity-generating technology. The overall capacity of all wind turbines installed worldwide by the end of 2019 reached 650.8 GW, capable of meeting 5.3% of global electricity demand (WWEA 2020). In just a decade, we have seen a 300% increase in global installed wind capacity (WWEA 2012). According to BloombergNEF (Mathis 2019), wind energy has seen a total of $1 trillion investment from 2010 through 2019. In that time, onshore wind saw a 43% decrease in cost, while offshore wind decreased by 51% in cost. Despite the increasing maturity of wind technology and the scale of global wind resources, uncertainty remains around the future cost of wind energy. This prompts a key policy question: how does the future cost of wind energy impact the global electricity generation and the role that wind energy could play in decarbonizing the electricity sector? Of importance to policymakers is understanding how a breakthrough, or a failure, in the technology could affect the energy sector, as well as the future costs of decarbonization.

Several papers have looked at the potential wind energy resource around the world that could be harnessed for electricity generation (Elliott et al. 1991; Lu et al. 2009; Zhou et al. 2011, 2012). A report by the Intergovernmental Panel on Climate Change (IPCC) shows wind's global contribution to electricity supply in 2050 could reach a share of 13–14% in the median climate change mitigation scenario (Wiser et al. 2011), while the Global Wind Energy Council has an even higher estimate, ranging from 17 to 31% by 2050 (GWEC 2017), and the International Energy Agency (IEA) estimates a range of 6–15% by 2040 (IEA 2017). Barthelmie and Pryor (2014) showed that depending on the precise climate forcing scenario, a moderate wind energy deployment by 2050 could delay crossing the 2° warming threshold by 1–6 years, and aggressive deployment could delay 2° warming by 3–10 years. These articles are based primarily on global wind resource potential. How uncertainty in the future cost of wind energy could affect these outcomes is not considered.

To model uncertainty in the cost of wind energy, we used data from a large-scale expert elicitation conducted by (Wiser et al. 2021) on the future cost of onshore and offshore wind energy. Expert elicitation is a structured process for eliciting subjective probability distributions from subject-matter experts. Unlike learning or experience curves, which rely on past trends to predict future trajectories, expert elicitation is able to characterize uncertainty around future technology cost and performance (Verdolini et al. 2018). The IPCC AR5 (Kunreuther et al. 2014) recommended expert elicitation for the characterization of uncertainty to provide insights into specific risks and to understand and design meaningful strategies and policies for dealing with climate change. In 2015, Wiser et al. (2016) conducted an earlier expert elicitation survey, concluding that there exist many possibilities for cost reduction despite significant uncertainties. The result of the updated 2020 elicitation of 140 global wind experts shows even more possibilities for further cost declines amid significant uncertainties (Wiser et al. 2021). For instance, experts predict 50% lower future costs for onshore and offshore wind than they did in 2015. We focus on uncertainties in wind energy cost and how this impacts climate change mitigation and electricity generation from other competing technologies.

The rest of the paper is organized as follows. In Section 2, we describe our methods, starting with a discussion of how the expert elicitations are aggregated into probability distributions. We then describe implementing the data into the Global Change Assessment Model (GCAM), focusing on how the wind energy supply curves are created. In Section 3, we describe the results of the simulation and conclude in section 4.

2 Method

Figure 1 provides an overview of the steps in our implementation. The first oval represents the probability distributions from the expert elicitation. The rounded rectangles represent the key steps in the process, starting with aggregating the expert beliefs about the future cost of wind energy for each of the three technologies—onshore, and fixed and floating offshore—from expert elicitation by (Wiser et al. 2021). We draw random samples of the technology cost from the aggregated distributions and use these to create a sample set of wind energy resource curves. We run GCAM across the sample set under three climate policies, including business as usual, a moderate carbon tax, and a stringent temperature cap. The second oval represents probability distributions over outputs of interest, including abatement costs, electricity generation by technology, and global mean temperature.

2.1 Aggregating expert elicitations

The Wiser et al. (2021) expert elicitation included 140 global wind energy experts who provided estimates for capital costs at the 10th, 50th, and 90th percentiles for the three wind applications. We aggregate the capital costs into three independent probability distributions for onshore, fixed bottom, and floating offshore wind technologies. The expert elicitations provide no information on possible correlations between the technologies. The technologies are not perfectly correlated, as the gaps between the different types of technologies narrow through time. There is likely some degree of correlation; however, we have assumed independence given the dearth of information. We used the percentiles to fit each expert elicitation to a triangular distribution, as shown in Fig. 2. We then average the triangular distributions across all experts to get a single empirical distribution for each technology and then fit that to a theoretical distribution. See supplementary information for details on estimating the triangular distributions.

We use simple averaging probabilities to aggregate the probability densities of the triangular distributions across the experts into a single empirical distribution for each technology. The simple averaging of probabilities has been found to be robust, straightforward, and as good as averaging quantiles (Rantilla and Budescu 1999). Specifically, we average the probability densities at 0.1-dollar intervals to create the empirical distributions. The empirical distributions for each wind technology are fitted to a theoretical distribution function using maximum likelihood estimation. We considered lognormal, uniform, gamma, normal, and Weibull distributions. The lognormal distribution gave the best fit for all three distributions.

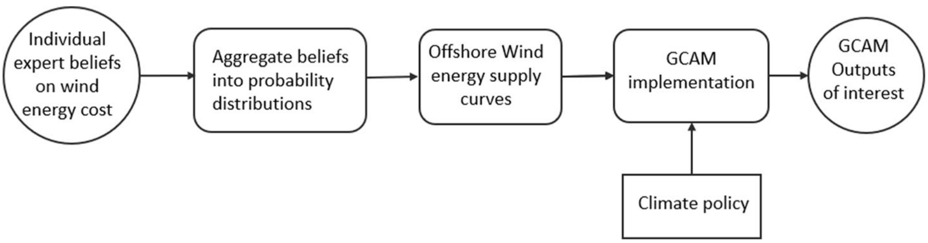

Fig. 1 A schematic diagram of the implementation of the expert elicitation into GCAM. The first oval represents the probability distributions from the expert elicitation; the rounded rectangles represent the key steps in the process. The rectangle represents different climate policies, and the second oval represents the distribution over outcomes

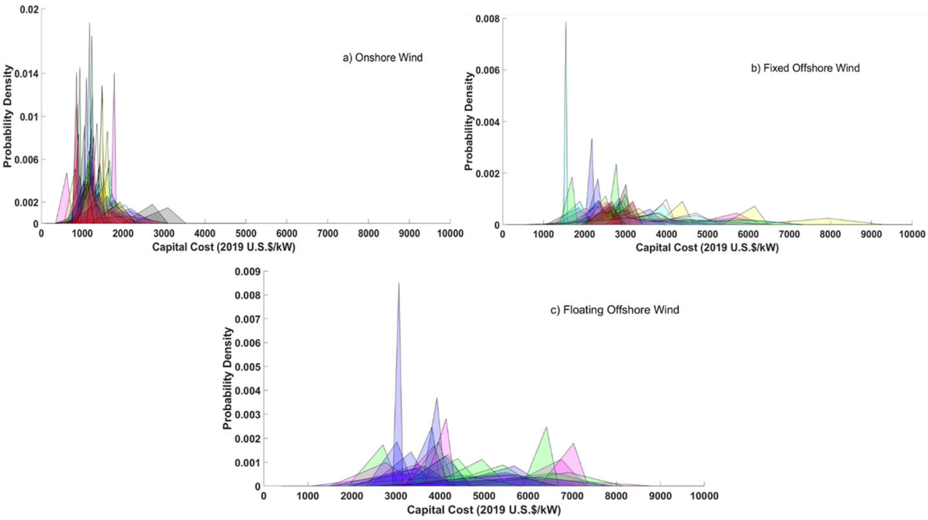

Fig. 2 Triangular distribution of each expert elicitation for **a** onshore wind, **b** fixed offshore wind, and **c** floating offshore wind. Note the horizontal axis is the same across the technologies, but the vertical axis varies

With the distributions, we randomly draw 1000 independent samples representing the capital cost for each technology in 2035. We call these samples the *elicitation data set* used as input into the model.

2.2 Implementing wind energy in GCAM

GCAM (PNNL 2020) is an integrated assessment model with a rich representation of the economy, the energy sector, land use, and water. GCAM is a dynamic recursive, partial equilibrium model that adjusts prices until supply and demand balance for all energy and agricultural markets. The model operates in 5-year time steps from 1990 to 2100 and comprises 32 regions of the world. The core energy module includes all primary, intermediate, and end-use energy markets, and greenhouse gas markets if a cap-and-trade mitigation policy is enabled. The electricity demand in the model is driven by GDP, population, and the price of the energy services. GCAM employs a vintage representation of electricity generation of capital stock, with existing plant and equipment assumed to operate until retired. New vintages are introduced in each period to satisfy new demands and replace retiring capital stocks, with alternative technology options competing at investment margin. Individual technologies compete for market share based on technological characteristics, costs of inputs, and the price of outputs. The cost of technology in any period consists of (1) its exogenously specified non-energy cost, (2) its endogenously calculated fuel cost, and (3) any costs of emissions, as determined by the climate policy (Calvin et al. 2019). The non-energy cost represents the capital cost, fixed and variable O&M costs incurred over the equipment's lifetime (Muratori et al. 2017). In wind and solar, the fuel or electricity cost is based on a resource supply curve, described in Section 2.2.2. In addition, GCAM addresses intermittency by requiring either a corresponding battery storage system (see Muratori et al. 2017 for battery storage cost) or dispatchable gas-fired backup generation, with the two methods competing to maintain system integrity and reliability. As the penetration of wind without storage increases, increasing quantities of storage or backup power are required, with one-to-one backup required once wind energy without storage accounts for more than 20% of electricity generated (Clarke 2009). For electricity generation, GCAM uses these terms to compute the levelized cost of energy within the model. GCAM uses a logit choice formulation (Clarke and Edmonds 1993) to determine market shares of each technology. Technology options are ordered based according to cost. This means that lower-cost technologies get a larger market share. Still, every technology is used in at least a small amount in a niche market (See Supplementary Information for details).

While GCAM includes most low carbon and conventional generation technologies, the core global version of GCAM does not currently have offshore wind energy for electricity supply. In this paper, we add offshore wind energy to the global release of GCAM. To do this, we divide offshore wind energy into two separate technologies, (1) fixed offshore wind and (2) floating offshore wind. We assume the two technologies are not directly competing for the same resources, as they have different site specifications, where shallow waters are suitable for fixed offshore wind and deeper waters for floating offshore wind. Hence, we develop distinct resource curves for each technology. In each time step, the electricity generated from offshore wind is the sum of electricity generated from fixed and floating offshore wind. Offshore wind competes directly against all other low carbon energy, including onshore wind and conventional generation technologies, for a global market share of electricity generation.

2.2.1 Generating a time path for technology performance

The elicitation data set contains static values, representing capital cost for the year 2035. To implement this in GCAM, we must make assumptions about how each sample will span the model's entire horizon, 2020 to 2100. We estimate costs for every 5 years from 2020 to 2100 and call this the *technology performance curve*. For each of the 3000 samples in the elicitation data set, we create a technology performance curve, using a slight modification of Moore's Law. Moore's Law models technology as improving exponentially through time (Nagy et al. 2013). There exist several methods for describing the cost evolution of technologies. Nagy et al. 2013 compared the performance of six formulations, including traditional learning curves (Wright 1936) and Moore's Law. Moore's Law forecasts the cost at a given time, whereas Wright's law at a given cumulative production. They find that for forecasting technological progress, these two methods are quite similar in performance. We use Moore's Law formulation for two reasons. First, the expert elicitations are tied to time rather than cumulative capacity. Second, GCAM is not compatible with traditional learning curves, and hence, prior work has used versions of Moore's Law (Muratori et al. 2017). The modification involves adding a price floor. The price floor is a lower-limiting (or in some cases an upper-limiting) bound, to which cost levels asymptote after 2035.

Let $y_{ij}(t)$ be the capital cost of technology j for sample i at time, where $i = \{1, 2, \ldots\ldots, 1000\}$ index the samples and j index the technology, from the set $\{Onshore, Fixed, \quad Floating\}$. Each technology j has one lower, and one upper bound, y_j^{min}, and y_j^{max}. y_j^{min} is the lower bound for sample ij and y_j^{max} represent the upper bound. The $y_{ij}(2035)$ are the individual elements of the elicitation data set, which represent the capital cost of the technology in 2035. The base year cost of technology j for 2020, $y_j(2020)$ is constant across all samples. Let m_{ij} be Moore's constant associated with the individual element $y_{ij}(2035)$. This constant is calculated for each sample i and technology j using Eq. 1, and then used in Eq. 2 to calculate $y_{ij}(t)$ for all other periods. Note, Eq. 1 and 2 represent a case where the cost in 2035 is lower than the cost in 2020; the approach is similar when costs are higher in 2035, with a ceiling in the place of a floor.

$$m_{ij} = -\frac{1}{2035-2020} ln\left[\frac{y_{ij}(2035)-y_j^{min}}{y_j(2020)-y_j^{min}}\right] \tag{1}$$

$$y_{ij}(t) = y_j^{min} + \left(y_j(2020)-y_j^{min}\right)e^{-m_{ij}(t-t_{2020})} \tag{2}$$

Figure 3 shows the technology performance curves of three samples for onshore wind for $y_{ij}(2035)$ equal to \$2408/kW, \$1520/kW, and \$1075/kW. For the initial cost of onshore wind, we used the GCAM baseline cost for the year 2020 (\$2233/kW in 2019 USD). The first sample, \$2408/kW, shows the cost of onshore wind energy increasing by 2035, as shown by the blue line with a Moore's constant $m = 0.0246$. The maximum and minimum price floors of \$2800/kW and \$450/kW included in the formulation provide an upper and lower bound to which cost levels asymptote after 2035. These values were chosen to represent the extreme tails of the distribution, with each having a probability of about one in a million.

Besides the CapEx, according to Wiser et al. (2021) the OpEx and capacity factor improvements are important to the overall LCOE reduction. To incorporate the OpEx for each wind technology, we used the sample mean for each wind technology; we did not incorporate the full range of uncertainty. For the rate of change of the OpEx through time, we used the GCAM baseline rate of change. All other parameters, like the capacity factor and project life, followed similar approach.

2.2.2 Offshore wind energy resource curves

In GCAM, technologies are represented by a *technology cost* (baseline capital and operating costs incurred over the lifetime of the equipment) and a *resource cost*. The resource cost captures the aspects of the cost that increase as more of the technology is installed. For offshore wind, we account for changes in cost due to decreasing capacity factors, as the

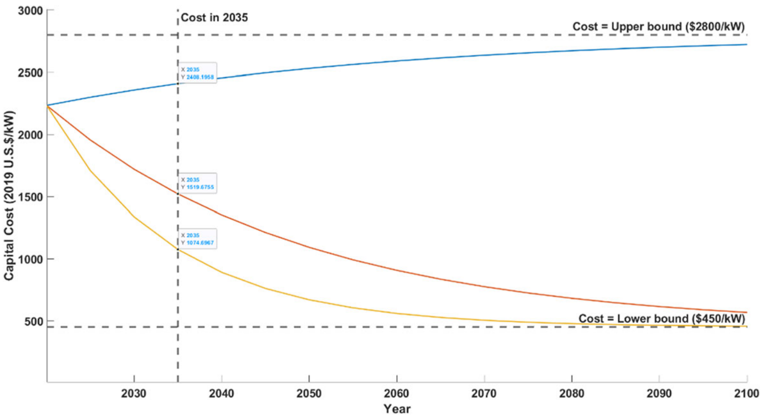

Fig. 3 Three illustrative technology performance curves, using Moore's Law formulation with a limiting bound

technology is assumed to be installed in the best sites first. We considered the impact of water depth by assigning fixed-bottom technology to all areas with water depths less than 60 m and floating to all other areas. The CapEx and OpEx are functions of the distance d from the coast in each wind class. The resource cost is parameterized in GCAM through a smooth S-shape resource curve. The resource cost of the first unit of power produced is 0 since it is added to the base technology cost. GCAM requires one resource curve for all periods for each region.

To estimate the resource curve, we estimate both the total energy available and the LCOE for each wind class in each region. Every offshore wind region is divided into nine different wind classes with each wind class assigned a capacity factor. The total energy available in each region for each wind class is estimated from the country level offshore wind power potential by Eurek et al. (2017). We calculate the LCOE for each of the 9 classes of wind and allocate that LCOE to the area in that region with that class. Since the additional LCOE that results from a lower capacity factor depends on capital costs, we estimate a resource curve for each sample in the elicitation data set as follows, using the data points for 2035 from the elicitation:

$$LCOE(d,k)_{ij} = \frac{\left(y_{ij}(2035) + C_{\text{trans}}(d)\right)CRF + OpEx(d)_j}{CF(k)*8760} \tag{3}$$

where $y_{ij}(2035)$ is defined as above. $OpEx(d)_j$ is the total annual operating expenditure over the project design life (\$/kW-year) as a function of distance for technology j. $C_{\text{trans}}(d)$ is the transmission cost as a function of the distance from the resource site to the nearest major power plant or big city, derived from (Bosch et al. 2019). $CF(k)$ is the capacity factor associated with class of wind k. There are a total of nine classes of wind, $k = \{1, \ldots, 9\}$,with the lowest quality offshore resource in class 1 (below 18% CF); and the highest quality in class 9 (above 46% CF). The value 8760 is the number of hours in a year.

To build the resource curve, we rank the LCOE in each region from the lowest to highest and associate it with the total energy available for each wind class for the respective area. Figure 4 illustrates examples of resource curves for fixed and floating offshore wind for Argentina, the USA, and India, created using the mean of the elicitation data set for both technologies. The range of LCOE calculated matches that in (Bosch et al. 2019). For 15 cents/kWh, the US could supply about 10 EJ for both fixed and floating offshore wind. At a higher price, the supply of floating offshore wind would outstrip fixed offshore wind. Argentina would produce about 10EJ of onshore wind and 32EJ of offshore at 15 cents/kWh. Offshore wind energy is more expensive in India, leading to minimal amounts at this price. Note that one of the features of the smooth S-shaped resource curve is that it passes through the origin; i.e., the cost of the first unit of power produced is 0. Therefore, we subtract the LCOE of the initial energy produced from the LCOE of any additional unit of energy that could be added. We fit the resource curves in Fig. 4 to the smooth S-shaped resource curve using three parameters. One parameter is the maximum quantity of offshore wind energy in that region and is provided by the data in Eurek et al. (2017); the other two parameters are estimated from the empirical resource curves, similar to those shown in Fig. 4.

2.3 The experiment

The technology performance curves and resource curves are implemented in GCAM to estimate the annual cost of abatement, the global mean temperature change, and electricity generation from 2020 to 2100. We run GCAM under three assumptions of climate policies: a

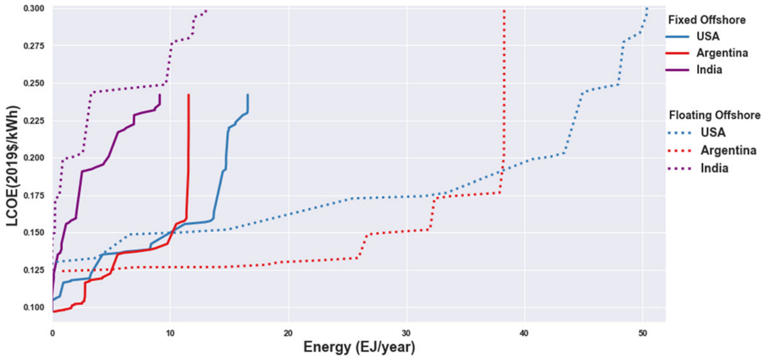

Fig. 4 Resource curves at the mean cost of fixed and floating offshore wind energy for the USA, Argentina, and India

business-as-usual scenario with no constraint on emissions (BAU), a moderate carbon tax starting at \$60/tC in 2025 and increasing at 5% annually, and a stringent climate policy where the global mean temperature change is stabilized at $1.5°C$ relative to preindustrial levels by 2100. In each case, we used the Shared Socioeconomic Pathway SSP2, which follows a path in which social, economic, and technological trends do not shift markedly from current patterns (Riahi et al. 2017). In this pathway, the intensity of resources and energy use declines, and global population growth is moderate and levels off in the second half of the century. Overall, the world experiences medium challenges to climate change mitigation and adaptation. We run 1000 simulations of GCAM for each of the three climate policies, making a total of 3000 computationally intensive GCAM simulations.

3 Results

We first discuss the aggregated probability distributions derived from the expert elicitation, and then present the results of the GCAM simulations, focusing first on the composition of the energy sector and then on the uncertainty in the climate value of wind energy. We consider three policy cases: BAU, \$60/tC starting in 2025 and increasing at 5% annually, and $1.5\,°\,C$ cap on temperature change by 2100.

3.1 Uncertainty in the cost of wind energy

In Fig. 5, we present the fitted theoretical distributions for the three technologies, aggregated from the triangular distributions. Table 1 compares the distributions to data compiled from over 50 reports and publications from 2009 to 2015 on onshore and fixed offshore wind energy costs in 2035 by the open energy information[1] (OpenEl). The expert elicitations are wider than the OpenEI estimates, shown by the vertical red dash lines in Fig. 5, and more optimistic than this and other projections (IRENA 2019; PNNL 2020). Beliefs about growth in turbine size and, for offshore wind, project size are the most prominent cost reduction drivers.

[1] OpenEI is a renewable energy and energy efficiency database created by the US National Renewable Energy Laboratory (NREL) to provide current information needed to make informed decisions on energy, market investment, and technology development: https://openei.org/apps/TCDB/.

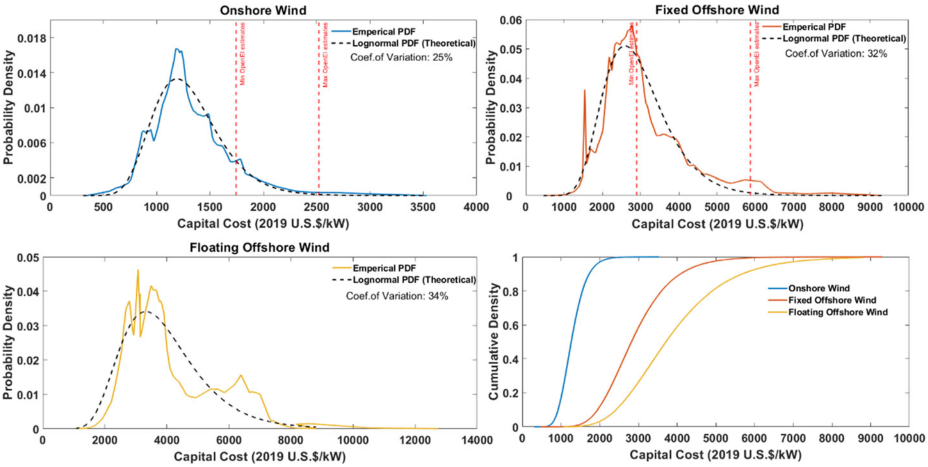

Fig. 5 Empirical and theoretical probability density function for the onshore, fixed and floating offshore wind for the 2035. The lower right-hand panel shows the CDFs. The vertical lines are the min and max projection for 2035 from the OpenEI data

While these projections are optimistic, they are consistent with the recent rapid cost reductions over the last 5 years; see Wiser et al. (2021).

We note that the coefficient of variation for each of the three wind energy technologies shows uncertainties in the expert estimates, with slightly more uncertainty in offshore wind energy's future cost than onshore.

3.2 The uncertainty in the composition of electricity generation

3.2.1 Wind electricity generation

We present the uncertainty in the global electricity generation from onshore and offshore wind energy for the years 2035 and 2050 for each policy. Figure 6 shows the probability density of electricity generation from both technologies across the policies for 2035 and 2050. The results indicate enormous uncertainty in generation from wind energy across all policies. In the BAU case, across the full range of samples, generation from onshore wind ranges between 4.7 and 39 EJ in 2035 and between 5 and 56 EJ in 2050. For offshore wind, this ranges between 0.5 and 32 EJ in 2035 and between 1 and 54 EJ in 2050. Under the assumption of independence between the wind technologies, combined onshore and offshore wind energy is likely to maintain or increase the current market share and generation level. For instance, at the 99th percentile cost, wind energy would contribute about 9 EJ of electricity by 2035. To put this

Table 1 Descriptive statistics from elicitation data set in USD 2019/kW

	Elicitation cost in 2035				OpenEl cost in 2035	
	Mean	Std. dev.	Min	Max	Min	Max
Onshore wind	1306	331	616	2769	1744	2521
Fixed offshore wind	2940	931	1031	8533	2897	5874
Floating offshore wind	3864	1299	1119	10,748	–	–

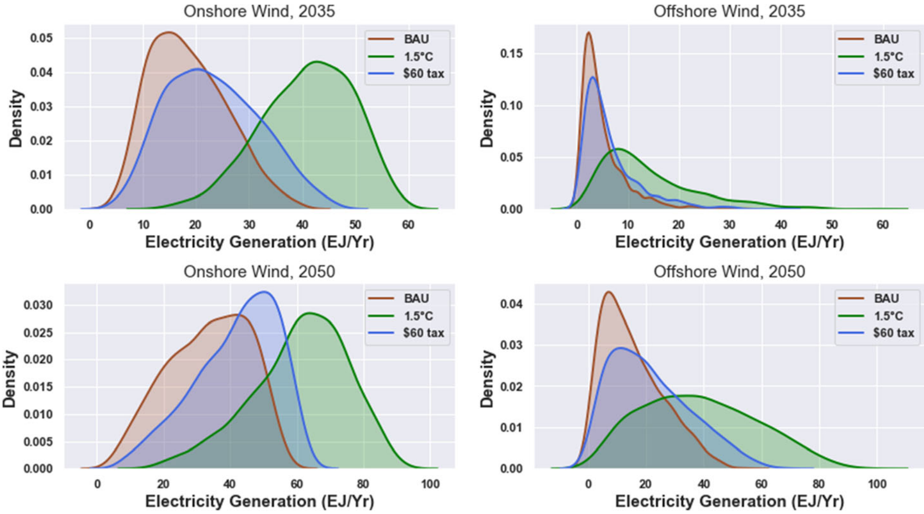

Fig. 6 Distribution of electricity generation from Onshore and Offshore wind for the year 2035 and 2050 under three climate policy cases

into perspective, wind energy in total generated 5.2 EJ (1430 TWh) of electricity in 2019, making up 5.3% of the world total electricity generation (BP energy 2020). The implication is that even in the case of a very bad outcome in cost, approximately 4 EJ of wind energy could still be added to the 2019 total. Across the policies, the level of generation and the uncertainty about a generation increase with the stringency of the climate policy, as shown in Fig. 6.

Figure 7 shows the share of electricity generation from both technologies under climate policies, showing the evolution under each scenario. The green and red lines indicate the

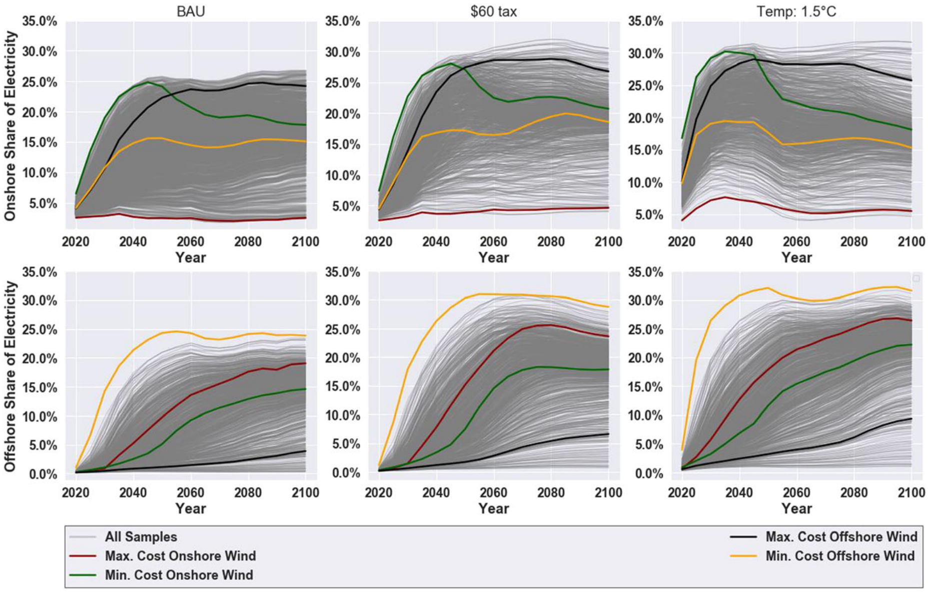

Fig. 7 Percent share of electricity generation from wind energy under different wind energy costs and climate policies. Top panels show onshore wind, bottom show offshore wind. Each line represents one sample

individual scenarios in which onshore wind is at its lowest and highest cost, respectively, in the elicitation data set. The yellow and black lines indicate the same thing for offshore wind. Under BAU, across the entire sample, we see combined wind energy contributing to a global share of electricity generation from anywhere between 4.4 and 27% by 2035. Given a breakthrough in costs (defined as the cost at the 10th percentile), the share of combined wind energy generation by 2035 is approximately 20% under the BAU case. This amounts to 34 EJ of electricity generation from wind energy, about seven times the level of electricity generation in 2019.

Under the carbon tax case, the combined share of wind energy by 2035 ranges between 12 and 25%, at the 90th and 10th percentile costs, respectively; under the 1.5C cap, the range is between 23 and 34%.

While these results are in line with established literature, our estimates provide context for the uncertainty in the global share of electricity generation from wind energy due to future cost uncertainty. Table 2 shows the probability of achieving or exceeding projections from some established international agencies under the three climate policies. For instance, looking at the IEA (2017) projection, we observe a 99.6% probability that wind energy will meet or exceed a 6% market share of electricity generation by 2040, even in the absence of a climate policy. The GWEC (2017) estimate of a possible 31% by 2050 is highly optimistic. In a BAU case, we see only a 3% chance of wind energy meeting or exceeding a 31% share by 2050. Under stringent climate policies, however, we observe an increasing probability of hitting these projections.

Comparing the performance of onshore and offshore wind under uncertainty in cost, consider the share of generation at the 10th percentile cost in a BAU case. At this cost, onshore wind makes up a share of 17% of global electricity generation by 2035 and 22% by 2050, while offshore wind contributes a 6% share by 2035 and 14% by 2050. Generation from offshore wind grows but remains relatively small in comparison to onshore wind. According to the expert elicitation, offshore wind is expected to remain relatively expensive, despite the abundant resources. It also very sensitive to uncertainty in cost: an unfavorable outcome in cost could reverse the current trend in the deployment of offshore wind energy, which has seen offshore wind grow from 8 TWh in 2010 to 67 TWh in 2018 (IEA 2019).

3.2.2 Other generation options

Figure 8 shows the uncertainty in the share of electricity generation from natural gas and coal. When onshore wind is at minimum cost across the full sample, the shares of generation from all the fossil fuel technologies decreases immediately, even under BAU, shown by the green lines in Fig. 8. This suggests some level of substitution between onshore wind and other

Table 2 Forecasted % market share from literature vs. probability of achieving share or better

			Probability of achieving share or better		
Group	Year	Forecast (% share)	BAU	tax	1.5 °C
IEA (2017)	2040	6:	99.6%	99.9%	100%
		15:	70%	89%	99.8%
GWEC (2017)	2050	17:	83%	100%	99.8%
		31:	3%	67%	77%
IPCC (Wiser et al. 2011)	2050	13:	93%	100%	100%
		14:	91%	100%	100%

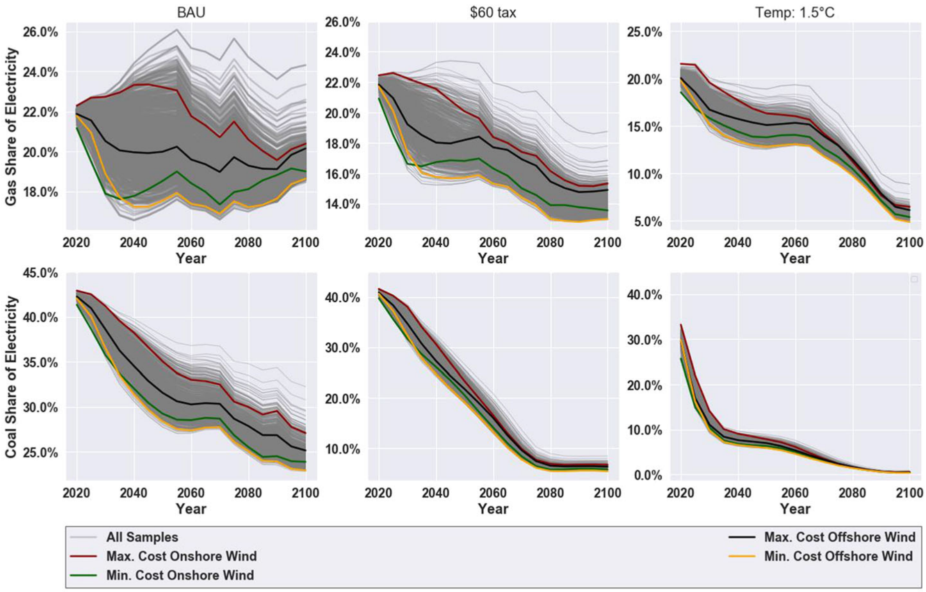

Fig. 8 Percent share of electricity generation from natural gas (top panels) and coal (bottom panels) under different wind energy costs and climate policies

generation technologies. We observe that coal declines throughout the century under all policies, no matter the cost of wind. However, uncertainty in wind cost affects the rate of decline in the share of generation from coal. For instance, in a BAU case, a breakthrough in wind cost could see the market share of electricity generation from coal decreased by as much as 12% by 2050. In contrast, with wind cost at the high end (90th percentile of cost), we could see only about an 8% decrease by 2050.

For natural gas, uncertainty in the cost of wind has implications for policymakers and planners. In the absence of a global CO2 emission policy, only a significant, low probability reduction in wind cost could lead to a flattening of the share of natural gas in the first half of the century. At the breakthrough cost of wind energy, we observe a reduction in the share by three percentage points from the current 22% market share of natural gas by 2050, resulting in a share of about 19%. In fact, across the entire range of wind energy costs, we observed a probability of 80%, a change of about ±3 percentage points in the market share of natural gas for electricity generation. This suggests that it is possible but unlikely to avoid natural gas as a bridge technology in the absence of stringent climate policy. We consider a bridge if its market share increases or remains relatively steady until mid-century, before falling. Under the $60 carbon tax policy, in 95% of the state of the world, we observe an immediate decline in shares with by average of 4% by 2050. Under the stringent $1.5°C$ limit on temperature increase, the effect of uncertainty in wind cost becomes less critical. We see an immediate and rapid decline in natural gas use to meet the climate goal regardless of the costs of wind energy.

The uncertainty in wind costs has a small impact on the demand for solar in GCAM. Under BAU, by 2035, the share of solar could vary between 1.4% and 1.6% at the 10th and 90th percentile cost of wind energy, with a mean share of about 1.5%. Under a global \$60/tCO_2 tax, solar share increases, fluctuating between 1.7% and 2.2% at the 10th and 90th percentile wind cost, with a mean share of about 2%. This implies some level of substitution between solar and wind. We note that GCAM baseline cost does not lead to optimistic projections for solar deployment. A comparative study taking the uncertainties in both technologies into account could provide a clearer picture of the competitiveness of these two technologies.

3.3 The climate value of wind energy

We define the climate value of wind energy as the difference between the present value of the total cost of climate change, with and without wind energy, holding everything else constant, following Cranmer and Baker (2020). The total cost of climate change is the sum of the present values of abatement cost and the cost of climate damages. GCAM estimates the annual abatement cost and global mean temperature change resulting from each state of the world in the elicitation data set. We use the annual abatement cost to estimate the total abatement cost and the global mean temperature change to estimate damages using the DICE damage function (Nordhaus and Sztorc 2013). The DICE damage function relates temperature change to economic welfare, using a power function of the temperature with an exponent equal to 2, to represent the severity of damages. We conduct sensitivity analysis on the exponent at 1.5, 2, and 3 for low, medium, and high damages, respectively. More details on calculating the climate value of wind energy under the different policies are given in supplementary information.

Wind energy plays an important role in the energy system under different climate policies. The climate value of wind energy depends on the technology cost, the magnitude of damages, and the climate policy. In Fig. 9, we show the climate value of wind energy at the 10th, 50th, and 90th percentiles cost of wind, broken down by the magnitude of damages (low damages: 1.5 and high damages: 3) and climate policies. The bar shows the climate value at the 50th percentile cost of wind; the top whisker is the climate value at the 10th percentile, and the bottom whisker is the climate value at the 90th percentile. Despite the differences in the policies, reducing the cost of wind from the 90th percentile to the 10th percentile approximately doubles the climate value of wind energy in all cases.

While the climate value under BAU appears small on the chart, it ranges between $151 billion and $269 billion at the 90th and 10th percentile cost of wind under a low damage

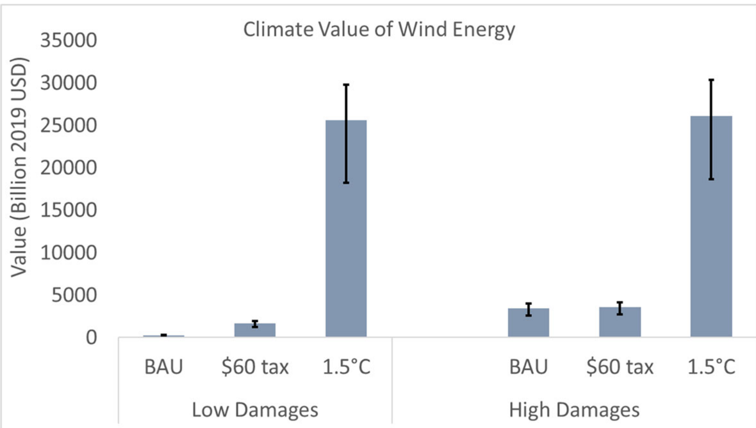

Fig. 9 Climate value of wind energy. The bar represents the climate value at the 50th percentile cost of wind. The top and bottom whiskers are the climate value at the 10th percentile and 90th percentile cost of wind energy

assumption, and up to \$4 trillion under higher damages and cost at the 10th percentile. Under the \$60 carbon tax, there is an 80% chance that the climate value is between \$1 trillion and \$2 trillion given low damages, and between \$2.7 trillion and \$4 trillion given high damages. Note that assumptions about damages have little effect on the climate value under a cap, such as our 1.5 °C policy. The policy largely prescribes the emissions path; there are small impacts due to the possibility of overshoot. While the uncertainty is huge under this policy, the key takeaway is that even if wind energy disappoints with minimal cost reductions, the climate value under a stringent cap is likely to be higher than \$18 trillion, with a probability of 90% or more depending on the policy. See supplementary text for the distributions of the climate value of wind energy.

4 Conclusion

This paper provides insight into how uncertainty in the future cost of wind energy implies uncertainty in the composition of electricity generation and wind energy contribution to climate change mitigation. Studies in the literature have investigated the role of wind energy in climate change mitigation, primarily focusing on the available resource potential harnessed for electricity generation. Our study combined information about wind energy resource potential with a large-scale expert elicitation on the future cost of wind energy for use as input in a large-scale IAM. To do this, we incorporated offshore wind energy, both fixed and floating offshore technologies into the global version of GCAM.

We propagate uncertainty in the future cost of wind energy in GCAM to examine the impact on electricity generation from wind, coal, and natural gas. We show that uncertainties in wind energy cost create significant uncertainties in electricity generation from wind energy, which implies the need for more flexible systems so that large amounts can be deployed if needed. In the absence of a global policy on CO2 emissions, our estimates indicate that the share of wind energy is likely to range between 9 and 20% by 2035, generating between 13 and 34 EJ. In the very best case, the share of electricity generation from wind energy could triple between 2019 and 2035. As policies get more stringent, the uncertainty in the resulting share of wind energy grows.

According to the IPCC special report on renewable energy sources and climate change mitigation (Wiser et al. 2011), furthering wind energy cost reduction could enable large-scale deployment of the technology, reducing emissions by displacing fossil fuel-based electricity generation. We see that a breakthrough in the future cost of wind energy could accelerate the reduction in the share of electricity generation from coal, with or without a climate policy. On the other hand, under BAU, natural gas is likely to remain competitive across nearly the entire state of the world of wind energy costs, with the share of natural gas remaining relatively stable. Under the \$60/tC tax scenario, we observed a 95% chance that wind energy costs are low enough to avoid natural gas as a bridge technology to a low carbon economy. This implies that wind energy can play a pivotal role in a medium-stringency policy. Under a stringent policy, wind energy cost becomes largely irrelevant. The share of natural gas decreases rapidly throughout the rest of the century under a $1.5°C$ policy regardless of wind energy cost.

Beyond the impact on the share of electricity generation, we estimated how uncertainty in wind energy cost propagates to uncertainty in climate change mitigation costs. The climate value of wind energy depends on the magnitude of damages and the stringency of the climate policy and varies significantly with costs. Reducing the cost of wind from the 90th to the 10th percentile more than doubles the climate value of wind energy under all policies and damage severities. Nevertheless, the climate value of wind energy is significant even under the 90th percentile cost and low damage severity, estimated at $151 billion in the BAU case and a whopping $18 trillion for a 1.5 °C cap.

Our results are subject to some limitations. First, our estimate of the climate value of wind energy is based on expert elicitation on the future cost of wind energy, analyzed using a specific IAM (GCAM, PNNL 2020) and a simplified damage function from DICE. According to Nemet et al. (2017), expert elicitation's usefulness could be limited in part because the choices in survey design and expert selection may bias results, leading to over or under-confidence. The literature on expert elicitation highlights the critical issues of properly designing an elicitation protocol that minimizes expert biases as much as possible and how to present, analyze, and aggregate the data collected (Verdolini et al. 2018). This makes the assessment of the quality of the information resulting from expert elicitation difficult. Therefore, the possibility exists that the experts could be over-or under-estimating the potential for cost reduction of wind energy. Moreover, we note that the range of uncertainty may be even greater than shown here if improvements in the other factors, such as OpEx, capacity factor, and project life, are correlated with improvements in CapEx. In this case, the probability of natural gas acting as a bridge would be slightly higher. However, it is also plausible that improvements in these other factors may be negatively correlated to improvements in CapEx, if the improvements are based partly on higher upfront investments, for instance.

Second, GCAM has its own unique set of assumptions and foibles. GCAM has restrictive assumptions regarding grid integration and technology competitiveness, so it is possible that our estimates of wind energy generation are low relative to other models. GCAM's use of the logit function for technology competition has implications. It means that a certain amount of each technology is used, even when costs are high; this could lead to an overestimation of the generation and mitigation potential from wind energy in the scenarios in which the costs are high. Moreover, GCAM does not model induced technical change. Technical change is modeled exogenously, which may lead to under- or overestimation of abatement cost and emission trends, depending on the degree of optimism in the expert forecasts. Further studies employing a range of IAMs and analyzing the interactions between uncertainties in multiple technologies could lead to broader and more robust conclusions. Finally, the function used to estimate climate damages are likely to be much more complicated than those represented by a power function. Nevertheless, this study is a first attempt to understand how the expert-derived uncertainty in wind energy propagates into the energy mix and climate value.

Altogether, our results imply that, while understanding the global wind resource is important, uncertainty in the future cost of wind energy also significantly impacts climate change through the impact on the electricity generation portfolio. The range of uncertainty in wind energy share provides an impetus for policymakers to invest in cost reduction and design flexible policies for siting and designing energy systems to achieve full climate benefits.

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Data availability Requests for raw data should be made to fkanyako@gmail.com.

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