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MODELING PORTFOLIOS OF LOW CARBON ENERGY GENERATION UNDER DEEP UNCERTAINTY

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MODELING PORTFOLIOS OF LOW CARBON ENERGY GENERATION UNDER DEEP UNCERTAINTY

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DEDICATION

To my mother Mahawa Kailie and family

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ABSTRACT

MODELING PORTFOLIOS OF LOW CARBON ENERGY GENERATION UNDER DEEP UNCERTAINTY

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In the 2015 Paris Agreement, nearly every country pledge through the Nationally Determined Contributions (NDCs) increased adoption of low carbon energy technologies in their energy system. However, allocating investments to different low carbon energy technologies under rising demand for energy and budget constraints, and uncertain technical change in these technologies involves maneuvering significant uncertainties among experts, models, and decision-makers.

We examine the interactions of low carbon energy technologies under the condition of deep uncertainty. Deep uncertainty directly impacts the understanding of the role of low carbon energy technologies in climate change mitigation and how much research and development (R&D) investment should be allocated to each technology. We complete three projects that advance the understanding of energy transition under deep uncertainty, including (1) conducting 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; (2) applying a new, rigorous, analytical framework to select portfolios of R&D

investments into low carbon energy sources that are robust across beliefs and models, and (3) investigate the benefit of regional cooperation for electric power capacity expansion, cross border electricity trade across the West Africa Power Pool (WAPP).

In the first part of this dissertation, we address parametric uncertainty. We integrate data on global onshore and offshore wind energy cost and resources into the Global Climate Assessment Model (GCAM), then propagate uncertainty based on distributions derived from an expert elicitation study on the future cost of onshore and offshore wind energy. We investigate how a breakthrough, or a failure, in the future cost of wind energy could affect the electricity supply sector and the costs of decarbonization. We find that the share of wind energy electricity generation in 2035, without a global policy on CO2 emissions, could either stay flat or more than triple the 2019 total share. This range only grows larger under medium to stringent climate policies, which has implications for conventional generation technologies like natural gas.

The second part addresses parametric and structural uncertainty. We expand on the work of Baker et al. [1] on Robust Portfolio Decision Analysis (RPDA), identifying all non-dominated portfolios of R&D investment across all beliefs and models. For example, under a \$125/tCO_2 tax on emissions, we find agreement among experts and models about high investment in Bioelectricity and Solar energy. High energy investment both energy sources are robust across all beliefs and models given the climate policy. We also find that the structure of the model is particularly important for allocating investment into Nuclear energy, especially under stringent climate policy.

In the third part, we developed a multi-region model for the long-term dynamics (2018 – 2040) of West Africa power pool (WAPP) capacity expansion and planning,

considering generation and transmission investments, cross-border electricity trade, national capacity expansion plans, and grid-connected renewable energy penetration. We find that cooperating to develop a common electricity grid has a significant economic advantage in the region.

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CHAPTER 1

INTRODUCTION

1.1 Objective

The central aim of this dissertation is to identify robust strategies to address climate change, including energy transition under climate policies and allocating R&D investment to low carbon energy technologies (LCET). We complete three projects that advance this understanding that include (1) investigating the role of wind energy in climate change mitigation under uncertainties in future cost, (2) Identify portfolios that represent common ground among experts and models about the allocation of R&D investment to low carbon energy technologies (LCET), and (3) investigate the benefit of regional cooperation for electric power capacity expansion, cross border electricity trade across the West Africa Power Pool (WAPP).

1.2 Motivation

There is an increasing consensus in the literature about the contribution of LCET in decarbonizing the electricity sector and the electrification of the energy system [2]. LCET in this text refers to renewable energy sources (RES) plus Nuclear and Carbon Capture and Storage (CCS). Designing policies to decarbonize the energy sector under rising demand for energy and budget constraints involves interpreting and maneuvering significant uncertainties among experts, models, and decision-makers. These uncertainties include the future cost of LCET, climate sensitivity, technical change and deployment rate, and climate policies. The overall question is, taking the uncertainties in climate damages and future technology cost and disagreement among policymakers, what role does the

individual LCET play in decarbonizing the energy sector? Can we find common ground among decision-makers and modelers about how much investment to allocate across the different LCET even when they disagree?

To answer these questions requires synthesizing multiple beliefs about the potential for improvement in each LCET, the choice of conceptual modeling platform that describe the relationships among the key driving forces of the human and climate systems, and how alternative outcomes are evaluated. For example, some LCET are experiencing rapid deployment and significant cost reduction [3], while some are new, not yet commercialized, such as CCS. As a result, future deployment of some LCET may be limited due to competition from other energy sources and high costs. For example, inexpensive wind energy can reduce the costs of abatement and increase mitigation. However, it will tend to be irrelevant when it is expensive, outcompeted by solar, nuclear, or CCS. Hence, divergent beliefs exist among decision-makers about investments in different LCET [4] and the potential for R&D investment to reduce the future cost of individual LCET, and how different LCET minimize the future risks of climate change.

Research and Development (R&D) hold the significant promise of improving the overall outlook of LCET [2]. But to what extent and which LCET to invest in when no assurance of success exists? And even if all LCET are successful, each will have a different impact on emissions. Furthermore, the choice of modeling platform used to evaluate the questions above and climate policies also significantly influence the answers to the questions. These constitute decision-making under deep uncertainty, including uncertainty in technology cost and model and policy uncertainty.

Thus, in the face of uncertainty about the future cost of LCET, the choice of modeling platform and the impact of R&D investment on technical change, it is important to synthesize the conflicting views and modelling platforms to understand the role of LCET on climate change mitigation, find common ground among decision-makers and modeling platforms and identify the economic benefit of cooperation for electricity capacity development and planning.

To this end, this dissertation is divided into the following sections: The remainder of this chapter is devoted to a review of the pertinent literature. In Chapter 2, we conduct an 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. Chapter 3 expands on the RDPA approach, identifying all non-dominated portfolios of R&D investment across all beliefs and models. In Chapter 4, we develop a cost-benefit energy-economic model to study electricity trade across West Africa. Finally, Chapter 5 summarizes our findings and makes recommendations for future work.

1.3 Literature

We define deep uncertainty, according to Lempert et al. [5], as "a state of the world where analysts and decision-makers disagree on (1) the appropriate conceptual models that describe the relationships among the key drivers of human development and how societal choices interact with and affect the natural world, (2) the beliefs about uncertain states of the world of key variables and parameters used in the models and (3) how to evaluate the desirability of alternative outcomes".

We define uncertainties in the input data as parametric uncertainty. Parametric uncertainty comes from issues around the data used to characterize the system, including

aggregation, simplification, approximation, and lack of data [6]. Below we introduced the literature on the beliefs about the future cost of LCET, followed by the introductions of the different models used in this dissertation. Models can never fully describe our social, economic, institutional, and climate systems. Different models calibrate and prioritize various features of the natural world differently, leading to a barrage of uncertainties and questions about appropriate analytical tools and methods. For example, how to model causal relationships among seemly interconnected systems? We identify these as questions due to structural uncertainty.

1.3.1 Technical Change and Expert Elicitation

Energy transition in the age of climate change — the transformative transition away from fossil-fuel-based energy production and consumption systems (oil, natural gas, and coal) and toward renewable and clean energy sources (wind, solar, and so on) is critically dependent on the future cost of low-carbon energy technologies. These costs substantially affect the composition of future energy systems. Unfortunately, predicting or forecasting future costs of energy technologies is a source of tremendous uncertainty. Moreover, our capacity to estimate uncertainty about the future prices of energy technologies is limited because we do not know how technological development will evolve in the future or how much cost reduction potential a technology may have. With rising pressure on decision-makers to decarbonize the energy sector, allocating R&D funds to various low-carbon energy technologies involves anticipation of their future performance.

However, past studies suggest the relationship between R&D investment and technological outcomes is highly uncertain [7]–[10] and coupled with decision-makers

with divergent views, make the whole decision-making process highly uncertain. One method is to study past trends in energy technologies through experience/learning curves to predict future trajectories [11] and ascertain whether government R&D spending has shaped this evolution [12]. However, according to Verdolini et al. [13], using historical data and experiences to estimate the uncertainty around future technology costs and performance ignores the reality that R&D is inherently unpredictable and that various technologies mature differently at different periods in time.

Lovering et al. [14] examined historical experience curves for overnight nuclear capital costs and observed that nuclear power technology does not exhibit an inherent learning rate or a predicted cost trend. They conclude that there are cost variables other than learning through experience that have dominated the nuclear power cost experience. There are similar conclusions in [9], [15], [16] that past trends may not accurately forecast future cost and performance evolution and are unlikely to distinguish between various technologies and funding amounts. Thus, decision-makers and researchers increasingly rely on another method, which involves eliciting expert judgments to help characterize the probability of improvements in technology performance and costs.

Expert elicitation is a systematic technique for eliciting expert judgments about uncertain values and classifying them into probability distributions for use in complex decision-making problems [17]. There is a growing body of literature utilizing expert elicitation to investigate the uncertain effects of R&D investment on the potential for success of mitigation technologies [18]. For more complete references, see Verdolini et al. [13], which conducted a comprehensive review of expert elicitations on energy technologies. They argued that the emergence of data on future energy costs through expert

elicitations enables more transparent and robust analyses of energy and climate change mitigation policies that incorporate technical uncertainty.

Chapter two of this dissertation will rely on data from a large-scale expert elicitation conducted by [19] on the future cost of onshore and offshore wind energy to model uncertainty in the cost of wind energy[1]. Chapter three draws on considerable prior research on expert elicitation to examine the possibility for public R&D to affect the future cost of energy technologies. Independent researchers from UMass Amherst ([4], [9], [20], [21]), Harvard ([15], [16], [22]) and FEEM ([10], [23]) collaborated with the goal to examine the robustness of policy under uncertainty concerning the cost of LCET. Each of these groups gathered the opinions of leading experts from academia, industry, and international institutions and aggregated them into probabilistic distributions of the future costs of the most promising clean energy technologies, conditional on various levels of R&D investment, classified as low, mid, and high.

The technologies comprise five critical LCETs: liquid biofuels, biomass electricity, carbon capture and storage (CCS), nuclear power, and solar photovoltaic (PV) power. Each technology's cost is evaluated, as is the efficiency of bioelectricity, biofuels, and CCS, for a total of eight uncertain performance metrics: solar PV levelized cost, nuclear power's overnight capital cost, and bio-liquids levelized non-energy cost and conversion efficiency, non-energy cost and conversion efficiency of bioelectricity, and capital cost and energy penalty associated with carbon capture and storage (CCS). Baker et al. [2] aggregated and

[1] Note: The expert elicitation on future cost of wind energy is separated from the expert elicitation of the other LCET because the Wiser *et al.*, 2021 expert elicitation was not based on R&D investment. Hence Wind energy is not included in the list of portfolios in chapter three that investment R&D investment.

harmonized these three distributions into a combined distribution, using Laplacean mixing and then smoothed using a fitted piecewise cubic distribution (see Baker et al. 2015 [2] for details). This process resulted in a combined prior probability distribution over the outcomes of technological change. Thus, the vector of realizations contains eight uncertain performance metrics, including a cost for each of the five technologies and an efficiency for CCS, biofuels, and bioelectricity. We use these vectors of realizations to create a set of technology outcomes that will serve as the model inputs for our analysis in chapter three.

1.3.2 Integrated Assessment Models (IAM)

Integrated assessment (IA) modeling has emerged as a key technique in climate policy research [24]. IA modelling is a structured process of combining interdisciplinary strands of knowledge and insights from the economic, social, environmental, and institutional dimensions into one framework. The goal is to provide integrated insights to decision-makers by representing tradeoffs and interactions between different parts of society. Various modelling platforms could give other answers to the same question and input parameters.

Below we provide a brief overview of the four IAMs used in this dissertation. We first introduce the technologically detailed cost-effectiveness model (GCAM), followed by the three high-level cost-benefit IAMs - DICE, PAGE and FUND. Each of these models have different assumptions about the climate variables, market economy, human relationships, and technological change, all aimed at providing insights to decision makers through trade-offs and interactions between these climate variables and the impact sectors. Detailed characteristics of the three cost benefit models, including input assumptions and

structures, degrees of regional and sectoral aggregation, and formulation of the damage functions, are found in Table 1.

1.3.2.1 GCAM – Description

The global change assessment model (GCAM) is a global change integrated multi-sector model that explores both human and earth system dynamics. GCAM is an open-source model developed and maintained by the Joint Global Change Research Institute (JCRI); the model's complete documentation is accessible on its GitHub website (http://jgcri.github.io/gcam-doc/overview.html).

GCAM depicts the behavior and interaction of five systems at the global and regional scales: energy, water, land, climate, and the economy, all of which are integrated into a unified computing framework. The climate model is used to investigate climate change mitigation measures such as carbon taxes, carbon trading, regulations, and rapid energy technology deployments [25]. The global energy-economic system is divided into 32 regions that are inextricably linked by international commerce in energy commodities, agricultural and forest products, and other items such as emission permits. The magnitude of economic activity is determined by population size, age, and gender, as well as labor productivity in each region.

GCAM is a dynamic recursive partial equilibrium model that solves each five-year timestep between 1990 and 2100, modifying prices until supply and demand equilibrium is achieved in all energy and agricultural sectors. It is based on the market equilibrium concept, in which representative agents in GCAM make resource allocation decisions based on knowledge about prices, costs, and other relevant aspects. These agents transmit

information about supply and demand for products and services to marketplaces. Markets exist for physical commodities such as energy or agricultural commodities, but they may also exist for non-physical products and services such as tradable emissions permits. GCAM finds a set of market pricing that balances supply and demand across all markets in the model. GCAM solves problems by iterating on market prices until an equilibrium is found within a user-specified tolerance threshold [26]. Following each period, the model will use as a starting point the resulting state of the world, including the impact of decisions taken in that period (for example, resource depletion, withdrawals from the capital stock and installations, changes in the landscape, and emissions) for the next period.

1.3.2.2 Energy Technology Competition in GCAM

GCAM's main energy module encompasses all primary, intermediate, and end-use energy markets, as well as greenhouse gas (GHG)markets if a cap-and-trade mechanism is implemented. Primary energy reserves and energy resources are expected to be substantial, which, along with projected technical advancement, leads to decreased extraction costs due to resource depletion. Coal, gas, oil, and biomass are all traded worldwide in the model, but wind, solar, geothermal, and hydropower are considered renewable energy sources that are not sold across regions in the model. The logit choice formulation is used to determine the market competitiveness and market share of each technology. [27]. Options/choices are ordered according to preferences, with cost or profit as the key determinant.

In the case of energy, the model considers input costs and output prices, and technological features to determine the market share of each technology. However, it should be noted that the best choice does not capture the entire market, as numerous factors

such as individual preferences, local variation in cost/profit, and simple happenstance may cause some of the market to gravitate toward alternatives that are theoretically inferior choices based on their cost or profit alone [26]. Relative cost differences drive substitution across energy types in the supply sector, and the logit formulation ensures a winner-take-all result is avoided. The precise share allocated to each technological choice is determined by the share weight of the logit exponent [26]:

$$s_i = \frac{\alpha_i c_i^{\gamma}}{\sum_{j=1}^{N} \alpha_j c_j^{\gamma}} \tag{1}$$

Where s_i, c_i, α_i are the market share, cost, and share weight of each technology, and γ is the logit exponent, which is determined exogenously and controls the extent to which cost affects the market share of each technology. The share weight calculated in the historical period is used in GCAM to ensure that the model can replicate historical data. The share weights are also used to phase in new technologies into the market gradually. To do this, GCAM initially sets the share weights for new technologies at low levels and progressively increases them as the technology becomes more generally accessible.

1.3.2.3 DICE Model

DICE-2013 (Dynamic Integrated model of Climate and the Economy) is an inter-temporal optimization model of economic growth for the world as a single region, developed in 1990 by Nordhaus [28]. The model balances the cost of mitigation against the costs of climate change-related damages. Damages are assessed using a quadratic relationship between temperature change and damage. The highly aggregated model accounts for many features such as the economic value of losses from biodiversity, ocean

acidification, extreme events such as changes in ocean circulation, the effect of adaptation and uncertainty implicitly through a simple damage function [28].

1.3.2.4 FUND Model

FUND (The Climate Frameworks for Uncertainty, Negotiation, and Distribution) model of climate economics is a simplified representation of development, energy use, carbon cycle, and climate developed by Richard Tol and David Anthoff [29]. The model has been used to investigate the costs and benefits of cost-effective, efficient, viable, and equitable climate policy. It is distinct from comparable integrated assessment models by its more thorough depiction of the economic consequences of climate change at the sectoral and regional levels, encompassing 14 different impact sectors and 16 main geographical regions. The costs of emission reduction are weighted against the avoided damage of climate change. The climate damages from each of the 14 impact sectors are analyzed and estimated separately for each of the 16 regions. The parameters that define these regional sectorial damages are estimated from parametric uncertainty analysis with thousands of Monte Carlo simulations. The damages in each sector are scaled with dynamic vulnerability. Exposure or vulnerability to climate impacts changes dynamically over time, depending on the socioeconomic parameters such as population, GDP growth, and technological change [30].

1.3.2.5 PAGE Model

The PAGE09 (Policy Analysis of the Greenhouse Effect) model developed by Hope [31] assesses climate change implications and the costs of mitigation and adaptation policies. PAGE09 models eight world regions, taking income, population, and emissions

policy as inputs. It estimates the impact of emissions on four impact sectors: “sea-level rise, economic damages, non- economic damages, and discontinuities” [31]. The four impact sectors are modeled independently and reflect damages as a proportion of GDP.

PAGE09 performs parametric uncertainty analysis with thousands of Monte Carlo simulations from each sector to estimate the total damages from climate change. Before adaptation, the economic and non-economic impacts reflect the vulnerabilities of different regions and use a polynomial function to estimate temperature impacts over time. Sea level rise is a lagged linear function of global mean temperature. Discontinuity, or the risk of climate change triggering large-scale damages, reflects a variety of different possible types of disasters. The model also includes two kinds of exogenously defined adaptation costs in each region. The increase in the modest sea-level rise or warming without suffering any damages represented by the ‘plateau’ and the reduction in ‘impacts’ from the remaining damage is characterized by the fixed percentage reduction.

Table 1. Key characteristics of the three-cost benefit IAMs

Model details	DICE2013	FUND	PAGE09
Regions	One region: world	Sixteen regions	Eight regions
Damage function	$D = \delta_1 \Delta T + \delta_q T^2$ δ_1 and δ_q are the coefficients of the linear and quadratic damage function and ΔT is temperature change	Sector-specific damages are formulated differently, with the damage function f scaled by a dynamic vulnerability term, for example: $D = f(\Delta T^x)\left(\frac{YPC_t}{YPC_0}\right)^{-\varepsilon}$ x is the exponent of the climatic variable, YPC denotes per capita income, t and 0 represent the current and reference periods, and ε denotes income elasticity.	Estimates residual damages as a percentage loss of regional GDP following adaptation: $D = \delta\Delta(T_r - T_{adapt})^x + C_{adapt}$ The exponent x is uncertain, ranging between 1 to 3.
Climate variable	Global mean temperature change, global mean seal level rise (SLR)	Global mean and regional temperature change, CO2 concentrations, global mean sea-level rise (SLR), ocean temperature	Regional mean temperature change, global seal level rise (SLR)
Socioeconomic drivers	Global income	Population, income, technological change, production cost, the land value	Productivity, regional capacity for adaptation and cost, Scaling factor at the regional level, moderate equity weights
Uncertainty	No	No	Exponent and uncertain threshold damages
Upper bound	Rational	By sector	No

CHAPTER 2

UNCERTAINTY ANALYSIS OF THE FUTURE COST OF WIND ENERGY ON CLIMATE CHANGE MITIGATION

2.1 Introduction

In the 2015 Paris Climate Agreement, the power sector was identified for emission reduction by nearly all countries [32]. Policymakers faced with the challenge of 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 most rapidly expanding electricity-generating technologies. By the end of 2019, the combined capacity of all wind turbines built globally had reached 650.8 GW, capable of meeting 5.3% of global electricity demand [33]. In just a decade, we have seen a 300% increase in global installed wind capacity [34]. According to BloombergNEF [35], 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 maturation of wind technology and the abundance of global wind resources, uncertainty about the future cost of wind energy persists. 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 [36]–[39]. Wind's global contribution to electricity supply in 2050, according to the Intergovernmental Panel on Climate Change (IPCC), might reach 13–14 percent in the median climate change mitigation scenario. [40]. The Global Wind Energy Council has an even higher estimate, ranging from 17–31% by 2050 [41], and the International Energy Agency (IEA) estimates a range of 6 – 15% by 2040 [42]. 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 degrees warming threshold by 1–6 years, and aggressive deployment could delay 2 degrees 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 [19] on the future cost of onshore and offshore wind energy. "Expert elicitation is a method of obtaining estimates of future technological performance based on expert judgment" [44]. Unlike learning or experience curves, which rely on past trends to predict future trajectories, expert elicitation can "characterize uncertainty around future technology cost and performance" [45]. Expert elicitation was suggested by the IPCC AR5 [46] to characterize uncertainty, give insights into specific risks, analyze and create effective policies and strategies for assessing climate change. In 2015, Wiser et al. (2016) conducted an earlier expert elicitation survey, concluding many possibilities for cost reduction despite significant uncertainties. The result of the updated 2020 elicitation of 140 global wind experts shows even more opportunities for further cost declines amid

significant uncertainties [19]. For instance, experts predict 50% lower future costs for onshore and offshore wind than in 2015. Next, we focus on uncertainties in wind energy cost and how this impacts climate change mitigation and electricity generation from other competing technologies.

The remainder of the chapter is laid out as follows. First, we discuss our approach in Section 2 of this report, 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. Finally, in Section 3, we describe the results of the simulation and conclude in section 4.

2.2 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 [19]. 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.

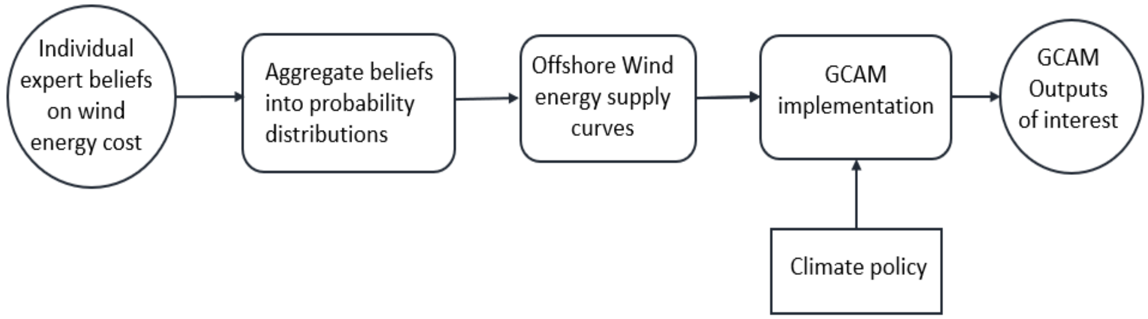

Figure 1: A schematic diagram of the implementation of the expert elicitation into GCAM. The first oval represents the probability distributions from the expert elicitation; the rounded rectangles represent the key steps in the process. The rectangle represents different climate policies, and the second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

2.2.1 Aggregating Expert Elicitation

The Wiser et al.(2021) [48] 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. 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.

A triangular distribution is a three-valued continuous probability distribution. The minimum value y_0, maximum value y_{100} and the mode, or most likely value (y_m). We estimate the mode using the three-point approximation technique for Continuous Random Variables proposed by Keefer and Bodily (1983). Specifically, let y be capital costs; y_{10}, y_{50}, y_{90}, are the cost at 10th, 50th and 90th percentiles respectively, $\bar{y}$ is the mean, and y_m the mode. From Keefer and Bodily [49]:

$$\bar{y} \cong 0.4y_{50} + 0.30[y_{10} + y_{90}] \tag{2}$$

From the mean ($\bar{y}$) in Eq. 2, we can estimate the mode (y_m):

$$y_m \cong \frac{[4\bar{y} - y_{10} - y_{90}]}{2} \tag{3}$$

With the mode calculated from Eq. 3 above, to calculate the minimum value y_0 and the maximum value point y_{100} we use the equation for the probability density function of the triangular distribution [50] to derive the two nonlinear simultaneous equations shown in Eq. 4 below:

$$\begin{aligned} [y_{10} - y_0]^2 &= 0.1[y_{100} - y_0][y_m - y_0] \\ [y_{100} - y_{90}]^2 &= 0.1[y_{100} - y_0][y_{100} - y_m] \end{aligned} \qquad 4$$

These three values, mode, minimum and maximum, allow us to define a triangular probability distribution for each expert, and each technology as show in Figure.2.

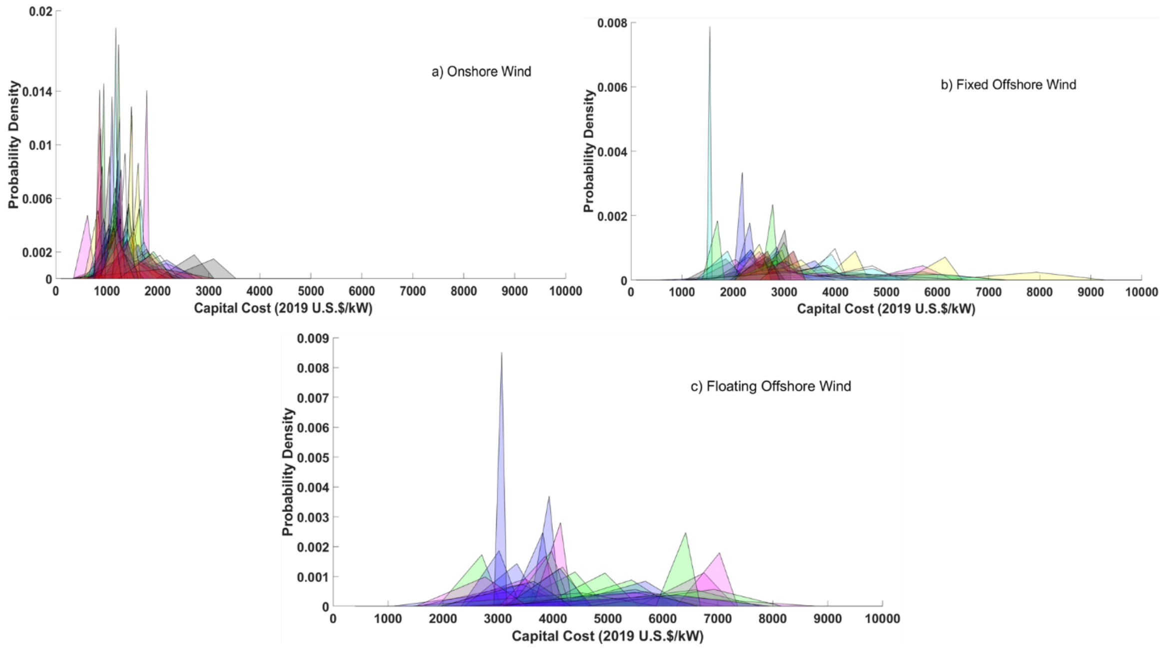

Figure 2: Triangular distribution of each expert elicitation for (a) onshore wind, (b) fixed offshore wind, and (c) floating offshore wind. Note the horizontal axis is the same across the technologies, but the vertical axis varies.

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 [51]. 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. 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.

2.2.2 Implementing Wind Energy in GCAM

GCAM [52] 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 pricing for all energy and agricultural markets until the supply and demand balance. It spans the years from 1990 to 2100 and includes 32 regions of the planet. The core energy module encompasses all primary, intermediary, and end-use energy markets, as well as greenhouse gas markets if a cap-and-trade policy is implemented. In the model, power demand is determined by GDP, population, and the cost of energy services.

GCAM uses a vintage depiction of the capital stock of electricity generation, with current plant and equipment assumed to run until retirement. Each era sees the introduction of new vintages to meet new demand and replace expiring capital stocks, with various technological choices vying for investment margins. Individual technologies compete for market share on the basis of their technical specifications, input costs, and outputs. A technology's cost at any time is composed of three components: (1) its exogenously stated non-energy cost, (2) its endogenously computed fuel cost, and (3) any emissions costs established by climate policy [26]. The non-energy cost includes the capital cost and fixed and variable operations and maintenance costs incurred during the equipment's life [53].

The fuel or electricity cost is based on a resource supply curve of wind and solar resources, described in Section 2.2.4. below. 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. The two methods compete to maintain system integrity and reliability. As the penetration of wind without

storage increases, increasing storage or backup power quantities are required, with one-to-one backup required once wind energy without storage accounts for more than 20% of electricity generated [54]. For electricity generation, GCAM uses these terms to compute the levelized cost of energy within the model. Finally, GCAM uses a logit choice formulation [27] to determine the 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. 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 electricity generation market share. A simplified nesting structure of the electricity supply sector for low carbon energy technology is shown in Figure 3 below.

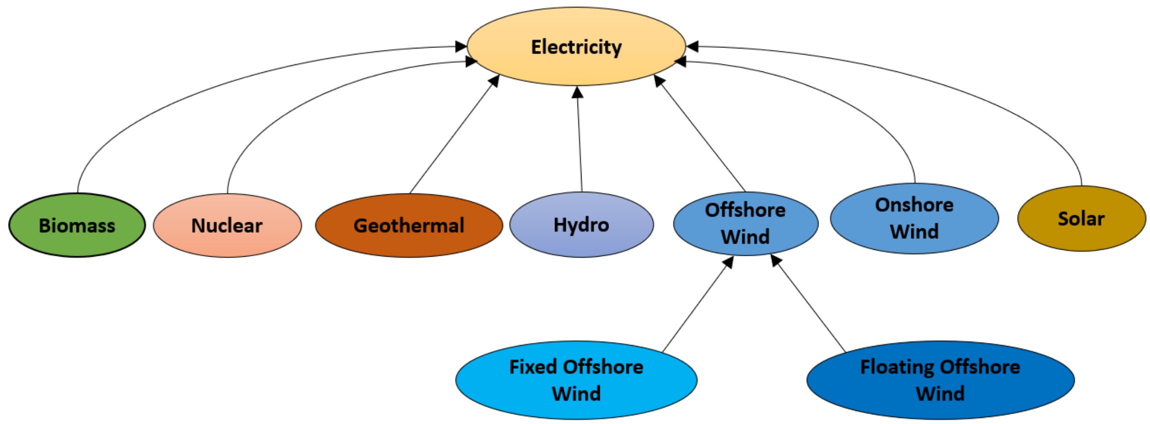

Figure 3: A simplified diagram illustrating the electric sector's nesting structure for low-carbon energy technologies.

2.2.3 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 five 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 [11]. Several methods exist for describing the cost evolution of technologies; for example, Nagy et al. [11] compared the performance of six formulations, including traditional learning curves [55] and Moore's Law. Moore's law forecasts the cost at a given point in time, whereas Wright's law anticipates the cost at a given cumulative production. They discover that these two techniques perform very similarly when it comes to anticipating technological advancement. 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 [53]. 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 $\{Onshore, Fixed,\ Floating\}$. 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. 5, and then used in Eq. 6 to calculate $y_{ij}(t)$ for all other periods. Note, Eq. 5 & 6 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.

$$m_{ij} = -\frac{1}{2035 - 2020} ln \left[\frac{y_{ij}(2035) - y_j{}^{min}}{y_j(2020) - y_j{}^{min}}\right] \tag{5}$$

$$y_{ij}(t) = y_j{}^{min} + \left(y_j(2020) - y_j{}^{min}\right) e^{-m_{ij}(t - t_{2020})} \tag{6}$$

Figure 4 shows the technology performance curves of three samples for onshore wind for $y_{ij}(2035)$ equal to \$2408/kW, \$1520/kW, and \$1075/kW. We used the GCAM baseline cost for the year 2020 (\$2233/kW in 2019 USD) for the initial cost of onshore wind. The first sample, \$2408/kW, shows the cost of onshore wind energy increasing by 2035, as

shown by the blue line with 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. We chose these costs to represent the distribution's extreme tails, each with a chance of around one in a million.

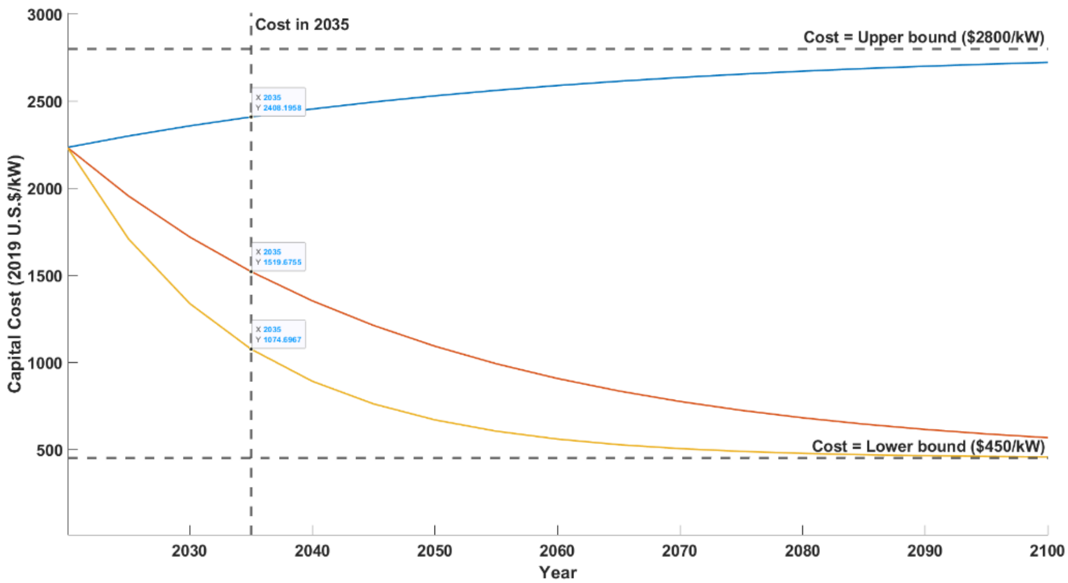

Figure 4: Three illustrative technology performance curves, using Moore's law formulation with a limiting bound.

Besides the CapEx, according to Wiser et al.(2021), the OpEx and capacity factor improvements are essential 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 include 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 a similar approach.

2.2.4 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 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 60m 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:

$$LCOE(d,k)_{ij} = \frac{\left(y_{ij}(2035) + C_{trans}(d)\right) CRF + OpEx(d)_j}{CF(k) * 8760} \tag{7}$$

Where $y_{ij}(2035)$ is defined as above. $OpEx(d)_j$ is the total annual operating expenditure over the project design life ($/kW-yr) as a function of distance for technology j. $C_{trans}(d)$ is the cost of transmission as a function of the distance between the resource location and the next major power plant or large city, extracted from [57]. $CF(k)$ 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. Fig. 4 illustrates examples of resource curves for fixed and floating offshore wind for Argentina, US, and India, created using the mean of the elicitation data set for both technologies. The range of LCOE calculated matches that in [57]. 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 Figure 5.

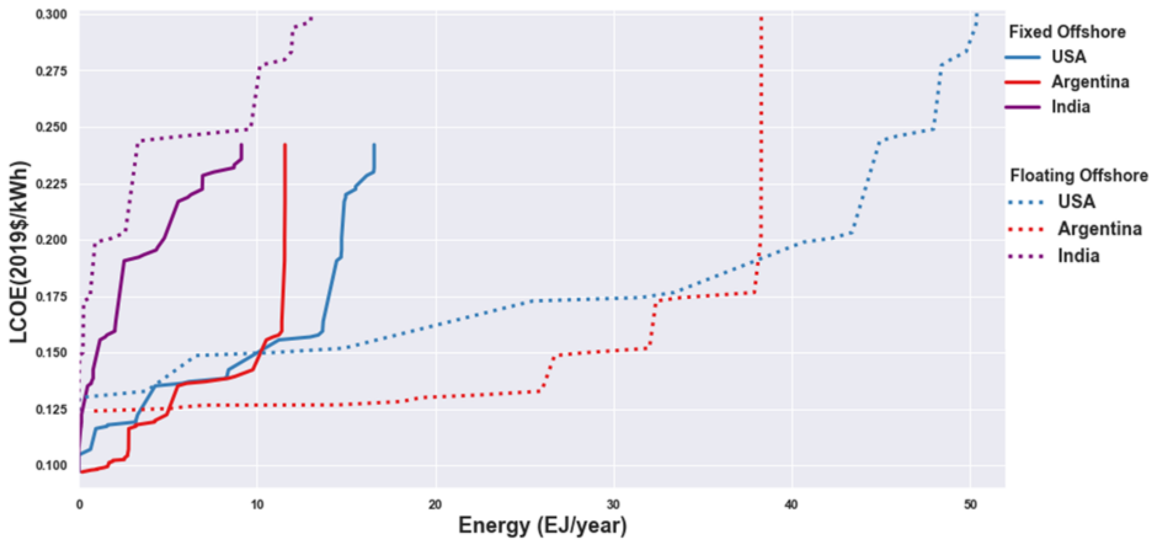

Figure 5: Resource curves at the mean cost of fixed and floating offshore wind energy for USA, Argentina and India

2.2.5 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 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℃ relative to preindustrial levels by 2100. In each case, we used the Shared Socioeconomic Pathway SSP2, which follows a pattern in which social, economic, and technical changes remain relatively constant compared to the present trajectory [58]. The intensity of resource

and energy usage falls along this route, and the global population grows moderately in the second half of the century. Thus, the world faces moderate hurdles in terms of climate change mitigation and adaptation. For each of the three climate policies, we perform 1000 GCAM simulations, totaling 3000 computationally expensive GCAM simulations.

2.2.6 Estimate the climate value of Wind Energy

According to Cranmer and Baker (2020), the climate value of wind energy is the difference between the present value of the entire cost of climate change with and without wind energy and the overall cost of climate change as the sum of the present value of abatement costs and 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 [28]. 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.

To estimate the climate value, we combine GCAM temperature-time paths, $T(s,i)$, total abatement cost, $TAC(s,i)$ and the DICE damage function, $D(s,i)$, where the superscripts w and o refer to the case with and without wind energy among the generation portfolio, respectively.

$$V(s,i) = [TAC(s,i) + D(s,i)]^w - [TAC(s,i) - D(s,i)]^o \qquad (8)$$

The cost of abatement is the cost of decreasing CO2 emissions below the BAU level, computed as the area beneath the marginal abatement curve (MAC) in GCAM. The MAC

denotes the cost of increasing emissions reductions by one ton [60]. By discounting future value at a real rate of 5% per year, the discounted sum of annual abatement costs from 2020 to 2100 equals the net present value of the total abatement cost $TAC(s,i)$ under policy s, sample i.

$$TAC(s,i) = \sum_{t} \delta^{t} AC(s,i)_{t} \tag{9}$$

Where G_t is the global GDP at time t, exogenous in GCAM, $T(s,i)$ is the global mean temperature under policy s, sample i at time t, δ is the discount factor. The parameter a is a multiplier that converts the global mean temperature change to a fraction of the GDP loss, calibrated at 0.00267. This implies that a one-degree Celsius increase of global mean temperature reduces global GDP by 0.267% [28] and b is a parameter for the severity of damages, DICE uses a value of b equal to two, which we take as a medium case. We conduct sensitivity analysis on this exponent where DICE default exponent $b = 2$ represent medium damages, $b = 1.5$ for low damages and $b = 3$ for high damages.

2.3 Results

We begin by discussing the aggregated probability distributions generated from expert elicitation. We next describe the findings of the GCAM simulations, concentrating first on the energy sector's composition and subsequently on the uncertainty associated with wind energy's climate value. Finally, we consider the three policy cases: BAU; \$60/tC starting in 2025 and increasing at 5% annually; and 1.5℃ cap on temperature change by 2100.

2.3.1 Uncertainty in the Cost of Wind energy

Figure 6 presents the fitted theoretical distributions for the three technologies, aggregated from the triangular distributions. Table 2 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[2] (OpenEl). The expert elicitations are wider than the OpenEI estimates, shown by the vertical red dash lines in Figure 6, and more optimistic than this and other projections [61] [52]. Beliefs about growth in turbine size and, for offshore wind, project size are the most prominent cost reduction drivers. While these projections are optimistic, they are consistent with the recent rapid cost reductions over the last five years (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.

[2] OpenEI is a renewable energy and energy efficiency database developed by the U.S. National Renewable Energy Laboratory (NREL) to offer timely information on energy, market investment, and technological development: https://openei.org/apps/TCDB/

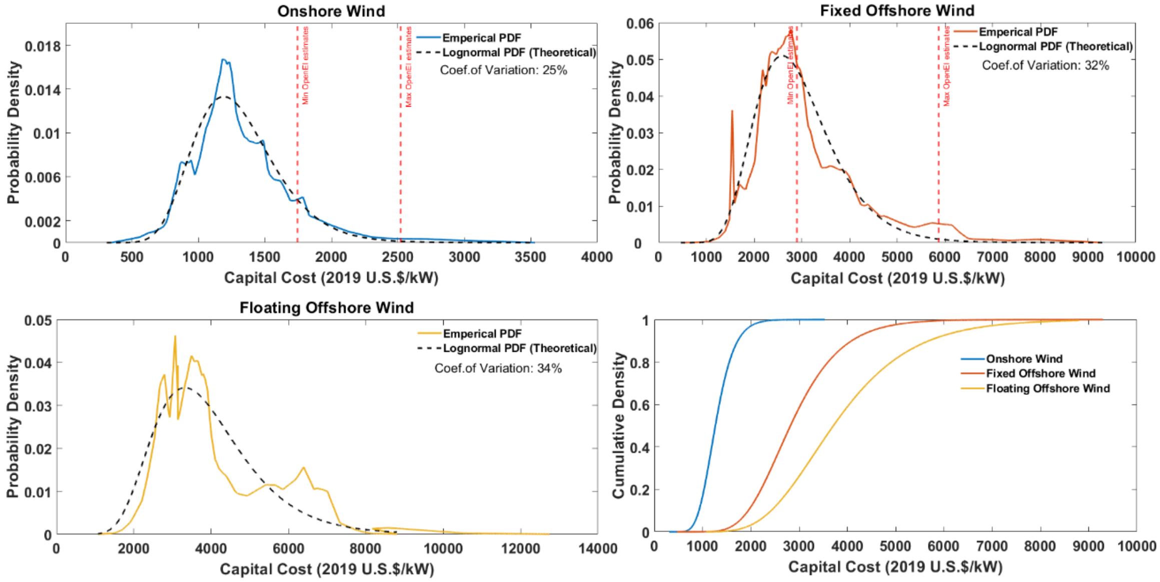

Figure 6: Empirical and theoretical probability density function for the onshore, fixed, and floating offshore wind for 2035. The lower right-hand panel shows the CDFs. The vertical lines are the min and max projection for 2035 from the OpenEI data

Table 2: Descriptive statistics from Elicitation Data Set in USD 2019/kW

	Elicitation cost in 2035				OpenEI 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	10748	-	-

2.3.2 The uncertainty in the composition of electricity generation

2.3.2.1 Wind Electricity Generation

We present the uncertainty in the global electricity generation from onshore and offshore wind energy for 2035 and 2050 for each policy. Fig. 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 EJ and 39 EJ in 2035 and between 5 EJ and 56 EJ in 2050. For offshore wind, this ranges between 0.5 EJ and 32 EJ in 2035 and between 1EJ 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 into perspective, wind energy in total generated 5.2 EJ (1430 TWh) of electricity in 2019, making up 5.3% of the world's total electricity generation [62]. The implication is that even in a terrible outcome in cost, approximately 4 EJ of wind energy could still be added to the 2019 total. Across the policies, the level of electricity generation and the uncertainty about electricity generation increases with the stringency of the climate policy, as shown in Figure 7.

Figure 8 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 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% to 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.

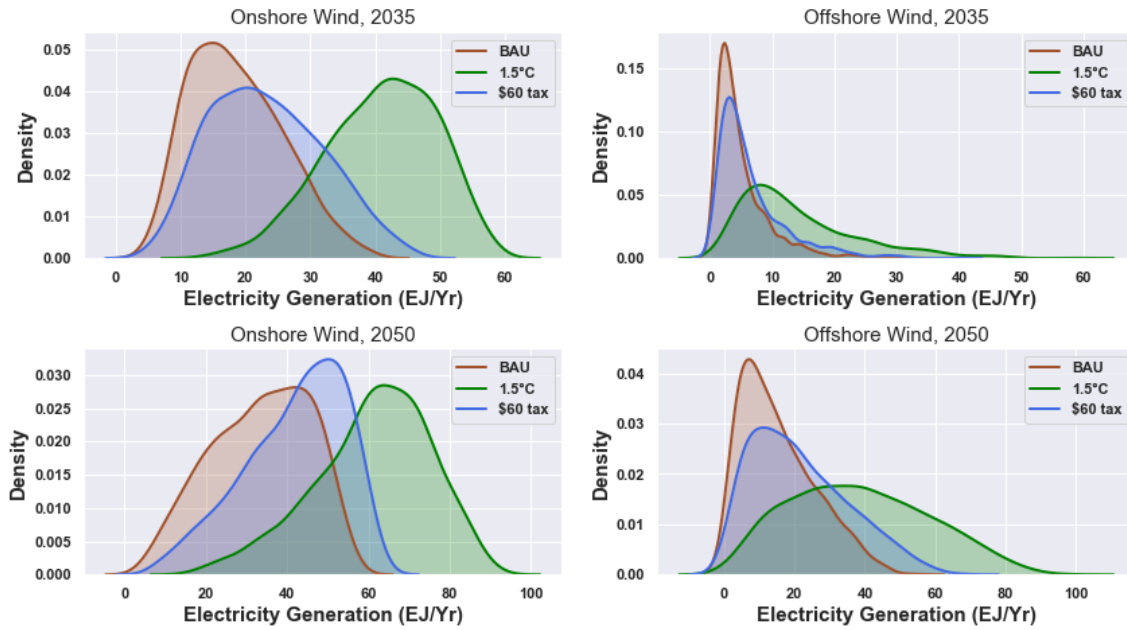

Figure 7: Distribution of electricity generation from Onshore and Offshore wind for the years 2035 and 2050 under three climate policy cases.

Under the carbon tax case, the combined share of wind energy by 2035 ranges between 12-25%, at the 90th and 10th percentile costs, respectively; under the 1.5C cap, the range is between 23-34%. While these results align 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 3 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.

Table 3: 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%

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 is also very sensitive to uncertainty in cost: an unfavorable outcome in cost could reverse the current trend in offshore wind energy deployment, which has seen offshore wind grow from 8 TWh in 2010 to 67 TWh in 2018 [63].

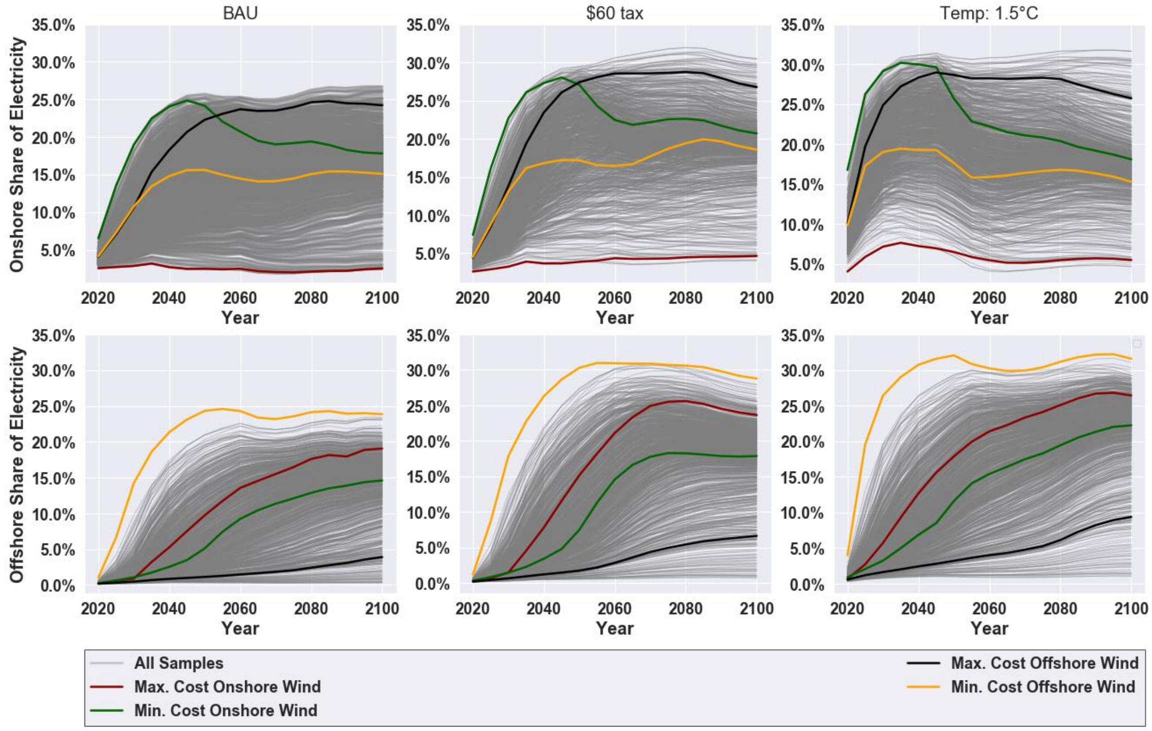

Figure 8:Percent share of electricity generation from wind energy under different wind energy costs and climate policies. Top panels show onshore wind, bottom show offshore wind. Each line represents one sample.

2.3.2.2 Other generation options

Figure 9 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 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 $\pm$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℃ 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.

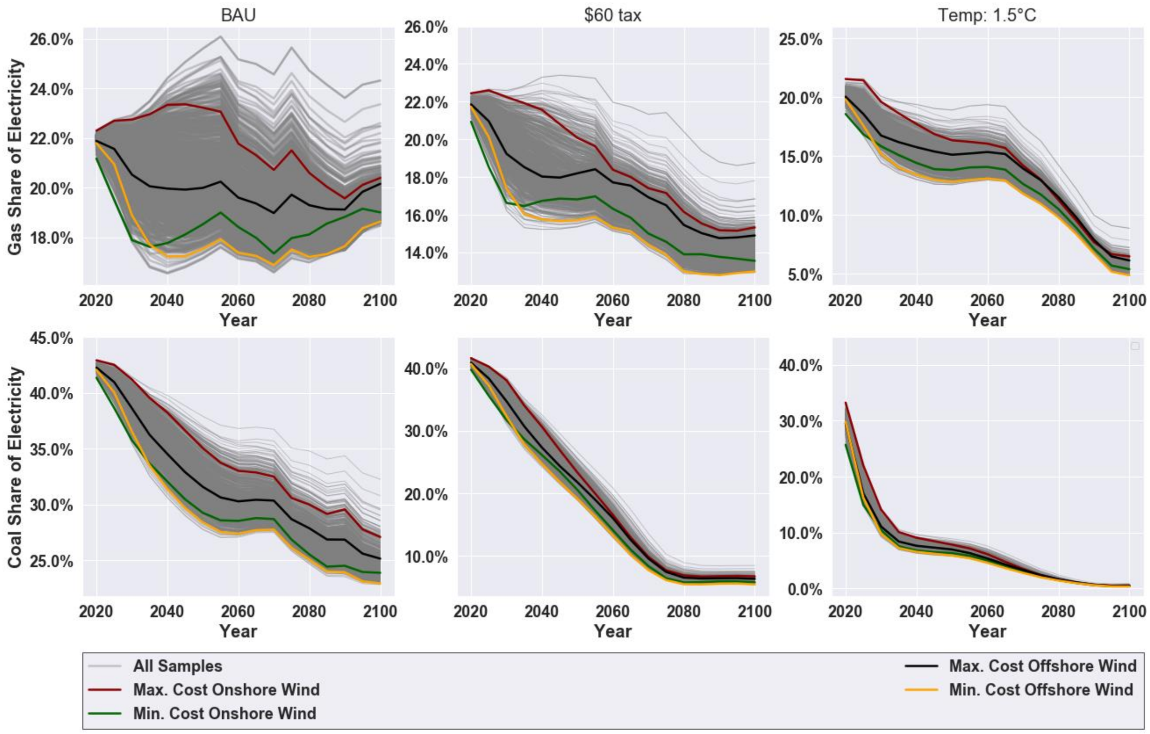

Figure 9:Percent share of electricity generation from Natural Gas (top panels) and Coal (bottom panels) under different wind energy costs and climate policies.

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% - 1.6% at the 10th and 90th percentile cost of wind energy, with a mean share of about 1.5%. Under a global $60/tCO2 tax, solar share increases, fluctuating between 1.7% - 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.

2.3.3 The Climate Value of Wind Energy

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 Figure 10, 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.

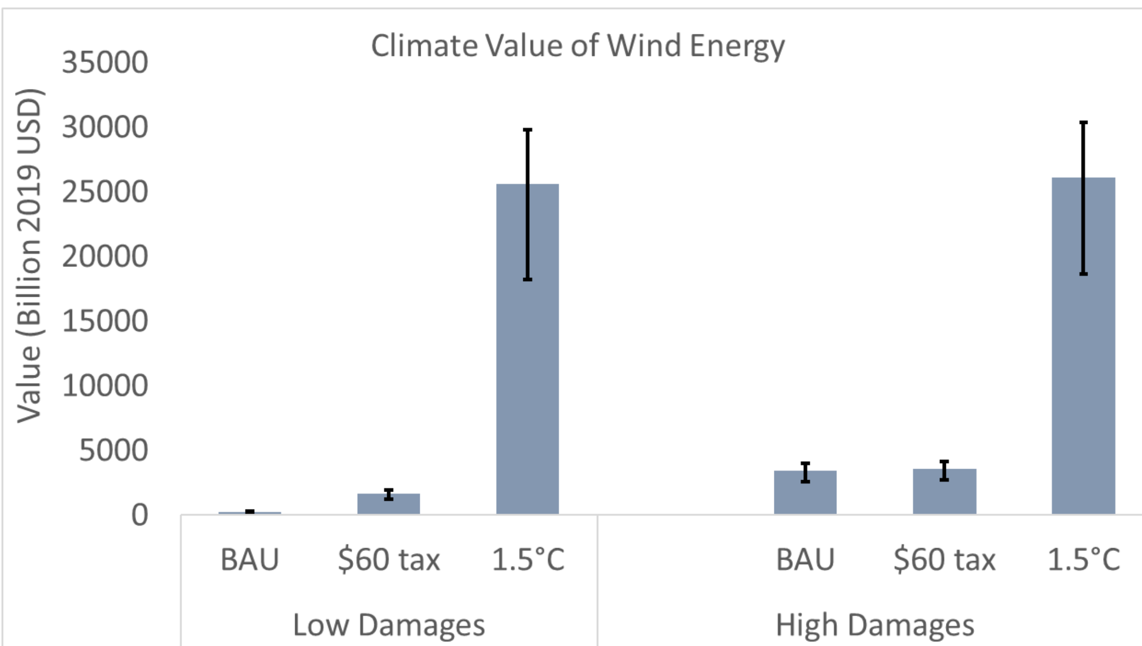

Figure 10: Climate value of wind energy. The bar represents the climate value at the 50th percentile cost of wind. The top and bottom whiskers are the climate value at the 10th percentile and 90th percentile cost of wind energy

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 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℃ 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. Figure 11 shows the cumulative distribution function (CDF) of the net climate value of wind energy across the three policies and three damage levels over the rest of the century (2020 -2100).

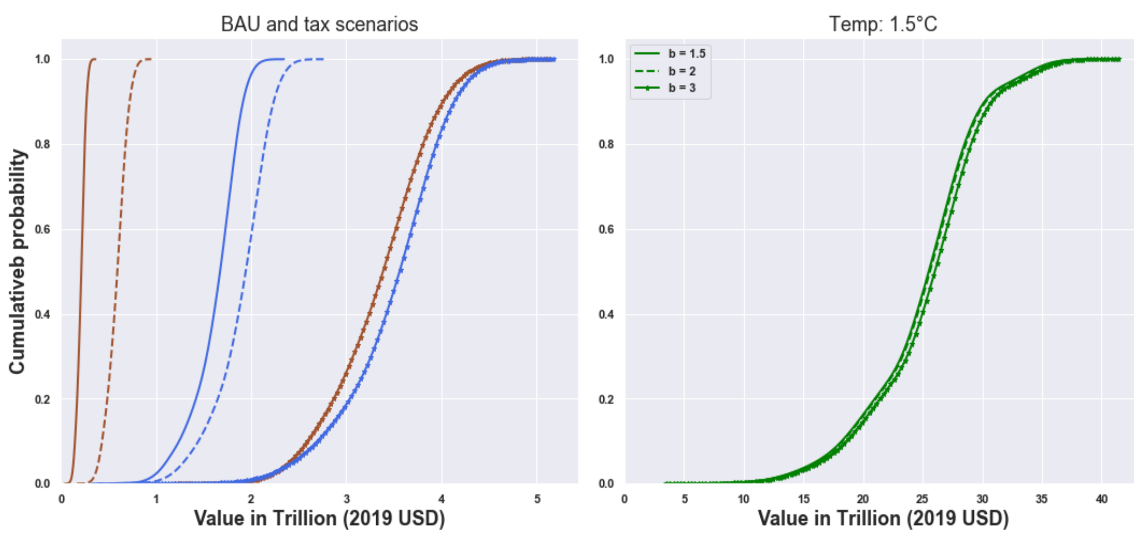

Figure 11:Cumulative distribution function (CDF) of the net climate value of wind energy across all policies

2.4 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. Energy literature has examined the role of wind energy in mitigating climate change, with a particular emphasis on the resource potential exploited for power generation. Our work integrated data on wind energy resource potential with a large-scale expert elicitation of wind energy's future cost to be used as an 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 to deploy large amounts 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 9-20% by 2035, generating between 13-34 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” [40], 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℃ 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 research on expert elicitation emphasizes the fundamental challenges of developing an elicitation process that reduces expert bias and accurately

aggregating the data obtained [45]. As a result, evaluating the quality of the information obtained through expert elicitation is challenging. Therefore, the possibility exists that the experts could be underestimating or overestimating the potential for wind energy cost reduction.

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, correlate with CapEx improvements. 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 is characterized by its own set of assumptions and shortcomings. For instance, because GCAM makes strict assumptions about grid integration and technological competitiveness; as a result, our predictions of wind energy output may be low in comparison to those of other models. Additionally, the logit function utilized by GCAM for technical competition has ramifications. For instance, it implies that a certain proportion of each technology is employed even when prices are high; this might result in an overestimation of wind energy's output and mitigation capabilities in high-cost situations. Additionally, GCAM does not model endogenous technological change. Rather than that, technology progress is exogenously predicted, resulting in an underestimate or exaggeration of abatement costs and emission trends, depending on the degree of optimism expressed in expert projections.

Additional research utilizing various IAMs and examining the interconnections between uncertainty in different technologies might result in more robust and

encompassing results. Finally, the functions used to assess climate damages are likely to be much more sophisticated than a power function used here. Nonetheless, this analysis is a first attempt to comprehend how expert-derived wind energy uncertainty propagates into the energy mix and climate value.

Altogether, our results imply that, while understanding the global wind resource is essential, 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.

CHAPTER 3

LOW CARBON ENERGY R&D PORTFOLIOS THAT ARE ROBUST TO MODEL AND BELIEF UNCERTAINTY

3.1 Introduction

Strategic R&D investment in low carbon energy technology is a critical path to addressing climate change [65]. But evaluating and comparing R&D portfolios is difficult due to significant uncertainties and disagreements about the technological, economic, and societal outcomes of the investments in the long run [18]. This chapter identifies low carbon R&D portfolios robust to two distinct types of uncertainty: parametric and structural uncertainty.

Parametric uncertainty refers to uncertainty over the specific future values of important parameters, in this case, the evolution of the costs and efficiencies of energy technologies in response to R&D [6]. Parametric uncertainty has been widely addressed in the literature [See Baker et al. (2017) [18] for a review]. The most often used technique is sensitivity analysis, which takes energy R&D investment as a given and examines the potential consequences of a range of technology assumptions [66]. Uncertainty analysis goes a step further, employing Monte Carlo or similar simulations to explore probability distribution over IAM outputs of interest using the probability distribution of future technology cost and performance as input[67]. The probability distributions are used in decision-making under uncertainty to provide insight into near-term strategies given the present state of knowledge. Dominance techniques, such as Robust Portfolio Decision

Analysis (RPDA), which was recently developed by Baker, Bosetti, and Salo [1], can discover portfolios that are non-dominated across a wide variety of plausible probability distributions. We build on this work, which explored energy R&D investment under parametric uncertainty. They take the model and stabilization as given, thus avoiding questions about the structure of damages.

Structural uncertainty refers to uncertainty about causal chains and is represented by the many different models used to understand, analyze, and assess climate change causes and effects [6]. We focus explicitly on the structure of climate damages as represented by three prominent cost-benefit Integrated Assessment Models, DICE, PAGE, and FUND. To calculate the social cost of carbon, the US government uses the three highly aggregated, integrated assessment models (DICE, FUND, and PAGE) to estimate the monetary losses caused by each extra unit of carbon dioxide (CO2). These models have long histories and have produced most of the SCC estimates in the recent scientific literature.

Structural uncertainty has been addressed much differently than parametric uncertainty, primarily through multi-model intercomparison studies [64][65]. These studies compare results side by side and provide some qualitative analysis of what drives the differences in the models. For example, Bosetti et al. (2015) utilized future technological prices in the three cost-effective global IAMs to explore the influence of technology assumptions on environmental and economic indicators across the models.

3.1.1 Robust Portfolio Decision Analysis – Belief Dominance

This chapter is an extension of work started in Baker et al. [1]. In that work, Baker et al. developed the concept of belief dominance. Briefly, belief dominance is related to the established concepts of Pareto and stochastic dominance, with significant differences. Under belief dominance, an alternative $\boldsymbol{x}$ dominates an alternative $\boldsymbol{x}'$ if $\boldsymbol{x}$ is preferred to $\boldsymbol{x}'$ for all plausible beliefs about the future state of the world. The concept of belief dominance was applied to develop the Robust Portfolio Decision Analysis (RPDA) framework. The RPDA framework is a promising strategy for decision-making in the face of significant ambiguity. It identifies non-denominated portfolios, which may then be studied further to get insight into robust portfolios' characteristics or categorize a specific portfolio as robust (e.g., present in all non-denominated portfolios) or non-robust (e.g., never present). For instance, a portfolio A dominates B if A is preferred over B for all conceivable probability distributions representing the outcomes of these portfolios [1].

Baker et al. [1] examined R&D investment portfolios into low-carbon energy portfolios. They showed that RPDA could be used to identify common ground among divergent beliefs about the future development of energy technologies. However, that work was confined to a single carbon policy (450ppm) and IAM. This chapter implements the rigorous analytical framework of RPDA to derive specific insights into low carbon energy sources (LCES) R&D portfolios of investment under both parametric and structural uncertainty.

We consider portfolios made up of investments in five low carbon energy technologies: biomass, liquid biofuels, CCS, nuclear, and solar, and three possible levels of investment in each technology, making a total of 3^5 possible portfolios of investment.

Using three large-scale expert elicitation studies and three damage models, we identify all non-dominated portfolios of R&D investment in LCET. A portfolio is non-dominated if no other portfolios outperform it in all models and elicitation studies. The expert elicitation studies provide forecasts of the costs and efficiencies of these five technologies, conditioned on R&D investments [65]. The studies were undertaken independently by three teams (Harvard, UMass, FEEM) in 2008-2013 and harmonized in Baker et al. 2015 [2]. We coupled the technologically detailed Global Change Analysis Model (GCAM) integrated assessment model [26] with the damage modules of three cost-benefit models, DICE [28], FUND [29], and PAGE [31]. GCAM's detailed energy module is used to estimate the impact of assumptions about technology cost and efficiency on emission abatement costs, temperature, and CO2 emissions and concentration. GCAM is a cost-effective IAM. Thus, it does not estimate damages from climate change. We use the cost-benefit IAMs to estimate damages based on the GCAM outputs (See Chapter 1 for an introduction of these models; and Chapter 3.2 below for details on the implementation). We implemented three global climate policy scenarios in GCAM: carbon taxes of USD 125/tCO2 and USD 50/tCO2 (each increasing at 3% annually beginning 2025) and a business-as-usual case with no global policy.

For the rest of this chapter, section 3.2 introduces the methodology. First, we explain implementing the expert elicitation into GCAM, followed by the problem's decision variables, objectives, and constraints. Finally, the results are discussed in section 3.3 and the conclusion in section 3.4.

3.2 Method

We employ a multi-model framework comprised of four IAMs and the RPDA framework to uncover non-dominated R&D portfolios across cost-benefit IAMs. Figure 12 is a schematic diagram representing the decision framework. The main decision shown by the rectangular node is the amount of R&D to allocate to each technology. The oval node represents the uncertainty around the performance of technologies in 2030. As illustrated by the arrow leading into the oval node, the probability distribution over technological performance is conditional on R&D spending. Finally, the technologically detailed GCAM selects technology deployment and estimates abatement costs and climate variables given a set of technology performance metrics and climate policy.

The cost-benefit IAMs (DICE, PAGE, and FUND) introduced in chapter 1 take the GCAM climate variables as input and estimate the climate damages. Despite their similarities, the models significantly differ in their input assumptions and structure, most notably in their degree of regional and sectoral disaggregation, damage function, and the management of adaptation and uncertainty. See Table 1 for a complete comparison of the models. The main objective is to minimize the cost of abatement and the cost of climate damage and R&D investment. We implement RPDA to identify the non-dominated portfolios for each of three policies: BAU and the two-carbon tax policy cases. Below we discuss how expert elicitations are implemented into GCAM and provide more detail on the objective and decision framework.

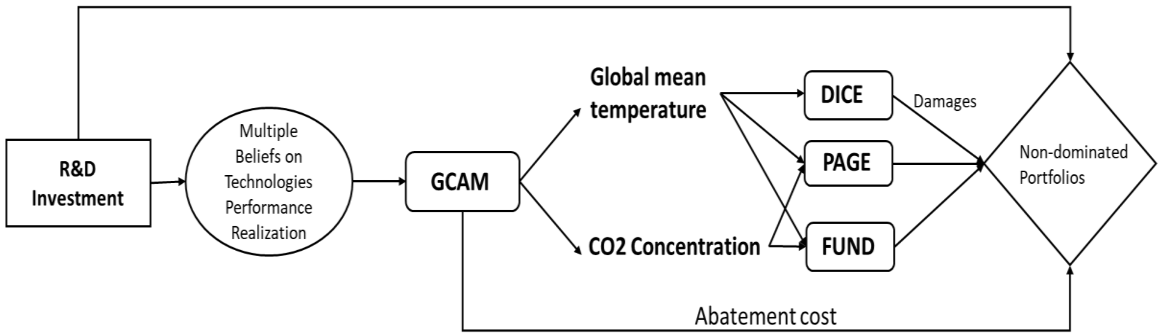

Figure 12: A schematic representation of the decision framework. The rectangular nodes denote decisions, the oval nodes denote uncertainty, the rounded rectangles represent model computations, and the diamond denotes the objective values.

3.2.1 Implementing the Expert Elicitation into GCAM

Technology competition in GCAM is based on the performance metrics of each technology, i.e., cost and efficiency of the technology. The performance metric for the LCET used as input in this chapter is sampled from the harmonized probability distribution of the expert elicitation by Baker et al. [2]. In total, eight probability distributions represent the cost and efficiency of the technologies in the year 2030. There is one distribution for each uncertain performance metric: solar PV Levelized cost of electricity, nuclear power overnight capital cost, bio-liquid Levelized non-energy cost and conversion efficiency, bio-electricity non-energy cost and conversion efficiency, and carbon capture and storage (CCS) capital cost and energy penalty.

We generated 1000 samples from the eight probability distributions using the Latin Hypercube sampling method, making a total of 8000 sample points to be evaluated. Each of the 1,000 samples reflects a potential future state of the world in 2030, comprising a unique value for each of the eight parameters. We implement each of the 1000 states of the world, one at a time, in GCAM, repeated for all three policy cases: business-as-usual case,

with no climate policy in place, and the two carbon tax policy cases. Thus, the elicitation data set contains static values representing the states of the world of technology in 2030. To run a state of the world in GCAM, spanning from 2015 to 2100, we account for the change in the performance metrics every five years between 2015 and 2030 and subsequent years after 2030 using a slight modification of Moore's law.

Moore's law concept assumes that technical development grows exponentially over time [11]. There exist several methods for describing the cost evolution of technologies. Nagy et al. [11] compared the performance of six formulations, including traditional learning curves [55] and Moore's Law. Moore's law predicts cost at a given point in time, whereas Wright's law predicts cost over cumulative production. They conclude that, when it comes to technological cost forecasting, these two approaches are about the same in terms of 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 [53]. 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.

Let Z be the data set and i index the samples, where $i = \{1, 2, \dots \dots, 1000\}$. Let j index the technology performance metrics, $j = \{1, 2, .., 8\}$. Therefore, $z_{ij}(2030)$ represents an individual element of the data set, $z_j = \{z_{1j}, z_{2j}, \dots, z_{1000j}\}$ represents sets of values for metric j for all state of the world i; and $z_i = \{z_{i1}, z_{i2}, \dots, z_{i8}\}$ is the vector of all eight metrics that represent state of the world i. Finally, $z_{ij}(t)$ is metric j (cost or efficiency) for sample i, at time t. Each metric j has one lower, and one upper bound, $z_j{}^{min}$, and $z_j{}^{max}$. The lower bound is the cost or efficiency with cumulative probability of 10^{-6} ; the upper

bound is the opposite tail. We use the lower bound z_j^{min} for sample ij, when the sample indicates cost decreasing after 2015; and an upper bound z_j^{max} if the sample indicates cost increasing after 2015. The base year value for each metric j for 2015, $z_j(2015)$ is constant across all samples; this value is taken from GCAM default assumptions for all the performance metrics [52]. Let m_{ij} be Moore's constant associated with the individual element $z_{ij}(2030)$. This constant is calculated for each sample i and metric j using Eq. 10, and then used in Eq. 11 to calculate $z_{ij}(t)$ for all other time periods. Note, Eq. 10 & 11 represent a case where the metric decreases in value approaching 2030, i.e., the metric's value is lower in 2030 than in 2015. The approach is similar in the case where metrics are higher in 2030, with a ceiling in the place of a floor.

$$m_{ij} = -\frac{1}{2030 - 2015} ln\left[\frac{z_{ij}(2030) - z_j{}^{min}}{z_j(2015) - z_j{}^{min}}\right] \qquad (10)$$

$$z_{ij}(t) = z_j{}^{min} + \left(z_j(2015) - z_j{}^{min}\right)e^{-m_{ij}(t - t_{2015})} \qquad (11)$$

3.2.2 Decision Framework – Implementing RPDA

We extend the RPDA framework by including disagreements between the three cost benefits IAMs. Output from GCAM and the cost-benefit IAMs are used in the RPDA decision framework to identify non-dominated portfolios of R&D investments in low carbon energy technologies in the face of multiple beliefs about the impact of R&D investment on technical change and uncertainties across cost-benefit models. The key decision is which level of investment should be allocated to each technology. The deep uncertainty involves (1) the performance of the technologies, given that expert study disagrees on the impact of R&D investment on technological change, and (2) the resulting

damages from climate change, given that cost-benefit models disagree on the damage function. Solar PV, nuclear energy, carbon capture and storage (CCS), biomass electricity (BE), and liquid biofuels (BF) are the five major low-carbon energy technologies that make up a portfolio x.

Here we describe the variables, objectives, and constraints of the decision problem. Let $x_{hd} = 1$ if technology h is invested in at the d^{th} funding level, and 0 otherwise. Let $h = \{1,2,..,5\}$ index the five technologies (note there are five technologies, indexed by h, and eight performance metrics, indexed by j). Each technology in the portfolio can be invested in at one of the three levels of investment ($d = low, mid\ and\ high$). Therefore, for the five technologies with three levels of investment, we have a total of $3^5 = 243$ possible portfolios. The total cost of R&D investment $B(x)$ for portfolio x is the sum of the individual R&D investments in each technology in the portfolio, multiplied by the opportunity cost multiplier $k = 4$ (See Baker et al. 2020 [1] for details on the opportunity cost multiplier). Table 4 shows the R&D cost assumptions for different levels of investment.

Let $m = \{1,2,3\}$ be the index for the three cost-benefit models: DICE, PAGE, and FUND and $\tau = \{Harvard, UMass, FEM\}$ index the individual elicitation teams. For a scenario $z_i = \{z_{i1}, z_{i2}, \dots, z_{i8}\}$, the probability of realization of the state of the world of a particular scenario $f_\tau(z_i|x)$, from team τ given the portfolio x. The damages depend on the model $m = \{1,2,3\}$. The overarching objective, therefore, is to minimize the cost of abatement (TAC) plus the climate damages (D_m) and the R&D investment in portfolio x, across all models, given a policy scenario s:

$$H(x;m;\tau) \equiv \left[\sum_{i=1}^{1000} f_\tau(z_i|x)\{TAC(z_i,s) + D_m(z_i,s)\}\right] + kB(x) \;\; For\ s = BAU, tax \tag{12}$$

$$s.t. \sum_d x_{hd} = 1 \; \forall t$$

The constraint assures that each technology is only invested in once. We begin by calculating the total expected cost, H, for each of the 243 portfolios using this equ (12). Then, using Yukish's simple cull method [69], we find the non-dominated sets. Therefore, a portfolio x belief dominates x' if $H(x;m;\tau) \leq H(x';m;\tau)\ \ \forall m,\tau$ with strict inequality for at least one of the beliefs. A portfolio x is non-dominated if it is not dominated by any other feasible portfolio.

Table 4: Annual R&D spending, in millions of dollars, for each project, considered constant throughout 20 years period.

Investment Level	Nuclear	Solar PV	Bioelectricity	Bioliquids	CCS
Low	6.2	1.7	1.4	1.4	5.3
Mid	19.2	4.0	3.0	3.7	17.1
High	178.3	33.0	16.9	20.3	168.1

3.2.2.1 Abatement cost (AC)

The cost of decreasing CO2 emissions below the BAU level is the abatement cost in the objective function above. The cost of abatement is calculated by GCAM as the area under the marginal abatement curve (MAC). The cost of decreasing emissions by one ton is referred to as the MAC [60]. By applying a real discount rate of 5% per year to future

values, the discounted sum of the annual abatement costs from 2020 to 2100 equals the total present value of the total abatement costs $TAC(z_i, s)$under policy s and scenario z_i

$$TAC(z_i, s) = \sum_t \delta^t AC(z_i, s)_t \tag{13}$$

Where $AC(z_i, s)_t$ is the annual abatement cost (in trillions of 2015 USD) under policy s and state scenario z_i at time t, and δ is the discount factor. Note in the BAU case, the cost of abatement is, by definition, zero. Hence in Equ. 13 above, $TAC(z_i, BAU) = 0$.

3.2.2.2 Damages (D*m*)

Each of the 1000 states of the world implemented in GCAM leads to different emissions and temperature paths and hence different estimates of damages in each IAM. Therefore, the climate variables that drive damage estimation in each IAM are replaced with the GCAM output for each scenario to account for the impact of technological change on these variables. For example, the global mean temperature estimate in DICE and PAGE is replaced by the global mean temperature change estimated from GCAM from 2010 to 2100 for each scenario. FUND is slightly more complicated. For each of the 14 sectors in FUND, the main drivers for each sector are replaced by either the global mean temperature change or the CO2 concentration from GCAM, depending on the variable that drives the damage estimate for that sector. For each climate policy: USD 125/tCO2 and USD 50/tCO2 (each increasing at 3% annually beginning 2025) and a business-as-usual case, damages are estimated for all 1000 scenarios for each IAM. The damages calculated from the cost-benefit IAMs and the abatement cost estimated from GCAM are used as inputs into the decision framework.

3.3 Results

3.3.1 Non-dominated portfolios

Under the \$125/tCO2 tax policy, we find that, out of the 243 possible portfolios, 16 portfolios are non-dominated across the probability distributions and the models. Figure 13 shows the objective values under each of the nine combinations of probability distributions and IAMs. The objectives, in this case, are the expected value of the cost of abatement, the cost of damages, and the opportunity cost of the R&D portfolio. The values have been normalized, with zero being the portfolio that performs worst under the specific combination of models and probability distributions and one being the best. We have highlighted the eight portfolios that are reasonable compromises among the complete set of beliefs. They are never below 70% of the highest possible value for any of the combinations. See table 5 below for the 16 portfolios ranked in ascending order of the R&D expenditure, where each row represents one portfolio.

The importance of model uncertainty can be seen by looking at the variation of the objective values within an elicitation team. For example, we see that the DICE model can lead to very different objective values, even while using the same UMass elicitations. In addition, the importance of disagreements over parametric uncertainty can be seen by comparing across the teams. For example, we see some portfolios, such as Portfolio 2 and 6, at the top under FEEM but toward the bottom of the non-dominated group for UMASS.

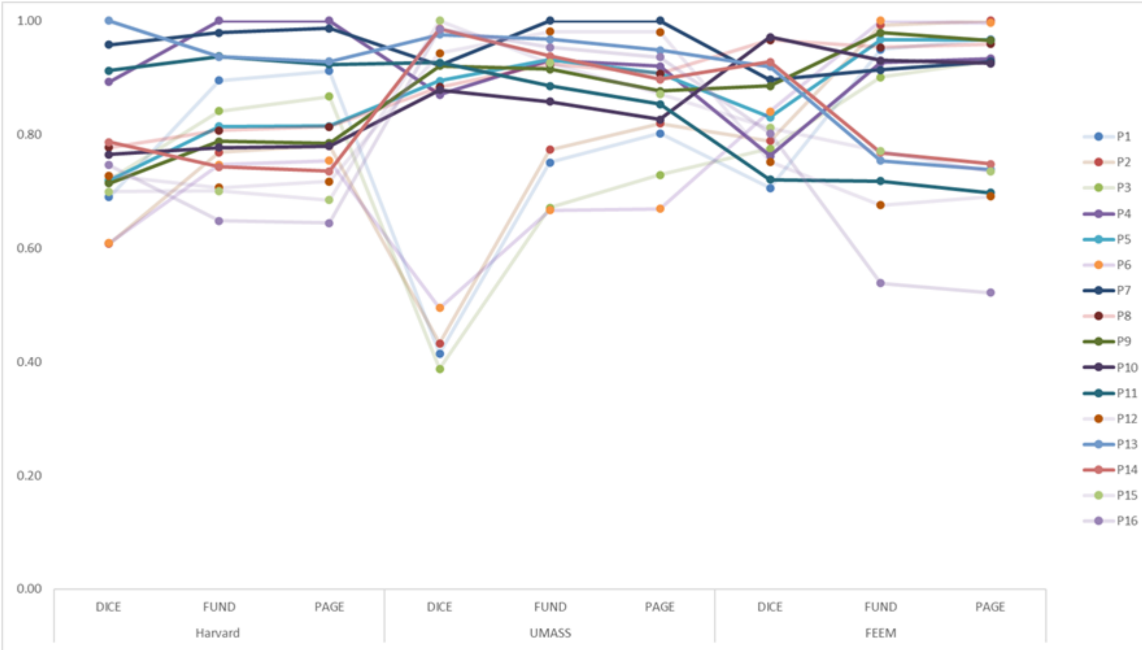

Figure 13: Objective values of the non-dominated portfolios across nine combinations of probability distributions and IAMs.

3.3.2 Insights into individual Technologies

Looking at Table 5, we see that under the \$125/tCO2 tax policy, it is always robust to invest in R&D at a high level in both Solar and Bioelectricity, regardless of the elicitation team, the damage model, or the investment in other technologies. On the other hand, we see investments at all levels (Low, Mid, and High) for Nuclear, CCS, and Biofuel among the non-dominated portfolios, suggesting that disagreement across elicitation teams and models is more relevant for these technologies.

Table 5: Non-dominated portfolios. Columns 2-6 indicate the level of R&D investment for each technology, classified as Low, Mid, or High. Column 7 shows the total annual investment in R&D for each portfolio.

Portfolio	Technologies					Total R&D (In million USD $2019)
	Solar	Nuclear	Biofuels	Bio-elec	CCS	
1	High	Low	Low	High	Low	80.75
2	High	Low	Mid	High	Low	83.66
3	High	Low	Low	High	Mid	95.88
4	High	Mid	Low	High	Low	97.42
5	High	Mid	Mid	High	Low	100.33
6	High	Low	High	High	Low	105.02
7	High	Mid	Low	High	Mid	112.55
8	High	Mid	Mid	High	Mid	115.47
9	High	Mid	High	High	Low	121.69
10	High	Mid	High	High	Mid	136.82
11	High	High	Low	High	Low	301.69
12	High	Mid	Low	High	High	306.56
13	High	High	Low	High	Mid	316.82
14	High	High	Mid	High	Mid	319.73
15	High	High	High	High	Low	325.96
16	High	High	Low	High	High	510.82

We explore to what degree this disagreement is driven by the structure of the damage models or by disagreement over beliefs. Figure 14 provides a visualization of how the different models and beliefs lead to different investments in individual technologies through a ternary diagram for each technology under each model. Each ternary shows the optimal level of investment for each weighting of the elicitation teams.

To see the importance of model uncertainty, read each row from left to right. Here we see the most striking difference between the models for Nuclear. Almost all combinations of beliefs lead to a high investment in Nuclear under DICE, whereas almost all combinations of beliefs lead to a mid-investment under PAGE and FUND. This is

because DICE damages are a quadratic function of temperature that increases smoothly with warming. PAGE response much stronger to warming above 3℃, "when the risk of a discontinuity is present, and adaptation capacity is reduced. FUND projects net *benefits* below 2.5 °C, and impacts increase only gradually with temperature" [30]. The $125/tCO2 tax policy that we consider here limits temperature change to less than 2.5℃. This, combined with the fact that GCAM implies that nuclear can be particularly effective at reducing emissions, may explain why DICE recommends more aggressive R&D investment in Nuclear energy than the other models.

For Biofuels and CCS, a different story emerges. There is much more agreement between the models about R&D investment in these technologies. For Biofuels, even though there are a few non-dominated portfolios with mid or high investment, most combinations of the beliefs and models lead to low optimal investment in Biofuels. Similarly, most combinations of the beliefs and model lead to an optimal mid investment in CCS.

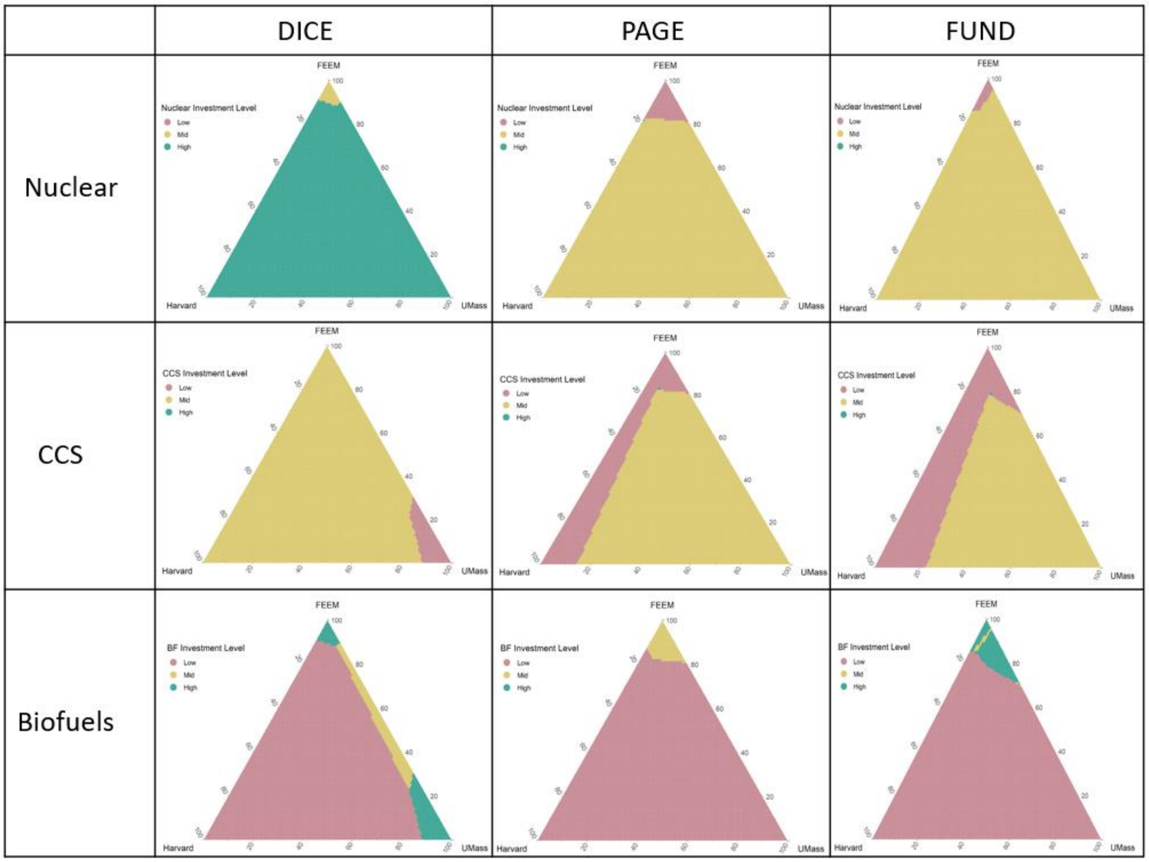

Figure 14: Each ternary diagram shows the optimal investment level for each combination of elicitation teams, given the specific technology and model.

3.3.3 Role of policies

We find that less stringent policies lead to more non-dominated portfolios across all elicitation teams and models. For example, under the \$125/tCO2 tax policy, 16 portfolios are non-dominated under all beliefs and models. On the other hand, under the \$50/tCO2 tax, there are 37 portfolios and 56 portfolios with no policy (BAU). As the policy becomes less stringent, emissions increase, and damages play a more significant role; thus, there is more room for disagreement among the models.

Among the non-dominated portfolios, we identified four portfolios that are non-dominated under each of the three policies, models and elicitation teams: portfolios 5,7,13, and 15 in

table 5 above. We highlight especially portfolios 7 and 13, as these include the investment levels that are most common across all teams and models, namely high investments in solar and bioelectricity; low in biofuels, mid in CCS; and either mid or high in nuclear. This finding indicates that these portfolios and investment levels into these individual technologies are reasonable choices regardless of policy stringency.

Not surprisingly, the level of investment tends to increase with the stringency of the climate policy, although it is not universally monotonic. Figure 15 illustrates, for each technology, the share of each level of investment in the optimal portfolio among all the weightings of the elicitation teams. We show this across the three policies and the three damage models. Each bar is similar to the ternary diagrams above but only highlights the overall share. We generally move towards high investment with stringency in climate policy within any one technology and damage model. One noticeable divergence from this is biofuels, where low investments dominate at $125 under all three damage models. One possible explanation for this could be that biofuels become uncompetitive at a high price, and hence its impact on mitigation is gradually reduced. We see some spots of agreement across the policies and damage models, including a lack of "high" investment in CCS and consistent high investment in Solar and bioelectricity under the $125/tCO2 tax policy. A takeaway is that while policy goals are essential, some portfolios (portfolios: 5,7,13 and 15) are non-dominated under all policies, models, and expert elicitation.

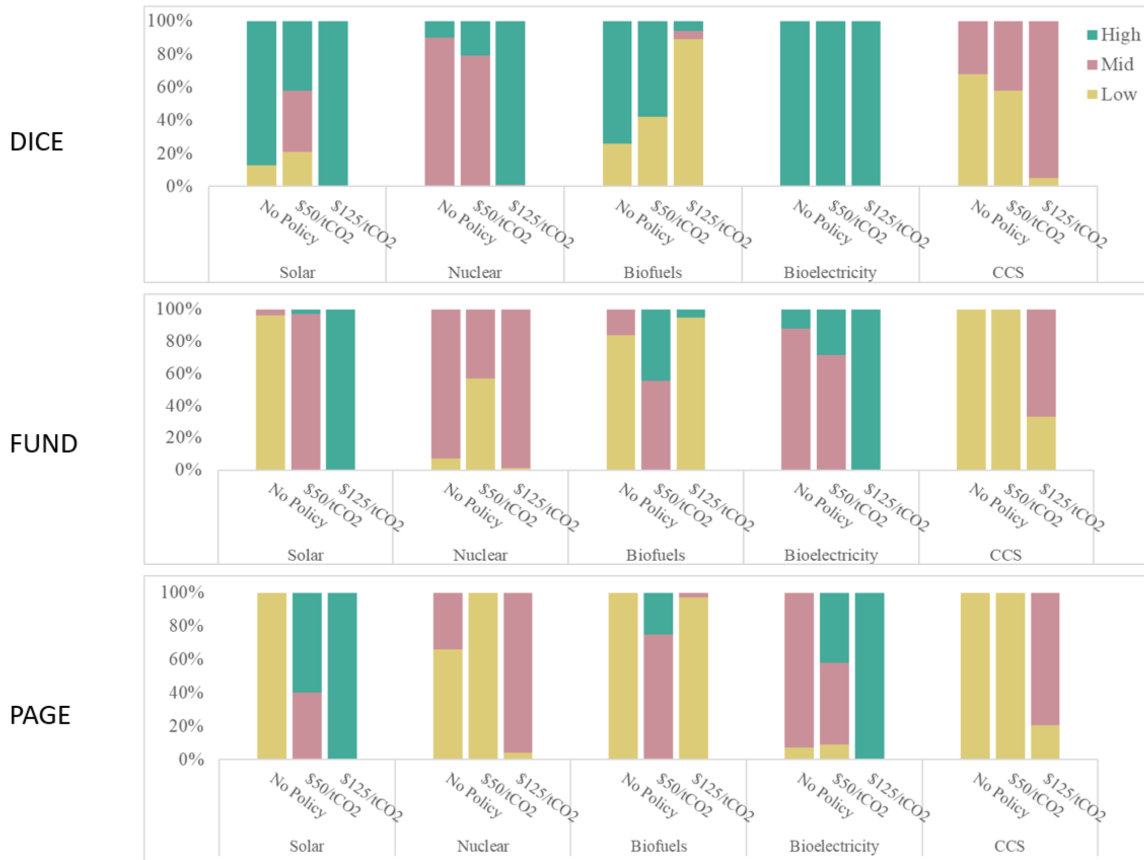

Figure 15: Non-dominated portfolios across different policies

3.4 Discussion

Over the last decade, expert elicitation and integrated assessment models have become integral to analysts and decision-makers formulating policy responses to climate change. For example, the IPCC AR5 [46] recommends expert elicitation to characterize uncertainty to provide insights into specific risks and understand and create effective strategies and policies to address climate change. The US government calculates the social cost of carbon, a monetary estimate of the societal costs of the climate damage caused by an extra unit of carbon dioxide (CO2) emitted into the earth's atmosphere, by averaging the three highly aggregated, integrated assessment models—DICE, FUND, and PAGE. These models have long histories and have produced most of the SCC estimates in the recent

scientific literature. However, while averaging is perfect for capturing central tendency, according to the flaw of averages by Savage [70], "decisions based on the assumption that average conditions will occur are wrong on average."

In this chapter, we combined deep parametric uncertainty, as captured in three expert elicitation studies about the future cost and efficiency of energy technologies, with structural uncertainty, as captured in three cost-benefit IAMs, to address the problem of designing a portfolio of publicly funded R&D investment in low carbon energy technologies. We expanded on the RDPA [1] approach, identifying all non-dominated portfolios of R&D investment across all beliefs and models. Under a $125/tCO2 tax on emissions, we find common ground among the expert beliefs and the models, indicating that high investment in Bioelectricity and Solar are robust to all beliefs and the models given the climate policy.

We did not see the same level of consensus about investment in Nuclear, Biofuels, and CCS. We investigate the technologies individually across the models and beliefs to identify the source of the disagreement. Firstly, the disagreement about investment in Biofuels and CCS are largely parametric, while Nuclear is largely structural. For Biofuels and CCS, even though each investment level shows up in some non-dominated portfolios, most combinations of the beliefs lead to low investment in Biofuels and mid investment in CCS across the three models. For Nuclear, the damage models play an important role. Almost all combinations of beliefs lead to a high investment in Nuclear under DICE and mid-investment under PAGE and FUND. The implication here is that our understanding of the structure of damages is particularly important for allocating investment into Nuclear, especially under stringent climate policies. If we believe that the DICE damage formulation

is more relevant than the formulations of PAGE and FUND, at least at lower temperatures, then a high investment in nuclear is warranted; if PAGE or FUND are better representations, then this investment does not pay off since they are mainly allocating mid-investment. We demonstrated the importance of climate policies on different portfolios under different models. However, the advantage of our approach is that under different policies, models, and elicitation teams, together making a total of 27 dimensions, we discover portfolios that represent common grounds across policies, models, and expert elicitation teams.

CHAPTER 4

INVESTIGATING THE BENEFIT OF REGIONAL COOPERATION AND RENEWABLE ENERGY PENETRATION IN WEST AFRICA POWER POOL: USING OSEMOSYS- WEST AFRICA POWER PLANNING MODEL (ECOWAPP)

4.1 Introduction

The "Economic Community of West African States" (ECOWAS) was created to promote economic integration in all areas of activity of its members[3]. One of the areas crucial to this integration is energy. In ECOWAS, which has a projection population of 391 million people as of 2019, access to electricity ranges from 20% in Niger to 80% in Ghana [71]. The region currently has an installed capacity of 22.7 GW with an available capacity of 13.7 GW and a peak load of 11.5 GW [72]. This is considerably less than the region's estimated demand for electricity of 25.6 GW and growing at 5% per year [73]. Overall, access to electricity in urban areas remained less than 50%, while 82% in rural areas have no access.

To address this problem, ECOWAS formed the West Africa Power Pool (WAPP), a specialized organization with the strategic goal of promoting national power system integration of the member countries. WAPP membership includes 14 out of the 15 countries[4] in ECOWAS. Together, they aim to form a unified regional electricity market

[3] Burkina Faso, Benin, Gambia, Ghana, Guinea, Guinea Bissau, Ivory Coast, Liberia, Mali, Nigeria, Niger, Senegal, Sierra Leone, Togo.

[4] As the only Island in ECOWAS, Cape Verde is not currently part of the West Africa Power Pool

that facilitates medium to long-term energy sector cooperation, unimpeded energy transit, and increasing cross-border electricity trade [74]. The power pool would function as a cooperative effort by member states' national utility companies to develop a reliable electricity grid and a single market for electricity at a competitive price for ECOWAS residents. Any governmental or private company active in electricity generation, transmission, or distribution in the ECOWAS region is welcome to join [75].

This chapter will develop a multi-region model for the long-term dynamics (2018 – 2040) of WAP countries' capacity expansion planning to investigate the benefit of regional integration for capacity expansion and cross border electricity trade and the penetration of renewable energy in the power pool. In this context, the benefit refers to any savings on the overall discounted cost of investment in the power pool.

The region is endowed with a variety of resources that are not uniformly distributed, and its members possess varying degrees of generating capacity. Nigeria, Ivory Coast, and Ghana are all-natural gas-producing countries with substantial hydro resources. Niger has the region's largest coal reserves, whereas other countries rely on imports. Combustible fossil fuels. The current generation portfolios in WAPP are made up of six electricity generation technologies categorized based on fuel type: natural gas, diesel, heavy fuel oil, coal, hydro and solar PV. The technologies within these fuel types also vary in emissions, efficiency, availability, and capacity factor. Based on data from the International Renewable Energy Agency (IRENA) [76], as of 2018, the region is heavily dependent on natural gas for electricity generation: almost 63% of total installed capacity comes from natural gas, followed by hydro and oil, as shown in the pie chart in Figure.16.

This is partly because Nigeria, the most populated country with the highest electricity demand, generates approximately 86% of its electricity from natural gas, followed by Côte d'Ivoire with 60%. Liberia, Gambia, and Guinea Bissau each have one primary source of fuel for electricity generation. Burkina Faso, Senegal, and Togo have the most diverse of generations in terms of fuel sources. The share of electricity generation from each fuel source in each country in 2018 is represented by small pie charts located within the map Figure .17.

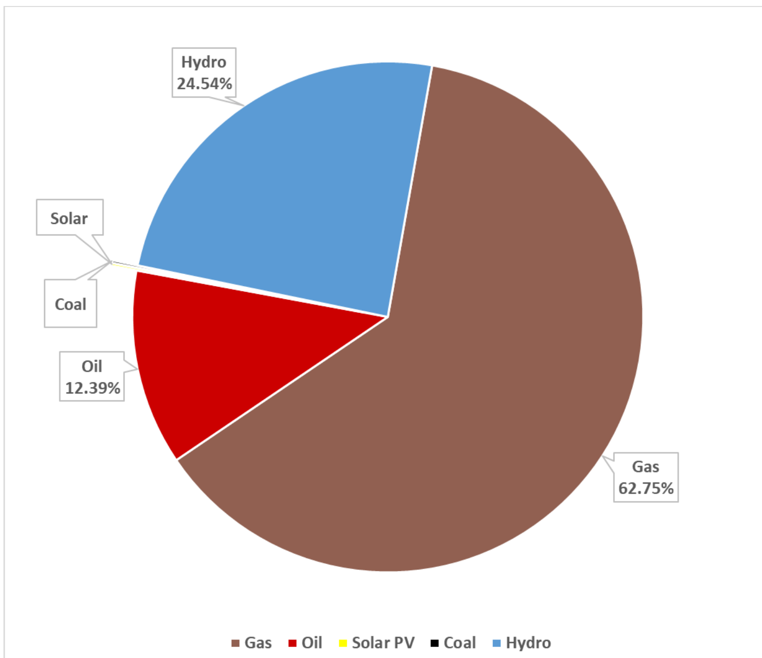

Figure 16: Total Share of installed Capacity of all WAPP countries in 2018 by fuel

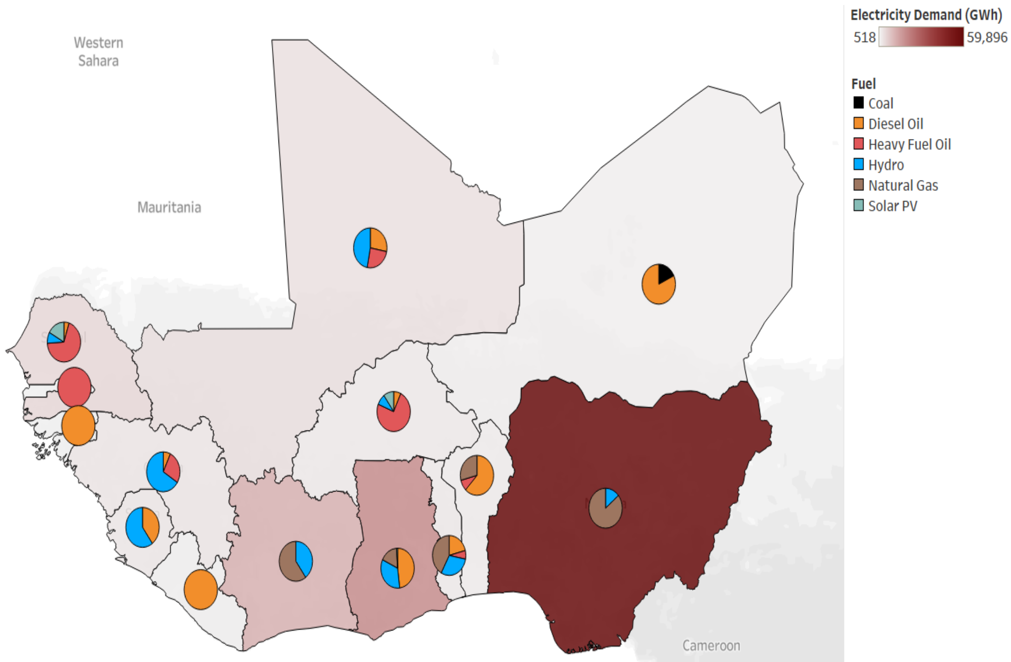

Figure 17: The pie charts show the share of installed capacity by fuel source in each country in 2018.

4.2 Motivation

The West Africa power pool consists of five distinct but mutually reinforcing sub-programs of cross-border transmission infrastructure that make up the regional power pool. The countries on each of these sub-programs and the capacity per transmission line are shown in Table.6. ECOWAS envisages the power pool as a competitive market consisting of independent system operators. The market will comprise of a day-ahead market and dynamic trade in the bilateral market, dependent upon generation, transmission infrastructure, and sufficient operational reserves in the countries [75]. The market is regulated by the ECOWAS Regional Electricity Regulatory and Authority (ERERA) [77] in collaboration with the WAPP Information and Coordination Center (ICC) [72]. ERERA regulates the cross-border electricity exchanges between members of the pool, established tariff setting methodology for regional power pooling, monitors the regional market

operations and resolves disputes among regional market participants. By encouraging this level of regional integration, ECOWAS hopes the unified regional market could ensure in the medium and long term a more reliable and affordable electricity supply to the population of the various member states.

Table 6: Proposed cross-border transmission infrastructure.

Sub-programs	Countries	Capacity per line (MW)
Coastal Transmission – Dorsale	Ghana, Benin/Togo, Nigeria	655.2
Inter-zonal Transmission Hub	Burkina Faso, Ghana, Mali, Côte d'Ivoire,	332.2
OMVG /OMVS - Interconnection	Gambia, Senegal, Guinea Bissau, Mali	340.7
CLSG - Interconnection	Côte d'Ivoire, Liberia, Sierra Leone, Guinea	337.6
North Corridor - Interconnection	Nigeria, Niger, Burkina Faso, Benin/Togo	653.1

Some studies have investigated the benefit of regional interconnectivity of the electricity market in ECOWAS. Gnansounou et al. (2007) looked at the benefit of integration and found potential for reducing the total cost by about 38% over 20 years. A similar study from Purdue University by Sparrow et al. [79] found a 20% saving in total operating cost over ten years using a cost optimization model. The SPLAT model developed by IRENA [76] estimated a $55 billion investment needed to achieve 56% of renewable energy share in the regional electricity generation mix by 2030.

According to a McKinsey report for the World Bank [80], significantly increasing regional integration through power trade within the Power Pool could result in cost savings

of US$5-8 billion per year by enabling WAPP countries to benefit from more cost-effective hydro or gas-based imports and reduce the cost of electricity by more than half in many West African countries. Adeoye et al. [73] developed a dispatch model to investigate the impact of solar PV integration across the WAPP. In their research, they focused on different levels of solar energy integration. Specifically, they examined the potential benefit of cross-border trade under the high integration of utility-scale solar PV. They concluded that savings could be as high as 40% in annual generation cost due to solar PV generation replacing a significant portion of diesel and gas generation.

While these studies examined capacity expansion and the benefits of cross-border electricity trade, they ignored the asymmetry in the load duration curves of the individual countries, and Adeoye et al.[73] concentrated exclusively on solar penetration across the power pool. For the first time, we used detailed monthly and hourly electricity demand patterns for each country sourced from Adeoye et al. [88]. Additionally, we modeled grid-connected renewable energy penetration, including solar, onshore wind, biomass, and hydro, under three policy scenarios: (1) no renewable energy targets; (2) national renewable energy targets; and (3) regional renewable energy targets.

4.3 Experiment

This study developed a multi-region model for the long-term dynamics (2018 – 2040) of ECOWAS capacity expansion planning, called ECOWAPP (ECOWAS Power Planning Model). We consider existing generation capacity, transmission infrastructure, cross-border electricity trade, national capacity expansion plans, and renewable energy targets using the bottom-up Open Source Energy Modeling System (OSeMOSYS) [81]. In

addition, we used ECOWAPP to investigate the benefit of regional integration for capacity expansion and cross-border electricity trade and the integration of renewable energy in the power pool. In this case, the benefit refers to the savings on the total discounted cost of capacity expansion and planning.

To investigate the benefit of the power pool to each country on the power pool, we implement two scenarios in ECOWAPP. In the first case, we develop a trade scenario based on the existing and planned transmission lines in WAPP. In this case, all the interconnected countries on each transmission infrastructure on the power pool can trade electricity. The electricity-generating systems of all the countries in the power pool are integrated such that investments in new capacities are chosen by optimizing the whole power pool. Figure.18 shows existing cross-border transmission lines in the power pool represented by the red arrow and the proposed cross-border interconnections by the black arrow. Single arrows indicate the flow of electricity in one direction, and double arrows indicate electricity flow in either direction. For example, as shown in Figure.18, Nigeria currently exports electricity to both Niger and Benin but does not import electricity from the two countries. The current grid infrastructure on the power pool is designed for electricity to flow from Nigeria to the two countries.

In the second scenario, we implement the model allowing no cross-border trade: each country independently develops its capacity and power generation on the assumption of self-sufficiency. To calculate the benefit of the power pool, we subtract the total discounted cost with electricity trade, and the total discounted cost without electricity trade on the power pool.

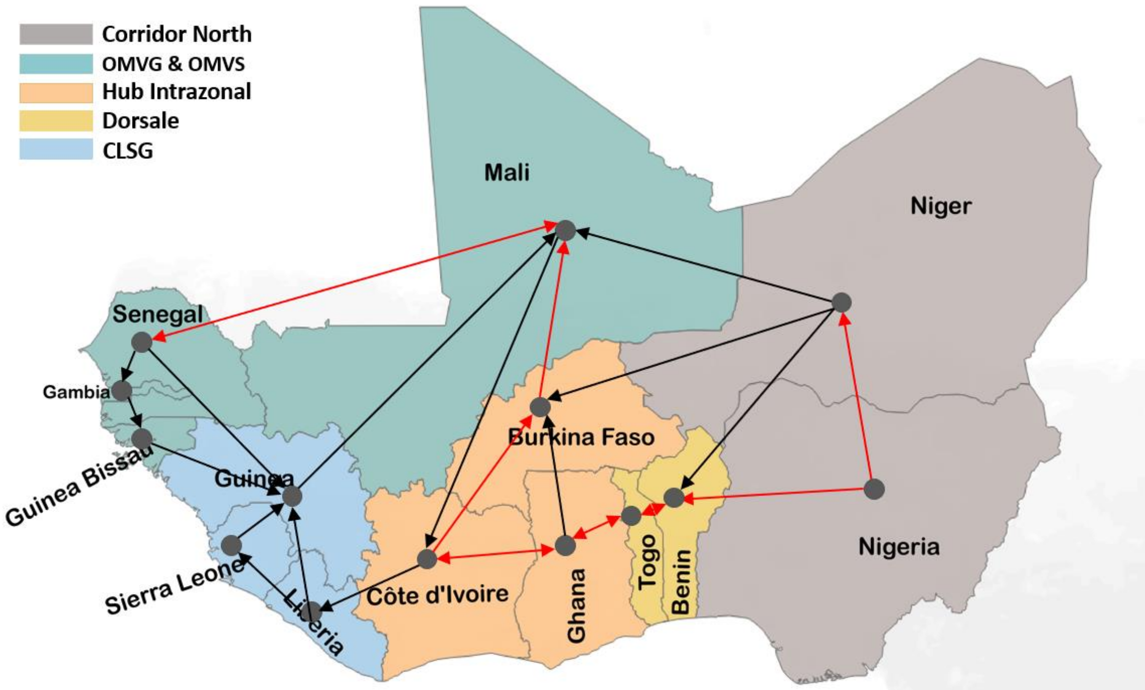

Figure 18: West Africa Power Pool by transmission expansion plan. The red arrow indicates existing interconnections, while the black arrow indicates the proposed interconnections.

Furthermore, we investigate the penetration of grid-connected renewable energy on the power pool under three policy assumptions (1) Reference scenario (RS), (2) National renewable energy targets (NT), and (3) Regional renewable energy targets (RN).

In the reference scenario, we examine renewable energy penetration on the power pool in the absence of national and regional renewable energy targets. Input into this model is based on a realistic representation of the existing installed capacity and the expansion plans as found in the WAPP Master plan [82]. We include only “decided Units,” i.e., generating units under construction or for which financing has been secured with fixed commissioning. We do not include generating units for which financing is not guaranteed yet.

We study renewable energy penetration in the national renewable energy targets (NT) scenario using country-level objectives for the proportion of renewable energy in the domestic generation mix. In the 2015 Paris Agreement, all the countries in WAPP submitted their Nationally Determined Contributions (NDCs) to UNFCCC [9]. The NDCs contained a national renewable energy target in total domestic electricity generation by 2030 [83] for each country. The implication for this policy is to examine the share of renewable energy in the generation mix in the power pool, provided countries honor their NDC commitments and pledges for renewable energy expansion.

For the regional renewable energy target (RT), ECOWAS's strategic goal is a regional goal of a minimum 31% share of electricity generation from grid-connected renewable energy sources by 2030. We impose this policy on the ECOWAPP without focusing on any particular country. Details of the policy targets and assumptions are found in table 7.

The rest of this essay is organized as follows. In Section 4.4, we introduce a description of the ECOWAS model and the modeling framework (OSeMOSYS) used in this research, including the main input parameters and assumptions into the model. Next, the main results and discussion are presented in section 4.5. Finally, section 4.6 summarizes the key outcomes' conclusions and suggests future research to build on the existing model.

Table 7: Overview of WAPP electricity access and renewable energy commitments

Country	Population in 2018 in 10^6	Total electrification rate	Electricity consumption (kWh/capita)	Total Installed capacity in 2018 (MW)	National RE commitment (Target year: 2030)	Regional RE commitment
Benin	11.5	34.50%	100.23	330.8	95MW solar PV, 15MW biomass	48% of grid-connected total RE, which includes 993 MW of wind, 1156 MW of solar PV, 1000 MW solar CSP, 2008 MW Biomass and 2449 MW small scale hydro
Burkina Faso	19.5	19.80%	61.5	363.13	20MW solar PV	
Côte d'Ivoire	25.1	63%	274.73	2515.2	42% of RE	
Gambia	2.3	47.30%	149	87.8	78.5 Gg CO2e reduction by 2025 using RE	
Ghana	29.8	84.30%	351.3	4648.9	10% of RE -- 150-250MW utility scale solar electricity.	
Guinea	12.4	27%	74	589.253	30%RE - 47 MW solar PV & wind, 1650 MW of hydro	
Guinea-Bissau	1.9	10.20%	17	15	80% RE in the national energy mix by 2030	
Liberia	4.9	11%	69	22.6	30% of RE, including 30MW of biomass	
Mali	19.1	40.10%	80	562.33	10% of RE, including solar PV, small hydro and biomass.	
Niger	22.4	12.90%	64	232.704	30% of RE, including 20MW from wind, 130 MW hydro.	
Nigeria	195.9	60%	144.53	12498	13 GW of solar PV	
Senegal	7.7	68.70%	229.35	714	160 MW of Solar PV, 150 MW wind and 144 MW hydro.	
Sierra Leone	15.9	25.10%	33	93	Not Applicable	
Togo	7.9	42.60%	141	221.32	50% of RE	

4.4 ECOWAS Power Planning Model (ECOWAPP)

This section describes the creation of the ECOWAS power planning model (ECOWAPP). ECOWAPP consists of the electricity supply system of all 14 countries of the West Africa Power Pool (WAPP), modeled individually and linked via a cross-border interconnected grid. The model minimizes the overall system cost over the entire modeling period (2018-2040) through linear optimization, with cost competitiveness and resource availability as the key drivers for deploying various technologies. The methodology and structure of the ECOWAPP model are developed using the Open Source energy Modelling System (OSeMOSYS) [81]. OSeMOSYS is completely free, from the source code to the solvers. It has been used to develop models for regional power system analysis such as The Electricity Model Base for Africa (TEMBA)[84], South America Model Base (SAMBA)[85], and the Open Source Energy Model Base for the European Union (OSEMBE)[86]. The development of the ECOWAPP model, especially the structure, mirrors the other three models.

4.4.1 Open-Source energy Modelling System (OSeMOSYS)

OSeMOSYS – the open-source energy modeling system is a model generator that converts equations representing the interactions among different energy system elements into a mathematic formulation. OSeMOSYS creates a dynamic, bottom-up linear optimization model that assumes a perfect market with perfect competition and foresight, suitable for medium to long-term energy planning [84]. An OSeMOSYS model determines power generation mix by satisfying an externally defined set of demands while minimizing the total discounted cost over the modeling period, considering:

- Demand projections
- Existing and planned generation and transmission
- Available generation technologies and investment costs
- Resource availability
- Fuel prices, and
- Operating constraints such as emission policies and renewable energy targets.

It can analyze capacity expansion and investment strategies against a backdrop of future developments by utilizing various demand predictions. OSeMOSYS is clear, having a simple code structure and algebraic formulation in plain English. Furthermore, with an active online community[5], the OSeMOSYS model is easy to understand, recode, and implement compared to other models. A detailed explanation of the model and its ethos can be found in [81] and [87].

4.4.2 ECOWAPP Reference Energy System (RES)

The ECOWAPP solves two problems (1) investment problem – which involves determining what type of power plants and transmission networks to build and where they are built and (2) operations problem - determines how to meet demand using different power plants at any given time. The energy/electricity system must be mapped in OSeMOSYS to determine all relevant technologies and fuels in the system. Thus, the Reference Energy System (RES) is a simplified model of the energy/electricity system.

[5] OSeMOSYS online community: https://groups.google.com/forum/#!forum/osemosys

Figure.19 depicts the RES that we created for the ECOWAPP, demonstrating the energy conversion process from primary energy resources to final demand for each country in the power pool. The RES comprises a variety of technologies and energy carriers, including electricity, heavy fuel oil, diesel, Solar PV, natural gas, etc. On the left-hand side of Figure.19, the available primary resources are shown, while the aggregated demand for electricity is shown on the right-hand side.

Technologies in WAP are represented by boxes and fuels by lines. Each technology uses and/or produces an energy carrier within the constraints outlined above and competes for a market share of the energy supply based on their techno-economic characteristics, including technology vintage, conversion efficiency, investment, and operating costs, capacity, and availability, and emission factors. The fuels used by the power plants to generate electricity are either imported or extracted domestically based on each country's available resources. Electricity is transmitted through national transmission lines and distributed to meet the aggregated final demand. Electricity can be exported or imported from the national grid to WAPP interconnected countries. Distributed generators such as rooftop PV and diesel generators directly deliver electricity to the final demand/end-user, while small-scale generators such as small hydro and biomass plants first transmit electricity to distribution networks before distributing to satisfy the final demand.

As shown in the ECOWAPP-RES, we modeled eight primary resources in total, including coal, natural gas, crude oil, diesel, biomass, water (hydro), sun (hydro), and wind (wind energy). Fuels from primary resources are either imported or extracted domestically. There are some constraints on how much fuel from each primary resource a country can export or import depending on the resource availability and potential present in each

country. Fuels are delivered to electricity generation technologies, which is the next layer in the ECOWAPP-RES.

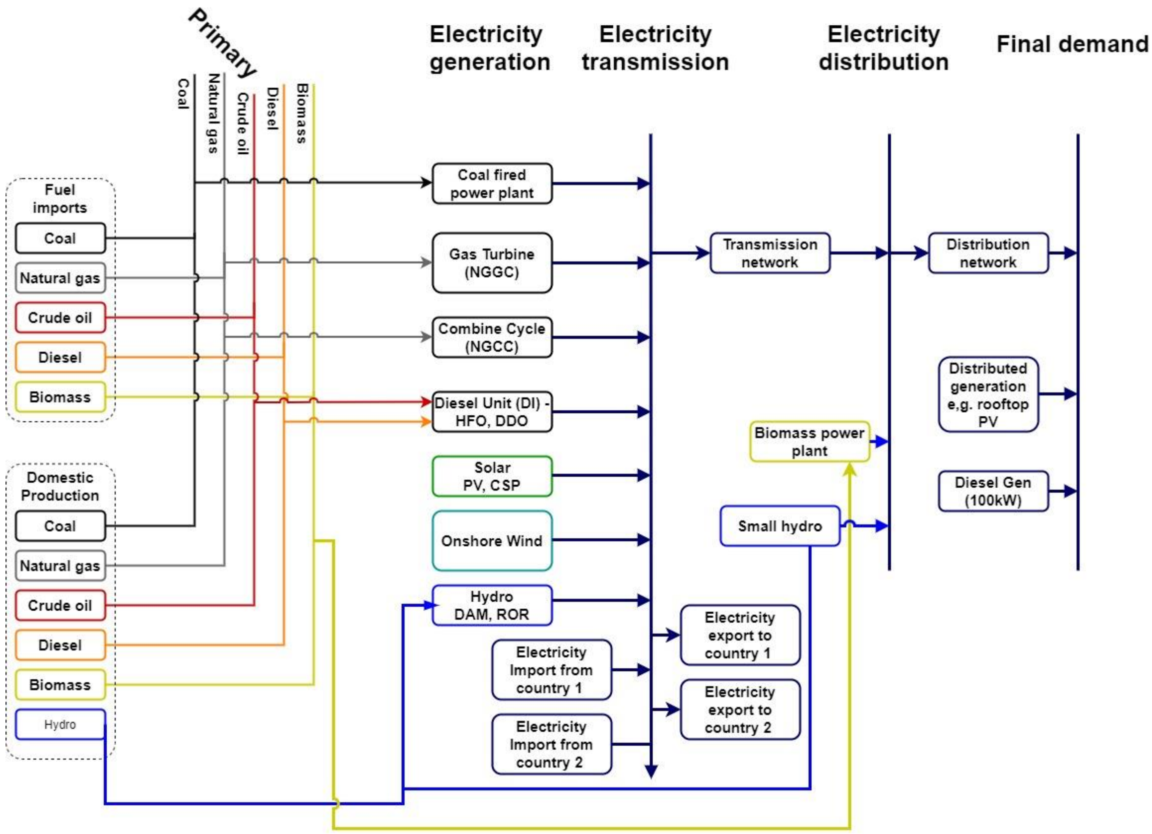

Figure 19: ECOWAPP Reference Energy System

We model twelve modes of electricity generation, considering the existing installed capacity and proposed expansion plan for generation technology in each country [82]. Uranium, the primary resource for nuclear power plants, is available in Niger; however, “developing nuclear power plants has not been considered a credible alternative for the West African region's power supply” [82]. According to the WAPP Master Plan 2018 [82], the region's essential energy resources, hydropower, gas, and renewables, are largely capable of meeting the region's electricity demand through a diverse and affordable energy

mix. Furthermore, nuclear power plants' discounted levelized cost of electricity (LCOE) could be 40% higher than natural gas and almost twice as high as renewables.

Electricity from the generation technologies is delivered to the national transmission grid, which performs the following services (1) receive imported electricity from the interconnected countries, (2) export electricity to interconnected countries, and (3) delivered electricity to distribution stations. The distribution networks receive electricity from the grid and deliver it to the residential (rural and urban), commercial, and industrial sectors. Due to the lack of detailed data for each sector in each country, we used the aggregated total electricity demand projection from 2018 to 2040 for each country. See the WAPP Master Plan 2018 [82] for details on how the sectors were aggregated.

The WAPP model considers all these techno-economic characteristics of all the primary resources and generation technologies in each country and determines the "optimal" mix of resources that satisfies the demand at the minimum cost. The outputs of interest include total investment in the energy system, total capacity including new power plants built and built, electricity production by technology, cross-border electricity trade, and the energy system's impact on CO2 emissions. Below we provide more details on the model's techno-economic characteristics, including the assumptions about the electricity demand, the variability of renewable energy and capital cost, and fuel prices in the region.

4.4.3 Data and Assumptions

Here we will highlight the input assumptions used in the model, including the electricity demand used in each country in the ECOWAPP, the fuel and capital cost of each

technology. We will also include a detailed section that highlights the variability of solar and wind energy technologies in each country.

4.4.3.1 Electricity demand and Consumption pattern in ECOWAPP

The source of data used for each country's history (2018) and projected electricity demand by 2033 is the 2018 WAPP Master Plan [82]. To extend the projection until 2040, we calculated the growth rate in each country and extrapolate the evolution of the electricity demand in each country from 2033 to 2040—figure 20. The electricity demand is expected to increase as the growth rate remains high. For example, we could observe from anywhere between a fourfold increase in Benin to a sevenfold increase in Nigeria.

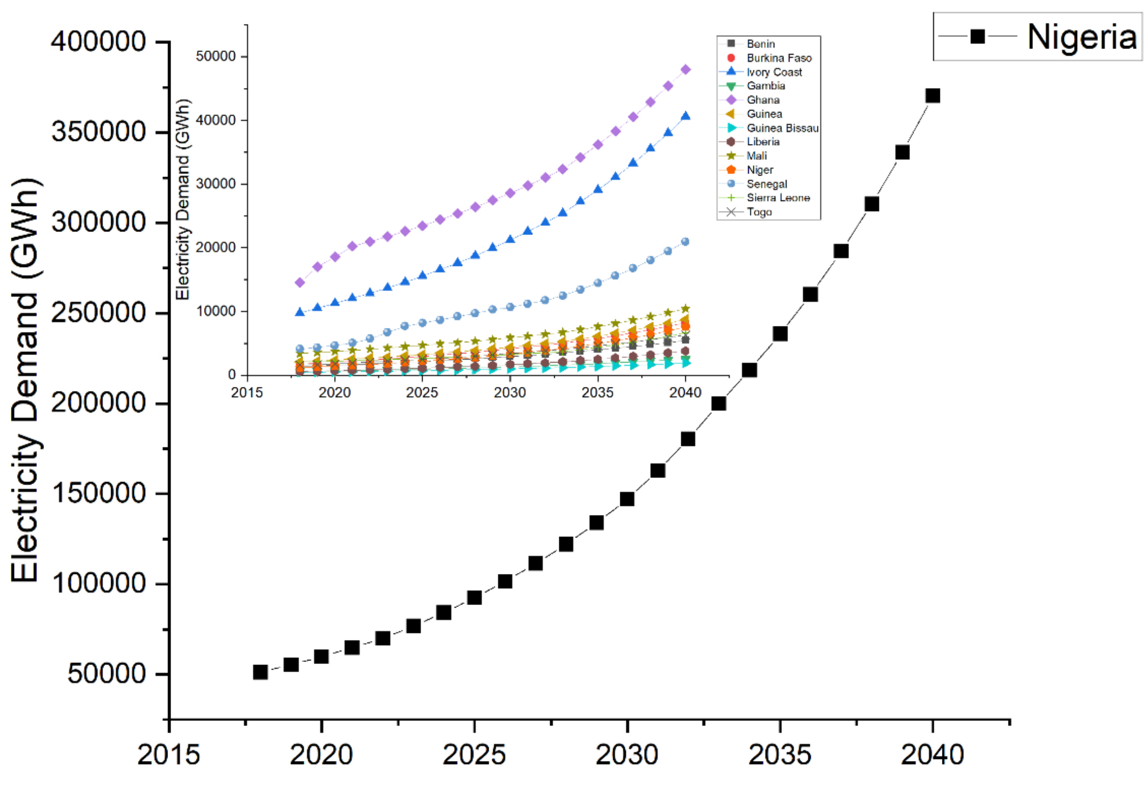

Figure 20: Electricity demand projections, 2018–2040, by country (GWh)

For lack of detailed data for the industry, residential, commercial, and transportation sectors in each country, we aggregate end-use electricity demand from 2018 to 2040 for each country. See the WAPP Master Plan 2018 [82] for details on how the sectors were aggregated. However, to capture consumption patterns in each country, we created country-specific load profiles characterized by various seasons and parts of the day. The data for each country's monthly and hourly electricity demand pattern is sourced from Adeoye et al. [88]. They calculated monthly and hourly power consumption for the 14 countries, taking into consideration electrification rates, available household appliances, household member occupancy patterns, day of the week, available daylight hours, and hourly weather conditions. As an illustration, Figure 21 depicts the average consumption curves for each weekday in October 2018 in Senegal.

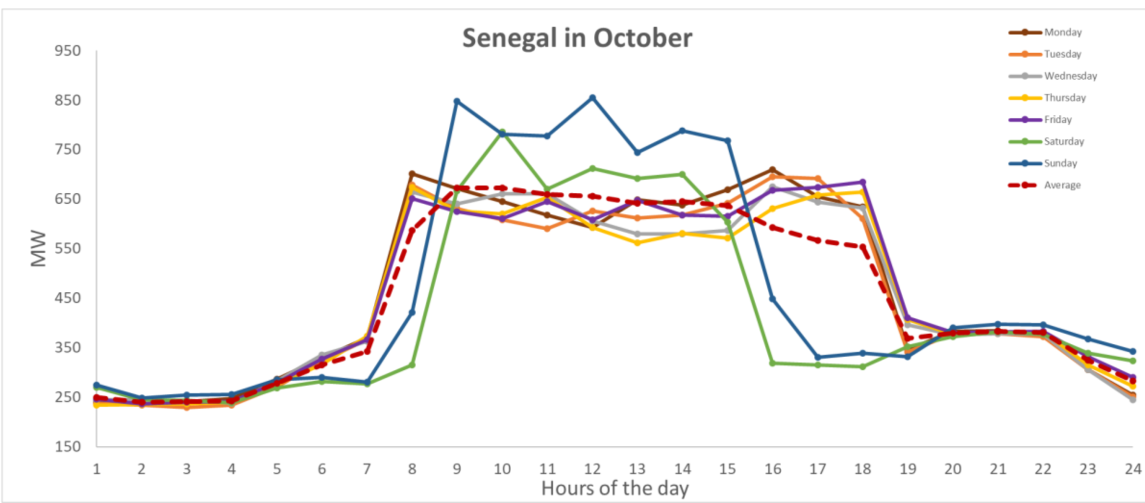

Figure 21: Load curves for a typical weekday in October, Senegal

To construct the load profile for each country, we split a typical year into 4 seasons, 1. Pre-Dry (PD) season (December to February), 2. Dry Season (DS) (March-May), 3. Raining Season (RS) (June-September), 4. Harmattan Season (HS) (October-November). The consumption pattern for a typical day in each season were calculated as the average

over the months in each season. For example, in Pre-Dry season (PD), there are three months (Dec-Feb), so the typical day in December, January and February were averaged at each hour to give the typical in pre dry season. Running the model at hourly resolution for each country will be computationally costly, so we further split a typical day in each season into six periods, 1. Late night (LN) (1AM-5AM), 2. Early Morning (EM) (5AM-8AM), 3. Morning (MD) (9AM to 12AM), 4. Afternoon (AN) (12PM-6PM), 5. Evening (EN) (6PM – 11PM), 6. Midnight (MN) (11PM -1AM). Therefore, for four seasons in a typical year and 6 periods in a typical day, we created 24 time slices. The first time slice could be named pre dry season early morning, the second pre dry season afternoon, etc. but to have short codes for them they are called: PDLN, PDEM, PDMD, PDAN, PDEN and PDMN. The first two letters stand for the season, the last two stands for the period of the day. With this approach, we calculated the "SpecifiedDemandProfile" i.e., the share of the overall annual electricity consumption in each time slice. This parameter is a necessary input to every OSeMOSYS model.

4.4.3.2 Variable Renewable Energy Resources

"Integrating solar PV and onshore wind into the power mix requires power system flexibility to enable matching supply and demand" [89]. Because PV and onshore wind have time-varying power production, they are difficult to accurately model due to the unpredictability and dynamics of weather systems, seasonality, and geographical locations, making it difficult to consider their capacity and limitations.

We avoided using a generic capacity factor for both technologies to preserve the variability inherent in the onshore wind and solar time series. Instead, we develop country-

specific generation profiles, accounting for hourly, daily and seasonal variability. Hourly annual power output from onshore wind and solar PV in each of the 14 countries for the representative year 2018, from Renewable.ninja[6] was used to calculate the capacity factor for each of the 24-time slices to correspond with the model's SpecifiedDemandProfile. An example of actual hourly wind and solar generation profiles for Ghana for the pre-dry season (December/January/February) is given in Figure. 22.

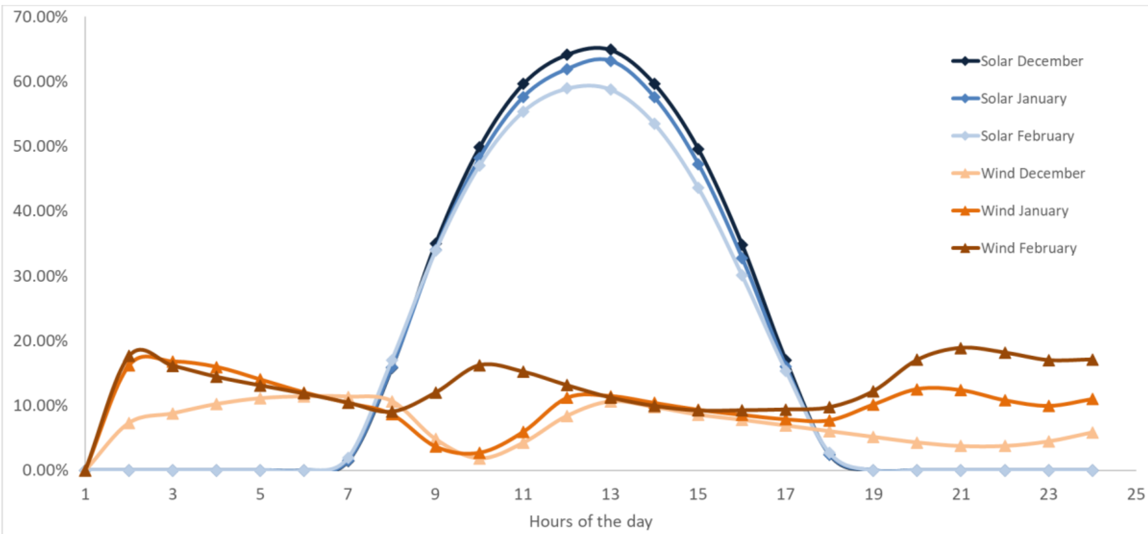

Figure 22: Pre-Dry Season hourly solar PV and wind generation profiles in Ghana.

4.4.3.3 Capital cost and Fuel prices

We applied a real discount rate of 10 %, consistent with the assumption in IRENA [76]. The overnight capital cost and fuel prices used here are taken from the "Planning and prospects for renewable power: WEST AFRICA" report from IRENA [76]. Figure. 23

[6] Renewables.ninja is a web tool developed by Imperial College London and ETH Zürich that shows the estimate amount of energy that could be generated by wind or solar farms at any location (https://www.renewables.ninja/)

shows the overnight capital cost for thermal and renewable energy generation technologies with all prices are in 2015 USD rate.

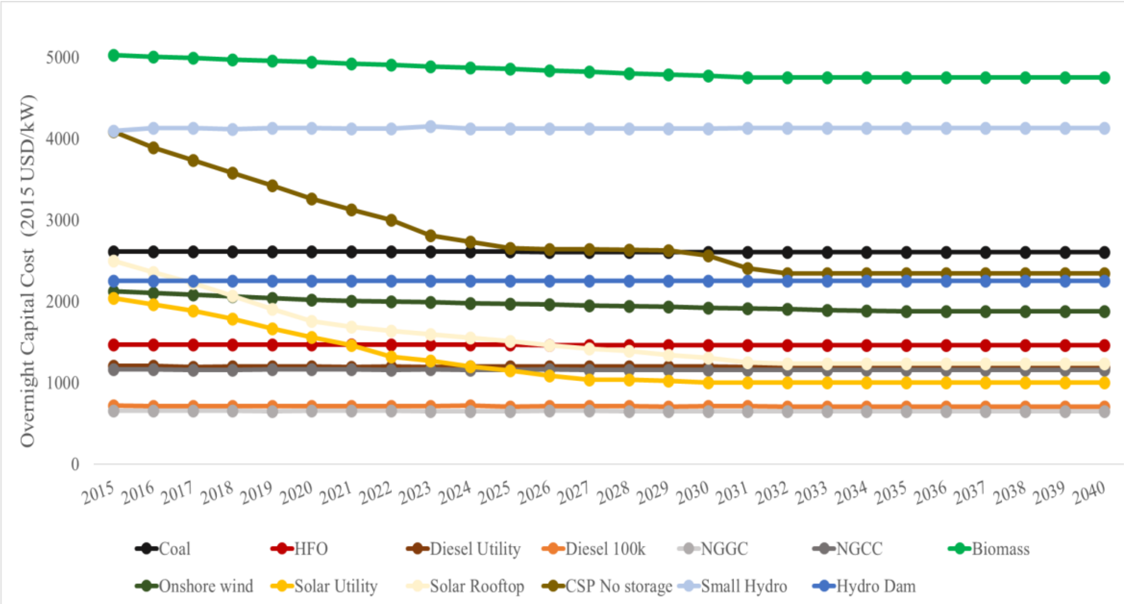

Figure 23:Overnight investment cost assumptions thermal and renewable technologies.

4.5 Results

In the first three subsections below, we present the result of the reference scenario focusing on the electricity generation mix by fuel type, cross-border electricity trade, and the benefit of the power pool to each country. Finally, in the fourth subsection, we discuss the penetration of renewable energy across the power pool in the reference scenario, national renewable energy target (NT), and regional renewable energy target (RT).

4.5.1 Electricity Generation mix

As seen in Figure 24, the total installed capacity across the power pool more than doubles from 24GW in 2024 to 56GW in 2030 and subsequently to 118GW in 2040. The

enormous rise in overall capacity results from the region's growing population, which results in strong electricity demand.

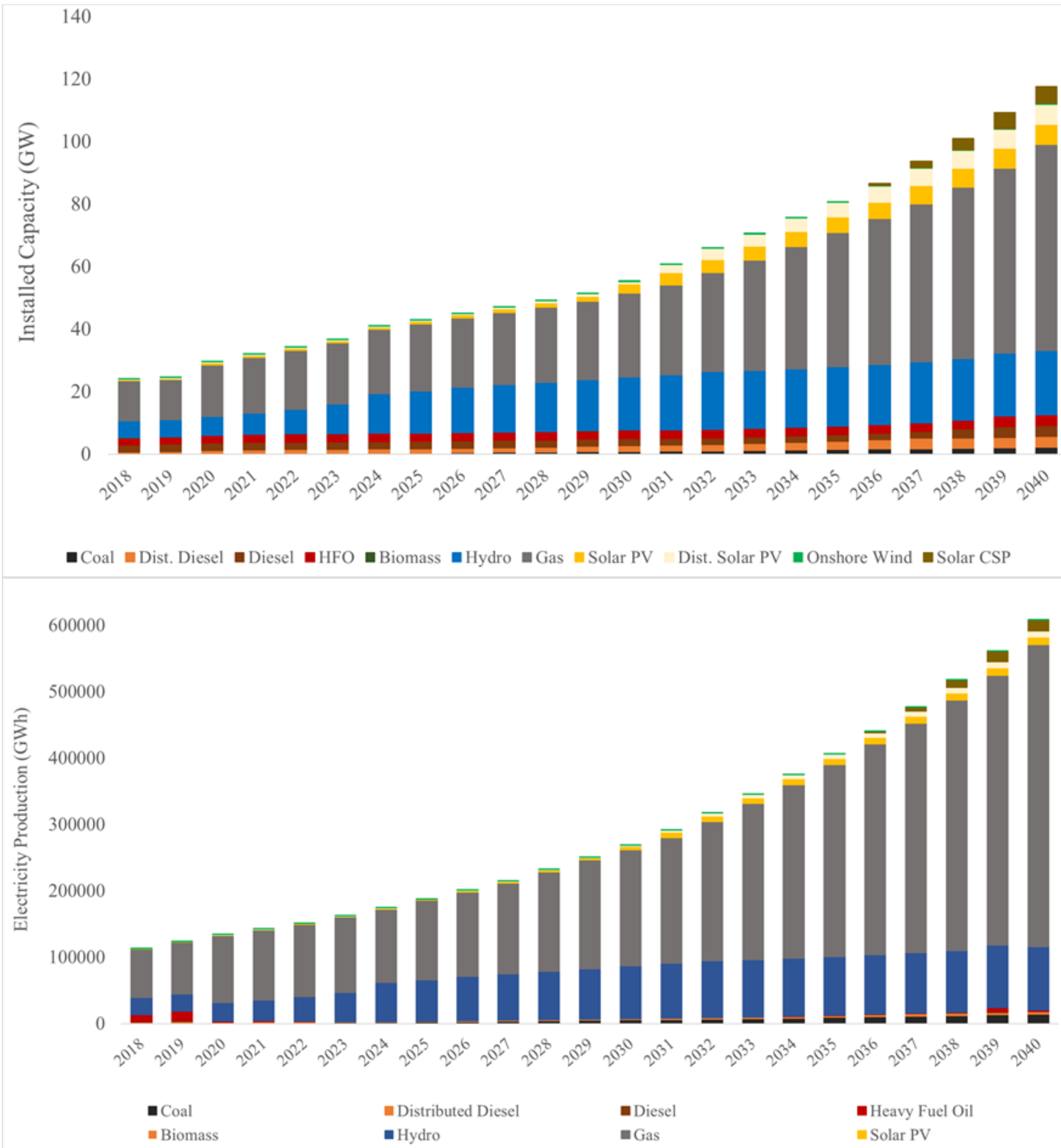

Figure 24: Total installed capacity (top) and electricity production (bottom) in ECOWAPP in the Reference scenario from 2018 -2040.

This increase is mainly driven by Nigeria, Ghana, and the Ivory Coast, which account for more than 80% of the total installed capacity by 2040. Among the electricity generation sources, natural gas remains the dominant electricity generation source in the

reference scenario, again mainly driven by Nigeria, Ghana, and Ivory Coast, Figure.24 below. Natural gas contributes about 64% to the region's total electricity production in 2018 and about 75% by 2040. We see an increase in natural gas electricity generation across the region because of locally produced gas in Nigeria, Ghana, and Ivory Coast. These countries have the most electricity demand. Due to the local availability of natural gas, it is more cost-competitive than other sources to meet their electricity demand without a constraint or fossil fuel or clean energy requirement.

Followed by natural gas is hydroelectricity. Over the same period, hydroelectricity's proportion of overall power in the region rises from 23% in 2018 to 30% in 2030, then drops to 16% by 2040. However, an increasingly competitive solar PV, biomass, and onshore wind energy are deployed to meet the increasing demand and replace retired generation capacity, growing from 0.4% in 2018 to 5% in 2040.

4.5.2 Cross border electricity trade

In Figure 25, we show the electricity generation portfolios for each country in 2018 and 2040. Some countries go from net importer of electricity in 2018 to net exporter by 2040, notably Liberia, Niger, and Mali. In 2018, Liberia met its electricity demand mainly from diesel sources, with roughly 70% coming from distributed generators. By 2040, approximately 60% of Liberia's generation will come from hydro, enough to meet its electricity demand and export about 30%. Niger goes from importing 70% of its electricity to exporting about 30% because of coal capacity to its generation portfolio.

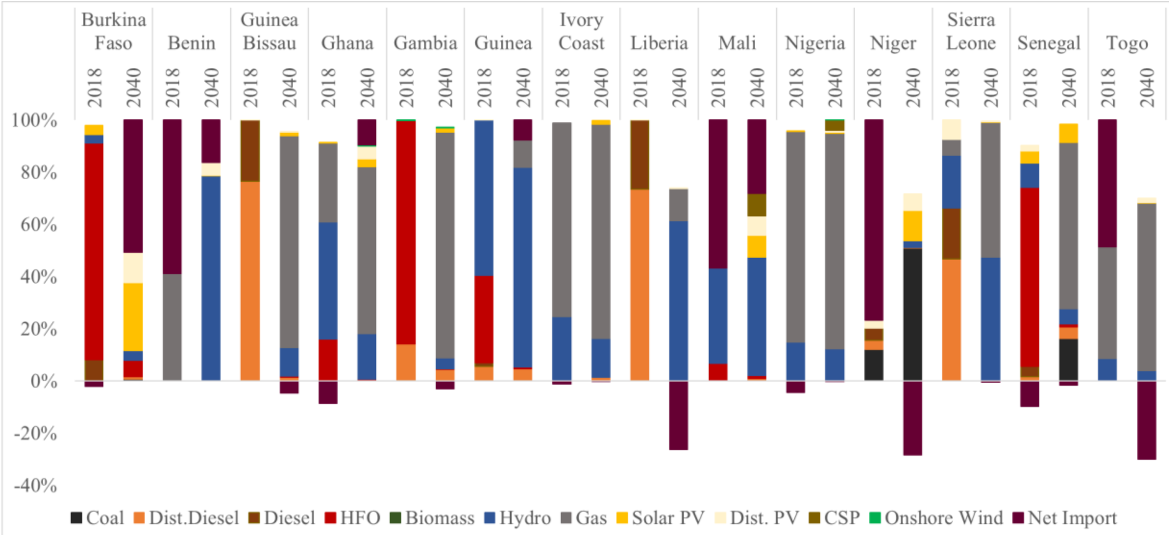

Figure 25: Share of the electricity generation mix in ECOWAPP in the Reference scenario for 2018 and 2040.

The chord diagram in Figures 26 and 27 display the cross-border electricity trade between countries in ECOWAPP under this reference scenario in 2018 and 2040. Each sector of the circle represents a country in the trade, and its width indicates the total amount of trade (i.e., import and export together) occurring in that country. The width of each link represents the total electricity trade from country A to country B indicated by an arrow. From the diagram, we can observe the largest exporters of electricity in 2018 are Nigeria and Ghana. Nigeria exports electricity to Niger and Benin as shown in Figure 26; roughly 50% of Benin electricity and 70% of Niger electricity came from Nigeria. In reality, the amount of electricity transmitted from Nigeria to both countries is slightly less than estimated. While Nigeria has significant gaps in meeting domestic requirements, exports to Niger and Benin are dependent on an energy deal with the Nigerian government. In return, the two nations promise not to build dams on the River Niger, the main water supply for Nigeria's large hydro facilities.

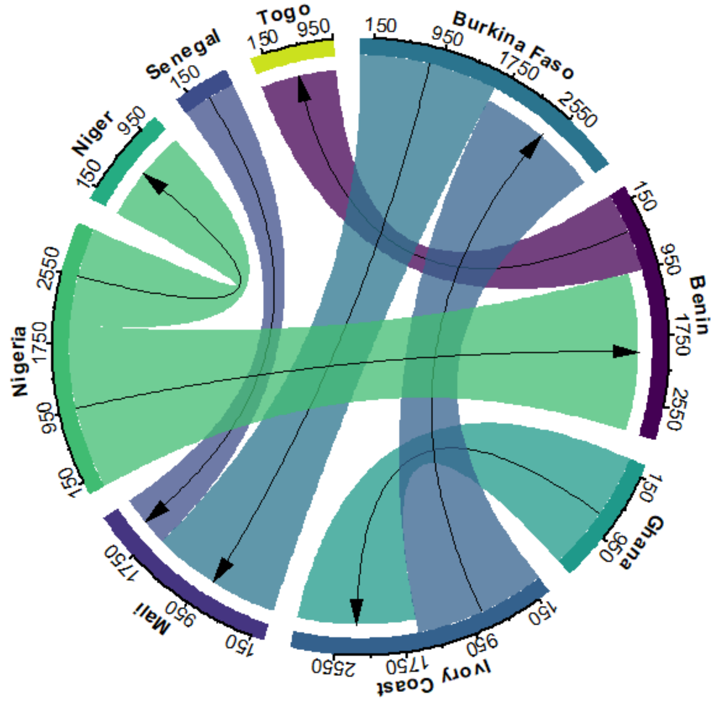

Figure 26: Cross border trade in the reference scenario in 2018 in GWh

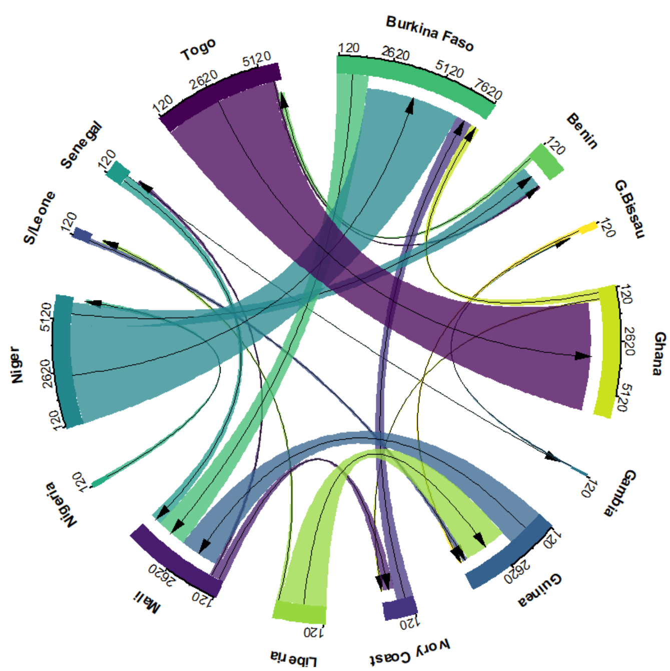

Figure 27: Cross border trade in the reference scenario in 2040 in GWh

The overall cross-border electricity trade in 2018 and 2040 becomes very different as more countries come online on the power pool. For example, as shown in Figures 26 and 27, in 2018, Togo imported about 950GWh of electricity from Benin to meet its electricity demand. It should be noted that the same utility currently manages electricity distribution in Benin and Togo. Since Benin does not have enough capacity to supply Togo, it imports about 1.8TWh of electricity from Nigeria, some of which is sent to Togo. Like Togo, Mali requires about 60% of electricity import using the Inter-Zonal transmission infrastructure from Ghana through the Ivory Coast, Burkina Faso, and Mali. Therefore, we can safely say Mali imported about 60% of its electricity from Ghana, transported through Ivory Coast and Burkina Faso.

By 2040, we see more cross-border electricity trade to complete more transmission infrastructure connecting more countries on the power pool. However, we see a significant shift in cross-border electricity trade as more countries expand their capacity. Ghana shifts from an exporting country to a net importer of electricity. Ghana currently has about 84% electricity access, the highest in the region. Apart from a 360 MW combined-cycle natural gas plant that came online in 2018, Ghana does not plan further future capacity expansion. So as more existing plants are retired, they are not replaced; Ghana instead imports from Togo. In Niger, with the addition of 68MW of a coal-fired plant to the already 58MW Sonichar coal plant coming online in 2022, the country will go from an electricity importer to exporter, using the North Corridor transmission infrastructure to export to Burkina Faso. This does not only reduce the reliance on the country’s electricity import from Nigeria, but it also replaces Nigeria's export to Benin with cheap coal.

4.5.3 Total Investment Cost across Scenarios

ECOWAS has a massive capacity problem. For the region to be fully electrified, it will require a minimum of a 7.4% increase annually in installed capacity from 2018-2040 on a current capacity of 24GW. The total discounted cost of investment across the reference scenario with and without trade is shown in figure 28, including the national and regional renewable energy target with trade. For the WAPP countries to be fully electrified and deliver their electricity demand, they will require a total investment of $181 billion (in 2015 USD) between 2018-2040 under the assumption of independent capacity expansion without cross border electricity trade (Reference Scenario-No trade). In the reference scenario with electricity trade on the power pool (Reference Scenario with trade), the total investment cost is $178 billion, $2.7 billion less expensive than the no-trade scenario.

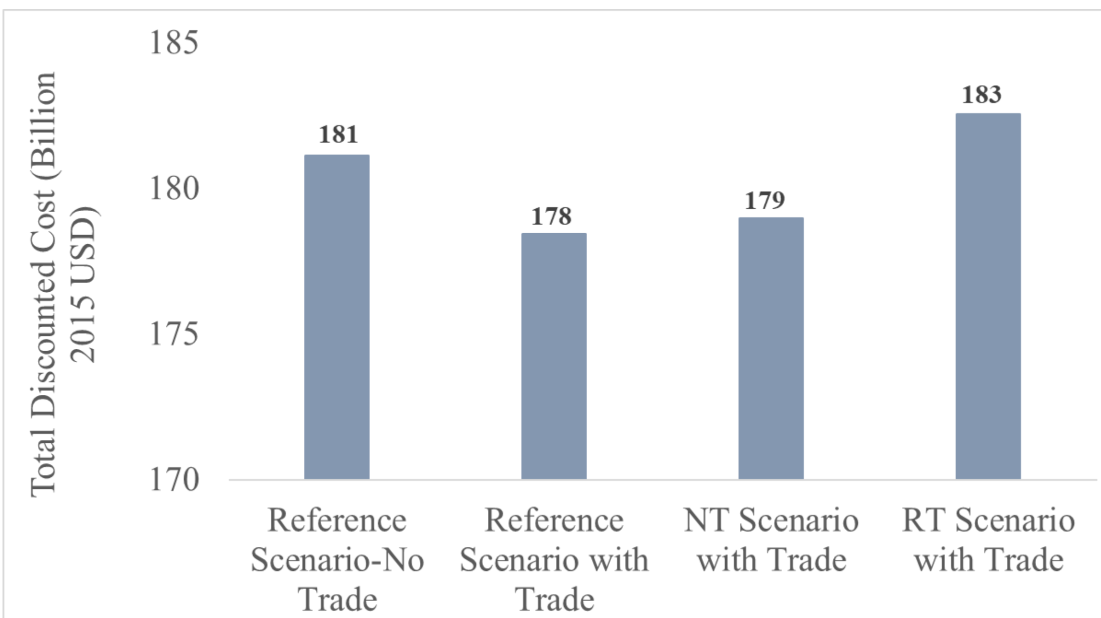

Figure 28: Total discounted cost of investment for the reference scenario with trade, without trade, National (NT) and Regional (RT) renewable energy targets.

As more countries come online and start trading in the trade scenario, the total installed capacity decreases by about 2%. This contributes to the lower investment cost and

highlights the benefit of strategic investments towards expanding cross-border electricity interconnections projects among WAPP countries.

Looking at the generation mix, the most significant reduction in capacity in this scenario is from distributed diesel, from 61GW in the no-trade scenario to 45GW in the trade scenario between 2018-2040. The capacity contribution from solar PV also decreases by about 21% in this scenario. With more countries trading on the power pool, some countries can decide on import from countries with cheaper sources of electricity generation such as coal and natural gas. Therefore, reducing the region's investment costs in this scenario could significantly improve the overall energy supply in ECOWAS.

4.5.4 Renewable Energy Penetration

Figure.29 shows the percent share of the total installed capacity across the three scenarios. In the reference scenario, renewable energy sources (including hydro) constitute 36% of the total installed capacity by 2030 compared to 24% in 2018. Hydropower contributes about 30% of this total, with non-hydro renewables contributing about 6%. However, this falls short of the region's aspiration for 48% of the total installed capacity by 2030. In fact, by 2040, under the reference scenario, the share of renewables will reduce to roughly 28% as more hydro plants are retired. The retired hydropower plants are substituted with non-renewable hydro, growing from 1% in 2018 to 10% by 2040. But these are not cost-competitive enough to stop the aggressive growth in natural gas expansion.

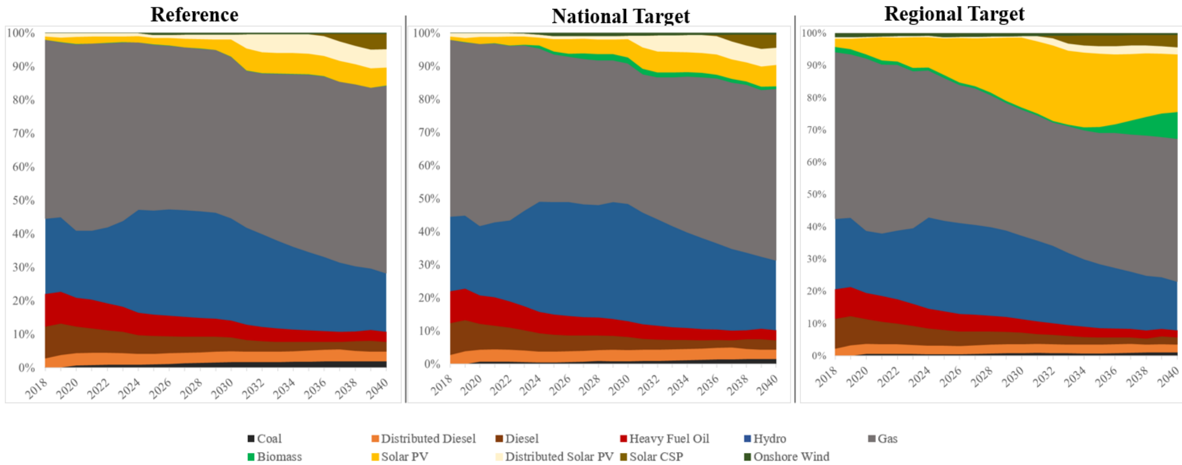

Figure 29: Total share of installed capacity in Reference, National, and the Regional Targets Scenarios.

If WAPP countries deliver on their commitments in the national and regional target scenarios, this could be enough to meet their renewable energy targets. The national target scenario falls short by only 4% by 2030. However, the regional target may result in an even higher percentage of renewable energy in the region's energy mix. In the regional target scenario, non-hydro grid-connected renewables (Solar PV, Onshore wind, Biomass, and Solar-CSP) account for 24% of installed capacity with solar PV, particularly about 14GW total share of 22%. In the scenario, 5GW and 3GW of solar PV are installed in Nigeria and Ghana, respectively; all the other countries contribute roughly 1% each. In this case, some countries may rely on others to undertake the bulk of the hard lifting necessary to accomplish the target.

Figure 30: Solar PV, wind and biomass capacity in Reference, National Target and Regional Targets Scenarios

Figure 30 shows the total installed capacity (MW) for utility scaled solar PV, Biomass, and Onshore wind across the three scenarios. Under the reference scenario and the national target scenarios, utility-scaled PV contributes about roughly 3GW by 2030. One explanation is that the committed capacity expansion for utility-scale solar PV in the 2018 WAPP Master Plan 2018 [82] is the same as the National Targets for most countries, not the case for Onshore wind and Biomass. This is because the capacity

addition promised under the National Targets for these sources has committed 2018 WAPP Master Plan 2018 [82]. In the Regional Target scenario, we observe a 367% increase in the total installed capacity for utility scaled solar PV, from 3GW in the National target to 14GW.

4.6 Conclusion

In this chapter, we used an open-source energy modeling system to develop a capacity expansion and power planning model for the West Africa power pool (OSeMOSYS). We examined two capacity expansion scenarios to determine the economic benefits of cross-border electricity trade in terms of capacity expansion and planning. In the first scenario, we model capacity expansion with cross-border electricity trade based on the region's existing and planned transmission infrastructure, which operates on the perfect competition and foresight principles. In the alternative scenario, we impose restrictions on cross-border electricity trade. Additionally, we investigate renewable energy penetration in each scenario, taking into account national and regional renewable energy targets.

Our results show a massive expansion of installed capacity to meet the region's growing population demand. By 2030, total installed capacity will have increased by approximately 138 percent from 22.7 GW in 2018 and another 119 percent between 2030 and 2040. Nigeria, Ghana, and Ivory Coast are driving regional electricity demand, accounting for approximately 80% of the region's installed capacity. To double installed capacity in less than a decade (2030) will be quite costly and will require massive investment and commitment on the part of all power pool members.

Indeed, our findings suggest that it could be even more expensive in the absence of cross-border electricity trade. As more transmission lines come online on the power pool, the overall cross-border electricity trade increases by approximately 130 % between 2018 and 2040 in the reference scenario with no renewable energy target. As a result, the total installed capacity decreases by about 2%, contributing to lower investment costs and saving the region approximately $2.7 billion. One explanation for this is that by 2040, some countries may transition from net importers to net exporters of electricity. While others could go from net exporters of electricity to being a net importer. For example, Ghana currently has the highest installed capacity in the region and is a net exporter of electricity with no planned additional capacity expansion. As more power plants are retired in the country, they increasingly rely on electricity imports to meet its demand, thereby contribution to the reduction the overall installed capacity.

Our result indicates that ECOWAS will fall short of its NDC commitment of 48 percent renewable energy penetration by 2030 without a regional target for renewable energy (RE) penetration. RE will account for around 36% electricity delivered in the region in the absence of a national or regional objective. When broken down further, hydroelectricity accounts for approximately 30% of the total, with non-hydro RE (solar, onshore wind, and biomass) accounting for only 6%. However, under the regional target, the region's energy mix will include a greater proportion of renewable energy. Our result shows non-hydro grid-connected renewables could account for 24% of installed capacity in the regional target scenario, up from 6% in the reference case. Solar PV is the most prevalent source of RE under this target, accounting for approximately 14GW or 22% of all RE supplied.

As with any model, this one has limitations that, if addressed, could result in a more detailed understanding of West Africa's electricity system. It is nearly impossible to predict with certainty all of the involving interplay that govern an electricity system that is subject to technical, economic, and behavioral factors. This model is developed to illustrate how the electricity system in West Africa will evolve over time under various scenarios. As a result, time, operational characteristics, investment decisions, projected electricity demand, and resource availability have all been simplified in this regard. For example, due to a lack of data, we used an aggregated projected electricity demand for each country, omitting residential, industrial, transportation, and commercial demand. Additionally, capacity expansion and planning decisions are made implicitly on the basis of perfect foresight, perfect competition, and perfect foreknowledge of future hydrological, solar, and wind resources. In reality, decisions must be made under conditions of uncertainty, which deviate significantly from perfect competition. Future research should concentrate on improving national-specific data, such as electricity demand and resource potential, and on examining the effects of various transmission costs and losses. Finally, an uncertainty analysis should be performed on the model's various parameters to increase the model's reliability, as well as a sensitivity analysis. The scenarios examined in this chapter are merely a starting point; additional scenarios should be examined to adequately represent the real-world transition.

CHAPTER 5

CONTRIBUTIONS AND FUTURE WORK

5.1 Contributions

We explored the role of low carbon energy technologies (LCET) in multiple contexts through a lens of deep uncertainty. We employed a variety of models and methods, including well known IAMs (GCAM, DICE, PAGE and FUND) coupled with expert elicitation and a capacity expansion and power planning model in order to examine the impact of LCET on cost of achieving climate goals. We provide useful insights for planning electricity infrastructure and investing in R&D under deep uncertainty.

In the first essay, we integrated data on global onshore and offshore wind energy cost and resources into the Global Climate Assessment Model (GCAM), then propagate uncertainty based on distributions derived from an expert elicitation study on the future cost of onshore and offshore wind energy. We investigate how a breakthrough, or a failure, in the future cost of wind energy could affect the electricity supply sector and the costs of decarbonization. Our first observation is that, in the absence of a global policy to reduce CO2 emissions, the share of wind energy electricity generation in 2035 could either remain constant or more than triple from its current level. The implication is that, in the absence of a global policy on emissions, what policymakers decide today about technology investment will have a significant impact on the future of wind energy in the generation

mix. Increased investment and rapid deployment have the potential to triple wind energy's market share; however, insufficient investment could easily result in wind energy being outcompeted by other renewable energy sources such as solar. However, under moderate to stringent climate policies, wind energy's share of total generation increases massively, which has implications for conventional generation technologies such as natural gas.

In the second essay, we applied the Robust Portfolio Decision Analysis (RPDA) approach to identify all non-dominated portfolios of R&D investment across all beliefs and models. We find agreement among experts and models about level of investment that should be allocated to certain energy sources such as Bioelectricity and Solar energy under certain policies. High energy investment both energy sources are robust across all beliefs and models given the climate policy. We also find that damage function formulation particularly important for allocating investment into Nuclear energy.

In the final essay, we used the Open-Source energy modeling system to develop a multi-region model for the long-term dynamics (2018–2040) of West Africa power pool (WAPP) capacity expansion and power planning (OSeMOSYS). The economic benefits of cross-border electricity and the penetration of renewable energy across the power pool were examined. We observe that for the region to meet its electricity demand by 2040, it will require an annual installed capacity increase of at least 7.4 % to 2040, compared to the region's current capacity of 24GW. A costly endeavor, that could be worse if each country's demand for capacity expansion is met without the possibility of cross-border electricity trade.

5.2 Future work

Apart from the specific findings discussed in the three essays, this dissertation makes a significant contribution by demonstrating the adaptability of the new Robust Portfolio Decision Analysis (RPDA) approach. We used one cost-effective model (GCAM), three cost-benefit models (DICE, PAGE, and FUND), and expert beliefs to derive investment portfolios. The results of this approach are significantly influenced by the structural uncertainty of the damage functions, which do not include detailed representations of energy technologies. Future research could employ more technologically detailed models that account for structural differences in the representation of energy, water, and land use change.

Another significant contribution is the development of a capacity and expansion model for West Africa. Numerous parameters, including time, operational characteristics, projected electricity demand, and resource availability, have been simplified significantly. Future research should focus on improving country-specific data, such as electricity demand and resource potential, hydrogeological seasonality, and the effects of various transmission costs and losses. Finally, an uncertainty analysis of the model's various parameters should be performed to improve the model's reliability.

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