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Climate change may impair the transition to a fully renewable energy system: A German case study

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ABSTRACT

Renewable sources are vulnerable to climate change. Despite this, the combined impact of climate change and the expansion of renewables in higher spatiotemporal details have not been thoroughly analyzed. In this manuscript, using the state-of-the-art model coupling framework, we address the following research question: How can wind energy and bioenergy be affected regionally considering weather and climate variability in Germany and its possible impact on the neighboring countries? To answer this, we link spatially, temporally, and technologically detailed power and energy optimization models with a physical simulation model for wind power production, taking into account climate and weather scenarios. Our results indicate that significant reductions in biomass production due to climate change may profoundly compromise reaching climate targets. It also damages the resilience of energy systems by decreasing the capacity of flexible bioenergy, thereby increasing vulnerability to other disruptions, such as fluctuations in renewable electricity supply. Our finding suggests that southern German states may require electricity imports from neighboring countries, emphasizing that extreme climate events in other parts of Europe can potentially further reduce resilience.

1. Introduction

According to International Energy Agency (IEA), in order to stay on the path toward 1.5 °C, the share of renewables in electricity generation should increase threefold by 2030 worldwide under the Net Zero Emissions (NZE) scenario [1]. While this goal remains highly ambitious, continued cost reductions in solar and wind energy due to the so-called "learning effect" [2,3] and the rising costs associated with fossil fuels [4] provide supportive trends [5]. Gómez-Calvet and Gómez-Calvet [6] suggest that solar power integration in Germany can be facilitated by bioenergy; however, renewable electricity generation – including biomass production – may itself be vulnerable to the impacts of climate change. The transition to renewable energy can mitigate energy security risks, whereas climate change intensifies energy-related challenges [7]. Several studies find that climate change may particularly impair electricity generation from wind energy [8,9] (due to changing wind patterns), hydropower [10] (due to increasing water scarcity) and bioenergy [11] (due to lower yields of bioenergy crops). Ravestein et al. [12] quantify the impact of climate change and climate variabilities in Europe using a climate model and found that climate change impacts wind power more than solar power. Germany (and Spain) may even benefit from climate change regarding solar power production, whereas other parts of the world face declining energy outputs [13]. Staffell and Pfenninger [14] show that Britain could expect dramatic changes to its electricity system due to climate change. Hence, climate change may lead to unforeseen shortages in the supply of renewable energy sources [15].

Such shortages would have important environmental and economic implications. First of all, they could mean that future Greenhouse Gas (GHG) emissions of the energy sector might be higher than expected, jeopardizing the fulfillment of ambitious emission reduction targets. This could happen, for example, if shortages in renewable electricity supply would have to be compensated by fossil-fuel electricity generation (i.e., avoidance failure), or if less electricity generation with BECCS is deployed (i.e., removal failure). Second, shortages in the supply of renewable energy sources could also increase energy system costs – either because more costly energy sources need to be deployed

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Abbreviations

BAU	Business-As-Usual
BECCS	Bioenergy with Carbon Capture and Storage
BENOPTex	extended Bioenergy Optimization
BWY	Bad-Wind-Year
CDR	Carbon Dioxide Removal
DAC	Direct Air Capture
ESMs	Energy System Models
FM	Forest Management
GAMS	General Algebraic Modeling System
GCMs	General Circulation Models
GHG	Greenhouse Gas
IAMs	Integrated Assessment Models
IEA	International Energy Agency
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project
IPCC	Intergovernmental Panel on Climate Change
LPJmL	Lund-Potsdam-Jena managed Land
LULUCF	Land Use, Land-Use Change and Forestry
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2.0
Mil ha	Million hectares
NETs	Negative Emission Technologies
NZE	Net Zero Emissions
RCP	Representative Concentration Pathway
RED	Renewable Energy Directive
REMix	Renewable Energy Mix
ReSTEP	Renewable Spatial-Temporal Electricity Production
RMSE	Root-Mean-Square Error
SSP	Shared Socioeconomic Pathway
TYNDP	Ten-Year Network Development Plan
VRE	Variable Renewable Energy

or because offsets have to be bought to compensate for higher energy sector emissions – leading to energy poverty [16]. Peter [17] finds that climate change increases costs of energy systems with large shares of renewables. In contrast, other studies conclude that energy system costs are relatively robust to variations in weather years [18,19]. Using 62 weather years (from 1960 to 2021) under net-zero CO_2 emissions European energy system, Gøtske et al. [20] demonstrate a change of ±10% in total system costs. Therefore, the jury is still out, and further studies are required to determine conditions under which climate variabilities impact the energy system's costs.

The impact of variabilities in climate and weather conditions on energy systems has often been overlooked [21] or assessed using climate and Integrated Assessment Models (IAMs) [11,22]. Unfortunately, the insights gained from these analyses are limited due to their relatively low spatial and temporal resolution [23] as well as their simplistic representation of energy systems. Power system models can also easily become intractable as their spatial resolution increases,[1] which is why these analyses were done at low temporal resolution—for instance, De Felice et al. [24] clustered multiple countries into a region in their analysis. Nonetheless, the interdisciplinary research on climate-energy nexus should take into account regional factors [25], as renewable technologies compete together and with other players outside the energy sector over the shared regional resources (e.g., land and investment) [1, 26], putting pressure on the economy, society, and environment. In the case of Germany, northern states, where the weather conditions are more appropriate for wind power production [27,28], also happen to be suitable regions for bioenergy production [29], carbon storage, and wetlands restoration options [30], while the southern federal states have greater potential for solar power[2] [31].

To address this challenge, a couple of recent contributions have made attempts to couple climate and weather data with energy system models [14,19] exhibiting a higher spatial and temporal resolution [18]. Kapica et al. [32] call for future climate research to integrate wind power studies with energy and power system modeling to identify key factors for improving power system resilience during renewable energy droughts, since climate scientists have not reached consensus across all renewable technologies and regions. McKenna et al. [33] also mention "integration into power systems at high penetration levels" as genuine issues that are currently difficult to solve. To identify the impact of weather-induced extreme events in highly renewable systems, Grochowicz et al. [34] suggest using shadow prices for electricity to avoid modeling complex interactions between low renewable availability, high demand, electricity transmission constraints and storage dynamics. However, providing access to such critical information in high resolution can pave the way for strategic gaming behavior, damaging energy affordability [35]. These advances notwithstanding, scientists still observe a disconnect between climate and energy system modeling [36]. Pickering et al. [18] state that "the true robustness of system designs to a range of weather conditions expected to occur over the decades of investment lifetime needs more work bringing together climate science, meteorology, and energy engineering". Consequently, scientists are calling for comprehensive risk assessments [37] which bridge the gap between energy system models and climate models in order to capture the impact of meteorological variabilities and climate change on intermittent renewable energy sources [38,39].

To address these shortcomings, with our analysis, we aim to improve the understanding of how variability in climate and weather conditions affect energy systems by providing an assessment with higher spatial resolution. We focus on a more accurate spatial assessment of onshore wind power and bioenergy supply — the two renewable energies which may be particularly affected by climate and weather variability. Germany is selected as the case study, as we need to tackle regional parameters; however, the developed framework can be applied to other regions if the required data is available. Our modeling approach soft-couples an energy-system model, the Renewable Energy Mix (REMix) model [40], with the Renewable Spatial-Temporal Electricity Production (ReSTEP) model [41], a physical simulation model for detailed power production data from wind energy, and the extended Bioenergy Optimization (BENOPTex) model [42] for bioenergy. All in all, our approach allows us to gain granular insights regarding two questions:

1. How may the amount and spatial distribution of electricity supply from onshore wind power and bioenergy in Germany be affected by variability in climate and weather conditions?
2. How do possible shortages in the supply of onshore wind power and bioenergy affect the overall energy system in terms of CO_2 emissions as well as energy system costs?

The remainder of this manuscript is organized as follows. Section 2 explains the proposed framework. Section 3 presents the results of each model, which are further analyzed and discussed in Section 4 to address the research questions. Finally, we conclude the paper and present some avenues for future research in Section 5.

[1] due to binary variables in the unit commitment models.

[2] See https://www.cleanenergywire.org/dossiers/onshore-wind-power-germany.

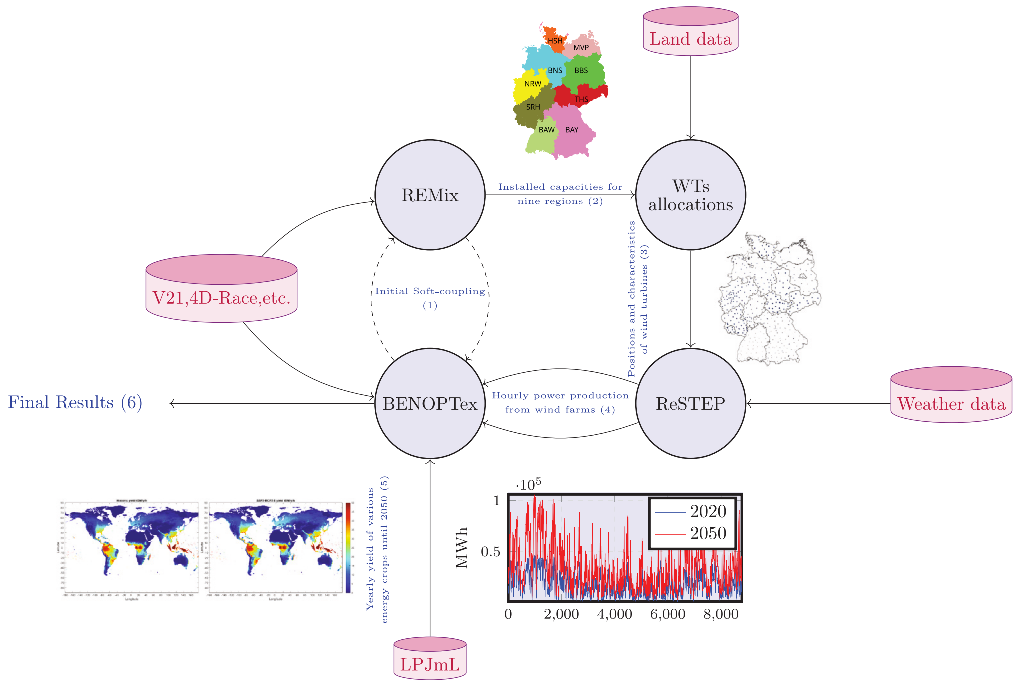

Fig. 1. The streamlined depiction of information flowing between various models, given regional demands and climate conditions. WTs stands for wind turbines. 4D-Race is a model that calculates the energy by the aviation sector. Vector 21 (V21) is a simulation model that calculates the energy demand by type for road transportation sector. LPJmL is a dynamic global vegetation model that simulates the response of carbon and vegetation patterns under climate change.

2. Material and methods

Fig. 1 depicts the information flow between various models in the proposed framework. This section is organized into four subsections, each corresponding to a step in the sequence illustrated in Fig. 1. The details of each model in the framework are presented in the Appendices. Through the modeling process, the outputs of the REMix model, which is characterized by its coarse spatial resolution but broad sectoral coverage, are refined for wind energy to an hourly temporal resolution using detailed GIS-based processing in Steps 2 and 3. These high-resolution datasets are then used to simulate more realistic wind power production under two scenarios within the ReSTEP model. Additionally, this refined information will be integrated with annual-resolution yield projections from the Lund-Potsdam-Jena managed Land (LPJmL) model for two contrasting scenarios to generate a more accurate and comprehensive outlook for the German energy system. By passing through multiple layers of spatial, temporal, and sectoral refinement, the resulting data carries significantly reduced uncertainty compared to the original model outputs.

2.1. Aligning energy and German bioenergy systems

In Step (1), the procedure begins with the soft-coupling of the REMix (see Appendix A) and BENOPTex (see Appendix D) models at a national level, as these models are placed at the two ends of the information flow [43]. Concerning bioenergy, instead of using off-the-shelf tools, we rely on BENOPTex – a temporally, spatially (NUTS-1), and technologically resolved optimization model – since the availability of biomass is the most critical factor in reaching declared targets [44], and the spatial and technological details of bioenergy in other Energy System Models (ESMs) are limited to the country level [45].

The initial convergence assists us with the harmonization of assumptions regarding the energy demand in various sectors, the price of electricity, the share of biofuels and synthetic fuels in various sectors, and the carbon intensity of electricity. REMix and BENOPTex rely on the calculations of Vector 21 [46] and 4D-Race [47] models for future trajectories of energy demand in the road and aviation sectors. The data regarding the availability of 77 residue types is also collected from the Deutsches Biomasseforschungszentrum gemeinnützige (DBFZ) resource database [48]. In this step, the results of each model are fed as inputs to the other one in an iterative manner until the solutions of BENOPTex and REMix converge to equilibrium, i.e., when the change in sectoral fuel production between two consecutive iterations is no more than 10% from 2020 to 2050 [49]. This criterion serves as the necessary termination condition, ensuring that the model outputs are stable and reliable. Both models reach convergence after 18 iterations, each taking multiple days.

In Step (2), we receive a detailed solution based on the nationally converged REMix results. REMix provides projections for the installed capacities of various technologies in nine regions of Germany in accordance with the German network development plan (NEP) of the B/C 2045 scenario. These projections start from the base year (2020) and extend until 2050, covering every ten years.

2.2. Optimal allocation of wind capacity to federal states

In Step (3), the REMix projections for wind power capacity in the nine German regions were disaggregated into individual wind turbine sites (see Appendix B). Based on the dataset by Ryberg et al. [50] for potential wind turbine sites in Germany, those sites within each region were selected to minimize levelized cost of electricity, while respecting the rated power installation requirements provided by REMix for each region. The utilized dataset for future wind turbine placements [50] has accounted for land eligibility, thereby excluding, inter alia, protected areas, a 5 km buffer around airports, areas near campsites, industrial and mining sites, leisure and camping zones, water bodies and rivers, wetlands, considering the terrain slope and elevation, among many other factors.

Eventually, these sites were aggregated again to 403 cells with estimated wind power capacities for 2020, 2030, 2040, and 2050.

2.3. Simulating wind turbines power production

In Step (4), we address two issues related to modeling wind energy: Data availability and accuracy. Disaggregated (i.e., spatially and temporally detailed) power production data of existing wind turbines are currently not publicly available in Germany due to strict data protection regulations [51]. Instead, the electricity generation from this intermittent renewable energy can be determined with the help of physical simulation models using detailed plant and weather data. To this end, the ReSTEP wind power model is used for these simulations, which has already been described and validated in [27,41]. Just as it is not possible to make reliable weather forecasts with time horizons of months or even longer, there are no usable weather data at the moment for the next decades with a temporal resolution of at least one hour for local wind speeds, as required for reasonable simulations of wind power production with physical models [52]. Furthermore, integrating the effects of climate change on such small-scale weather conditions is hardly possible at present, as existing climate models of the fifth Intergovernmental Panel on Climate Change (IPCC) cycle for various scenarios (RCP2.6, RCP4.5, and RCP8.5) produce only negligible changes in local wind speeds, as shown for 22 different coastal locations in Germany [53]. Thus, the ReSTEP simulations for 2030, 2040, and 2050 also use the Modern-Era Retrospective analysis for Research and Applications, Version 2.0 (MERRA-2) [54,55] weather data for two scenarios, providing more accurate "what-if" cases that offer a realistic range of outcomes, especially when combined with the grid structure and regional hourly power consumption in subsequent steps.

In Step (4), based on the installed wind turbine capacity at these sites and the local weather conditions, the ReSTEP model (see Appendix C) computes the electricity generation from each site under two weather scenarios: Business-As-Usual (BAU) and Bad-Wind-Year (BWY). The BAU scenario corresponds to the calculated values in 2020 with weather data from that year; however, for the BWY scenario, we use weather data from 2010, which is a typical low-wind year from a meteorological perspective [56]. We utilize the low-wind year for the second scenario as some studies on climate change scenarios suggest a reduction in wind speed for many European countries, impacting wind power production [57,58] and total system cost [20]. By integrating extreme weather conditions with the German network development plan scenario, we aim to assess the impact of these anomalies on the energy system's planned targets, which are primarily based on average conditions. The wind energy calculated by the ReSTEP model is utilized in BENOPTex to evaluate the availability of renewable electricity for meeting load demands and producing synthetic fuels.

2.4. Modeling the impact of climate change on bioenergy

BENOPTex regards the impact of climate scenarios on the yield of energy crops using the results of the LPJmL model [11,59] under two climate scenarios: Representative Concentration Pathway (RCP) 2.6 and 6.0. Since these climate scenarios have not yet been downscaled sufficiently to model regional wind patterns with high spatial resolution, we assume alternative weather scenarios for onshore wind power: BAU, and BWY. We use different combinations of the climate and weather scenarios to examine energy system impacts.

In Step (5), the BENOPTex model collects the results of ReSTEP for wind energy as well as the LPJmL model regarding the yield of energy crops in different states of Germany. Comparing the outcomes of these four future scenarios enables us to assess how varying factors influence energy systems through the planning horizon, thereby assisting policymakers in foreseeing challenges and devising appropriate strategies [60]. Using climate projections from General Circulation Models (GCMs) and RCP scenarios (i.e., RCP2.6 and RCP6.0) available from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) database[3] [61], we calculate the yield values of various energy crops (12 crops in the LPJmL model) under two RCP settings for 16 federal states in Germany from 2020 until 2050. Shared Socioeconomic Pathway (SSP) scenarios can also be used in BENOPTex instead of RCPs; however, all the connected models (i.e., Vector21, 4D-Race, REMix, LPJmL, etc.) and relevant parameters (e.g., energy demand as a function of population and income) and assumptions would need to be adjusted to consistently reflect the changes in the socioeconomic parameters of these scenarios. Thus, we solely focused on the physical climate response to different GHG levels in the RCPs. The raw yield values, in the corresponding LPJmL output file,[4] cover the entire world with 0.5° resolution. Next, the collected points are mapped to their corresponding states in Germany when inside those regions. For states with multiple data points, the average value is calculated.

BENOPTex endogenously determines the optimal crop to cultivate on the available land allocated to bioenergy production, as outlined in Millinger and Thrän [62]. This decision is driven by the demand for the final energy carrier,[5] as well as by the feedstock prices based on crops yields. To estimate the feedstock price, the per-hectare profit of a benchmark crop (wheat) is added to the per-hectare production cost of each energy crop. In order to incorporate the social impact of low and high yields in RCP2.6 and RCP6.0 (known as "Ambitious" and "No climate action" climate futures [63], respectively) and to create a wider gap between climate scenarios, we reformulate these two scenarios by considering the past yields. Under RCP2.6, we presume that the yield ($y_{t,f,r}$) of energy crop f at year t in region (i.e., state) r can improve every year according to $\hat{y}_{t,f,r} = \max\{y_{t,f,r}, \hat{y}_{t-1,f,r}\}$, whereas under RCP6.0 the yields deteriorate according to $\hat{y}_{t,f,r} = \min\{y_{t,f,r}, \hat{y}_{t-1,f,r}\}$. This scenario generation strategy attempts to model farmers' belief of the last year's yields as the point of reference for decision-making (similar to a Markovian process) when climate change affects the food and feed supply chains.[6] Consequently, the bioenergy system invests in safer options under RCP6.0 and riskier options under RCP2.6. Furthermore, to reflect the impact of climate change on straw as residue, we normalize the available residue in 2020 based on the future wheat yield change (i.e., $\hat{y}_{t,f,r}$) under RCP6.0. Finally, we assume the availability of forest residues is reduced by 1.5% every year under RCP6.0, while remaining unchanged under RCP2.6.

In BENOPTex, the modified yield values ($\hat{y}_{t,f,r}$) are translated to the land demand for energy crops – considering their energy density and dried matter content as described in Millinger et al. [42] – at each year (i.e., $Y_{t,f,r}$ in hectares per petajoules) and used as a parameter in Eq. (1):

$$\sum_{i,f,c} (Y_{t,f,r} \times \dot{m}_{t,i,f,c,r}) \leq \Lambda_{t,r} \qquad \forall t \in T, r \in R \tag{1}$$

where $\Lambda_{t,r}$ is the available land for energy crops in each region at year t and $\dot{m}_{t,i,f,c,r}$ is a decision variable representing feed f used in region r from category c by technology i at year t in petajoules (PJ). Eq. (1) restricts the expected production of energy crops from different regions. To comply with the National Biomass Strategy (NABIS) in Germany [64], we assume that the current land area used for bioenergy in Germany (approximately 2.4 Million hectares (Mil ha)) serves as the maximum limit, which gradually decreases by 10% toward mid-century.

3 https://www.isimip.org/

4 The yield values are collected from *lpjml_gfdl-esm2m_ewembi_***RCP***_2005soc_co2_yield-***CropName***-firr_global_annual_2006_2099*. Each term has a specific meaning, described in the ISIMIP2b Simulation Protocol.

5 Not all energy crops are suitable for all processes and applications.

6 The difference in future crop yields between the two climate scenarios may be either positive or negative. However, by applying this strategy, we are able to define a range using lower and upper bounds, thereby avoiding the need to run the model across a full ensemble of scenario combinations.

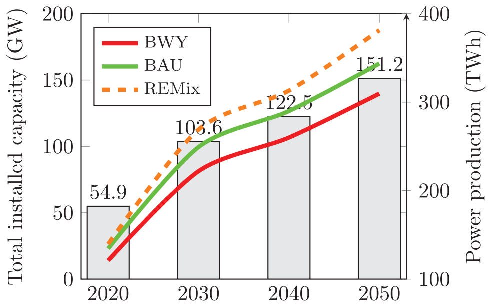

Fig. 2. Total installed capacity (bar chart) and corresponding power production of onshore wind turbines in TWh for BAU (in green) and BWY (in red). The dashed orange trend illustrates how REMix overestimates power production.

3. Results

In this section, we present and discuss in detail the key results on the impact of weather variability and climate change on wind energy (Section 3.1) and bioenergy (Section 3.2), respectively. The implications of such an energy system for Europe are examined in Section 3.3. Additional results and analyses are provided in Appendix.

3.1. Wind energy under various weather conditions

Fig. 2 provides an overview of the total installed capacity of the onshore wind turbines in Germany as predicted by the REMix model and the simulated annual power production for 2020 to 2050 under the BWY and BAU scenarios using the ReSTEP model. Please note that although wind power production for 2020 is available in 2024, under BWY, we conducted the simulation based on 2010 weather data and the existing capacity, which explains the discrepancy between the two trends. Hence, the 2020 values under BWY should be viewed as one possible outcome that could have occurred. Furthermore, technical barriers (e.g., land use competition and slow expansion of the transmission network) hinder onshore wind energy from achieving the milestones set in the NZE scenario. As shown by the dashed orange trend, in the absence of precise turbine locations and weather conditions, REMix overestimates power production. The difference between the trends highlights the refinements introduced by the proposed framework.

Fig. 3 illustrates the regional distribution of wind power production in 2020, 2030, 2040, and 2050 under both the BAU and BWY scenarios. Darker shading indicates greater onshore wind electricity generation in 2050 for each state. Lower Saxony has the greatest potential for onshore wind energy. Northwestern German states also exhibit a faster pace of wind energy development compared to southern states. Furthermore, the generated power under the BAU scenario is consistently higher than under BWY across most years and regions. However, we have a few exceptions, such as Bavaria and Saxony-Anhalt. In the BAU scenario, Bavaria – located in the southeast of Germany – exhibits steady growth. In contrast, Bavaria under the BWY scenario features a more pronounced acceleration in wind energy expansion between 2030 and 2040.

3.2. Climate change impact on bioenergy

In this section, we evaluate the impact of climate change on bioenergy using the BENOPTex model, given the availability of wind energy.[7] To display the spatial and temporal transformation of bioenergy in Germany, Fig. 4 exhibits the cultivation of 11 energy crops in different states until 2050 to be used in the energy sector and chemical industries

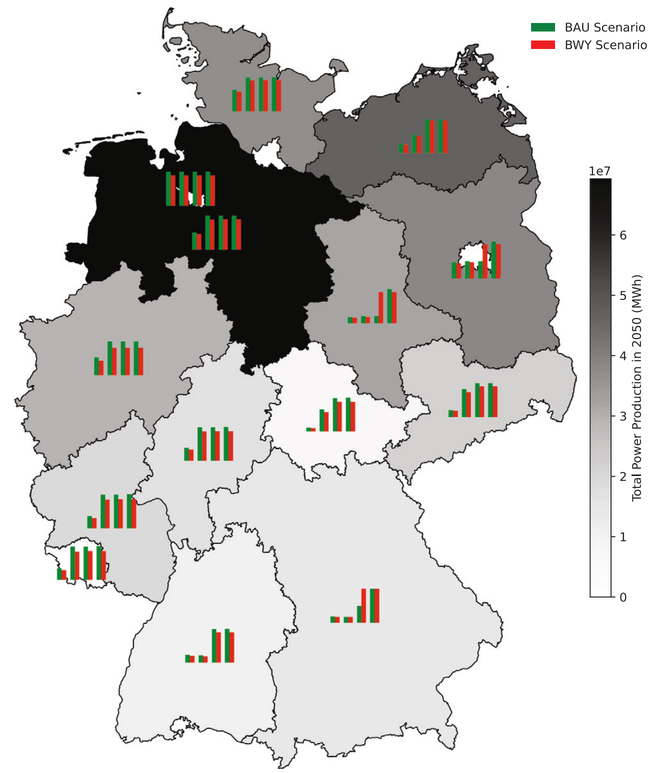

Fig. 3. Regional distribution of onshore wind energy in Germany under BAU (green bars) and BWY (red bars) scenarios for 2020, 2030, 2040, and 2050 (bars from left to right). Darker shades indicate higher electricity generation from onshore wind turbines at the end of planning horizon.

under the BAU-RCP2.6 scenario. The darker a state is, the higher the percentage of the cultivated energy crops in that state. The lines between states represent the transmission network. The light green lines show that the transmission grid will not be congested if we optimally distribute the production of energy crops in different states. However, we can see that expanding transmission lines between states and more distributed renewable electricity could assist in relaxing congestion (i.e., red lines) until 2040. The quantitative data, which is the base for all figures, is provided in the GitLab repository, as indicated in the Data Availability section.

As illustrated in Fig. 4, there are two significant transformations: The first shift appears in the early years when conventional energy crops are replaced with more advanced woody biomass. This phenomenon is due to Renewable Energy Directive (RED) requirements, which incentivize advanced bioenergy (i.e., second and third-generation bioenergy) and has also been reported in other publications [65, 66]. The second pattern emerges when looking at the latter years (i.e., 2050), with northern federal states consuming mostly paludiculture and flower mix, while the major sources of biomass in southern states are miscanthus and sugar beet. It should be noted that Lower Saxony has the highest share in bioenergy production owing to vast wetlands that can be used to cultivate paludiculture under RCP2.6. For plots related to other scenarios, please check Appendix D.3.

The negative impact of climate change on the availability of biogenic materials is visible in Fig. 5 when comparing the amount of consumed biogenic feedstock in 2050 by different energy and non-energy sectors (i.e., chemical industries). To compensate for the lack of biogenic materials, the optimal solution under RCP6.0 scenarios used slightly more excess renewable electricity.[8]

[7] To produce synthetic fuels or directly fulfill electricity demand.

[8] BAU-RCP2.6: 2182.62 PJ, BAU-RCP6.0: 2204.5, BWY-RCP2.6: 2183.68 PJ and BWY-RCP6.0: 2196.88 PJ.

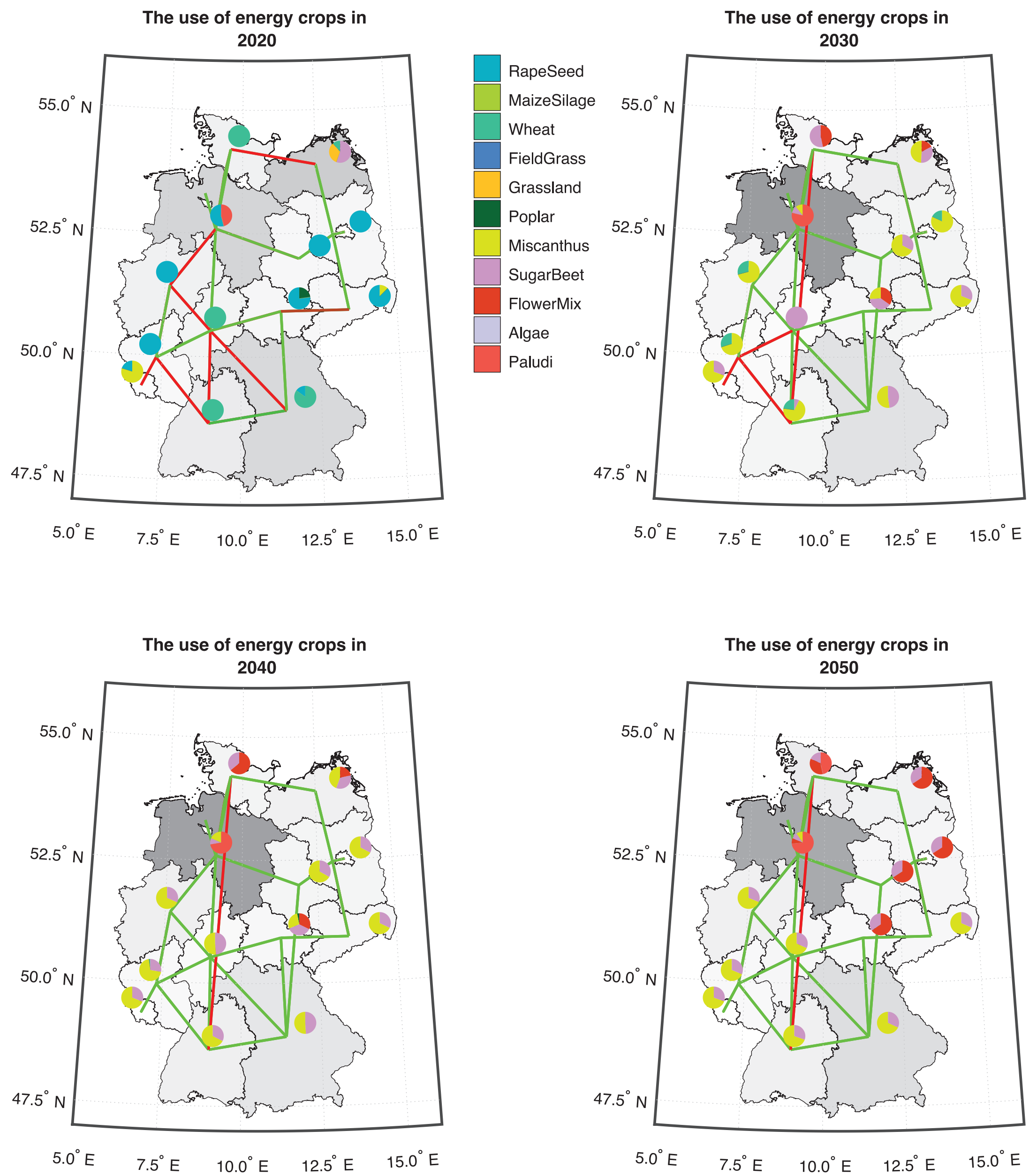

Fig. 4. Energy crop production (from agricultural lands and wetlands) in each decade until 2050 and their impact on relieving congestion in the grid under the BAU-RCP2.6 scenario. The pie chart in each region shows the composition of energy crops by type. Lines between states represent the transmission network. The transmission lines in the network are drawn in red when fully congested, and in green otherwise.

By presenting all scenarios side by side for 2050, the last year of the modeling horizon, Fig. 6 facilitates the comparison of regional variations in energy crop production across different scenarios. The composition of energy crops in each state varies with changes in the climate scenario; however, more renewable electricity under the BAU scenario, compared to the BWY scenario, can utilize the available capacity of the north–south transmission line. This behavior demonstrates the complementary relationship between bioenergy and intermittent renewable energy, indicating that a diverse portfolio of options should be invested simultaneously in order to create a resilient energy system. Comparing RCP2.6 and RCP6.0, one can immediately notice a shift from paludiculture to other energy crops in the northeast of Germany. This shift can be due to the lack of water, which negatively affects wetlands and paludiculture yields.

As biomass is the key component of many Negative Emission Technologies (NETs) and Carbon Dioxide Removal (CDR) concepts, we are also interested in comparing how climate change affects the viability of these options in Germany. Fig. 7 displays the contribution of forest-based carbon removal concepts and BECCS technologies in removing atmospheric CO_2 under different scenarios. As the biomass is more available under RCP2.6, BECCS technologies can remove larger amount of CO_2. The pressure over BECCS_04_Combustion_Wood[9] is more visible between the two climate scenarios.

Immediately, we can see that the cultivation of paludiculture can remove CO_2 in the form of peat as well as extract CO_2 downstream by using paludiculture as feedstock in BECCS technologies. Another synergy happens between ethanol-producing BECCS and chemical industries to convert bioethanol into Ethylene, which has been reported in [67].

[9] It combusts woody biomass to generate electricity by turning the turbine and removing CO_2 using a post-combustion carbon capture unit.

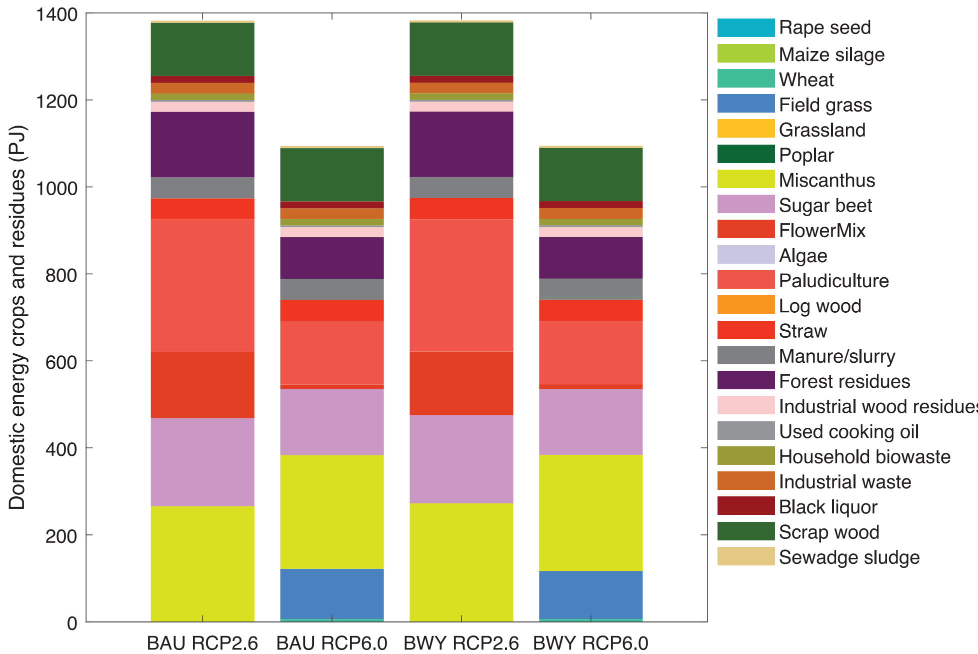

Fig. 5. Energy crop and residues (from agricultural lands and wetlands) consumption in 2050 under various scenarios in petajoule (PJ).

According to the BENOPTex outcomes, BWY-RCP6.0 and BAU-RCP6.0 are 17% and 15% more expensive than the cheapest scenario, BAU-RCP2.6, respectively. Moreover, BWY-RCP2.6 is only 1% costlier than BAU-RCP2.6. Therefore, the impact of wind generation is minimal in terms of costs; however, climate change can significantly affect the energy system.

Fig. 8 shows the cost difference between scenarios, when compared with 2020 values, together with the GHG emissions in Mt CO_2-eq. One can see that the annual system cost first increases to 109% of 2020 value in 2029 and then drops to lower values in the latter years. The transition from nuclear and coal to natural gas is the main driving factor for the mid-term cost growth (see Fig. 9). Most variation between scenarios appears in the latter years when the land capacity to produce biomass is affected. Another important observation is that, under the RCP2.6 scenarios, the annual system costs after 2040 can be on par with the 2020 values; however, under the RCP6.0 scenarios, the yearly costs raise again after 2040. Concerning GHG emissions, the variations between scenarios ranges from −9 to 31 Mt CO_2-eq in 2050. The sharp drop in GHG emissions in 2040 is due to the LULUCF concepts contributing to Germany's net GHG neutrality target in addition to technical sinks (such as BECCS), as described in the Climate Protection Act [68]. Finally, under these four scenarios, Germany will still have positive emissions (i.e., the gap between the dashed line and trends) in 2045, which should be either removed using new concepts (e.g., utilizing biochar in the construction sector) or compensated via external CO_2 credit to reach carbon neutrality targets.

Fig. 9 depicts the German energy mix from 2020 to 2050 in two contrasting scenarios. The figure delineates Germany's planned nuclear phase-out by 2023 and coal phase-out by 2038 [69]. It also clearly highlights the impact of climate change on domestic biomass availability, leading to a higher natural gas consumption under BWY-RCP6.0.

Fig. 10 illustrates the impact of biomass and wind energy scarcity in the power sector. BECCS contribution has been replaced by gas-and-steam turbines (GUD) that use natural gas when biomass is a scarce resource, causing the system to fail in meeting both GHG avoidance and removal targets.

3.3. Pan-European implications

As Germany is not an electric island but the largest energy consumer in Europe integrated in a European transmission network, the implications of the shown results with respect to the transmission capacities and flows to and from the neighboring countries are described in the following. Unlike results in Figs. 4–8, the analysis in this section is based on the REMix base runs with a comprehensive European model with national grid nodes outside Germany and a similar model node setup within Germany.

Moreover, the runs are not constrained by the Ten-Year Network Development Plan (TYNDP), allowing for the analysis of the cost-optimal grid expansion within and outside Germany under a 100% renewable energy supply. The ranges shown in this section describe the deviation between three scenarios, focusing on direct electrification, a hydrogen economy and synthetic fuels with respective implications on the electricity supply infrastructure.

We find German cross-border grid capacity additions of 150–180 GW, as being cost-optimal. These capacities are mainly expanded in the period 2030–2040 (80–90 GW) with still significant expansions in the following decade (30–50 GW). These are significantly higher interconnection capacities than the around 40 GW planned by the German grid agency (BNetzA).

The cost-optimal cross-border flows illustrate a changing balance from today's export surplus of German electricity cross-border flow. Because of Germany's high population density as well as high electricity, heat and fuel consumption due to (among others) its high industrial energy demand, Germany could become a strong electricity importer with exports significantly reduced to around 20–30 TWh per year while imports are significantly increased to 110–470 TWh per year.

Both, cross-border grid capacity and flows exhibit the significantly changing role of Germany as an interconnected grid zone in its European context. These findings relativize the grid line congestions shown in Figs. 4 and 6 if the European transmission grid is taken into account in the analysis. However, both, inner-German grid capacities as well as interconnection capacities to neighboring countries in the cost-optimal solution in REMix are higher than currently planned capacities in all cost-optimal scenarios, as BENOPTex does not optimize transmission lines.

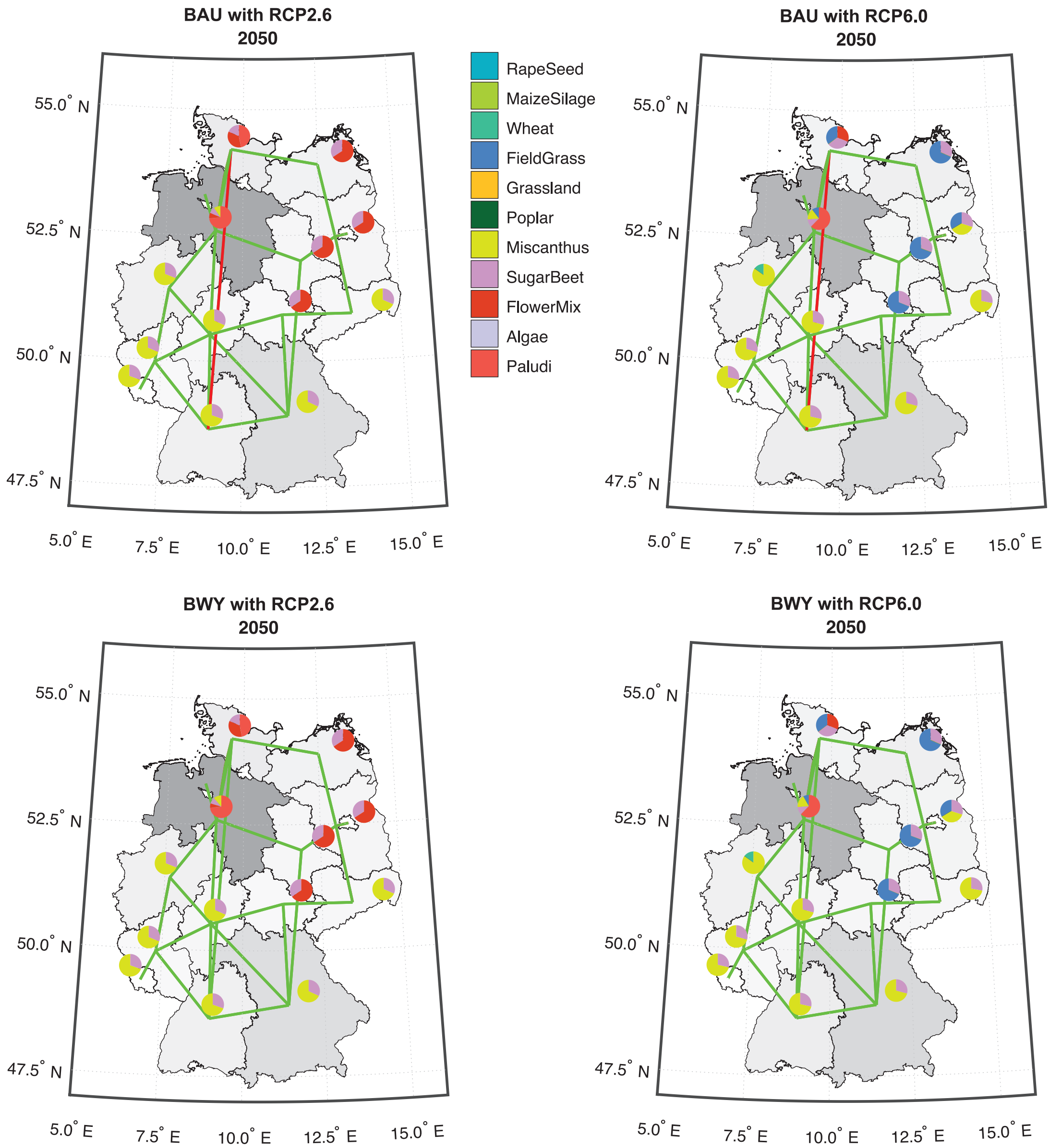

Fig. 6. Energy crop production (from agricultural lands and wetlands) in 2050 under various scenarios.

As shown in Fig. 6, the transmission line congestion of the transmission line between Schleswig-Holstein in the north and Baden-Wurttemberg in the south of Germany depends on wind power feed-in. The BWY scenario does not show the same level of congestion as the BAU scenario. Also, the high imports described above are driven by inner-German hydrogen production being cheaper than given import alternatives.

4. Discussion

This section begins with a discussion of the study's limitations and then presents managerial insights to aid in the development of more resilient energy systems.

4.1. Limitations

The presented framework consists of many intertwined models, making interpretation challenging. However, many interdisciplinary problems suffer from the same issue [70,71]. For instance, IAMs are becoming as complex as the real world, while subject to criticism, is often accepted in the literature [72]. In this study, no single model sufficiently captures all the dimensions (land-use competition, defossilization of energy system, climate change, weather variabilities, etc.), which is why we couple multiple models. We utilized well-established models with a strong track record of publications in reputable journals. Furthermore, the information exchanged between models to support the results of this study is made available in the GitLab repository, as indicated in the Data Availability section. Another valid criticism is with respect to the utilized scenario. This study utilizes yield projections from the LPJmL model based on RCP2.6 and RCP6.0. Although SSP scenarios are now gaining traction, RCPs can be directly mapped to SSPs, which are used in the latest IPCC assessment report [73], and continue to reflect a valid range of climate outcomes. It also facilitates comparison with previous findings in the literature [74]. However, future research may take advantage of SSPs instead of RCPs, respecting the need for alignment of assumptions and parameters across the connected models.

The focus of this study was on the interplay between wind energy and bioenergy with the rest of the energy system, as its land use intensity is greater than solar power and is simultaneously more susceptible

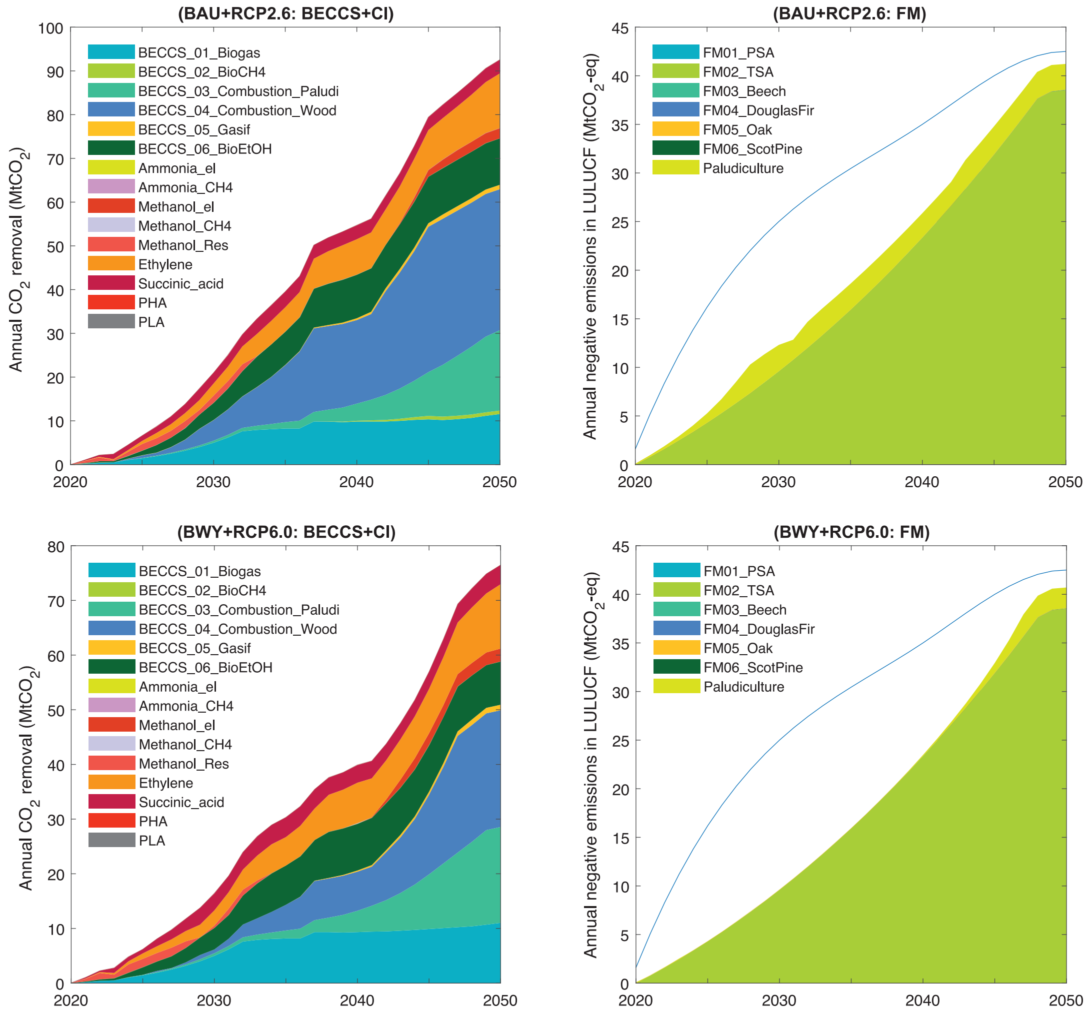

Fig. 7. CO_2 removal by FM concepts, BECCS and chemicals (CI) between two extreme scenarios. The blue line interpolates Germany's LULUCF targets. PHA and PLA stand for polyhydroxyalkanoates and polylactic acid, respectively.

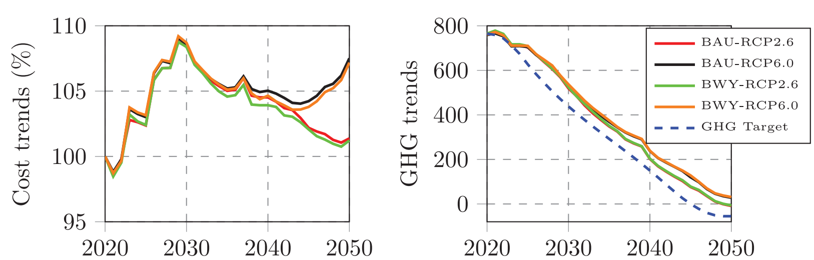

Fig. 8. The cost developments compared to 2020 values (in %) and the GHG emissions trends (in Mt CO_2-eq) for various scenarios from 2020 until 2050. The dashed line interpolates the declared targets in Germany.

to being influenced by climate change [1]. Wind energy and BECCS are key technologies driving emissions reduction and carbon removal in future net-zero energy systems [75]. However, there is merit in analyzing the combined effect of solar and wind energy under different climate scenarios.

Although some studies on climate change scenarios suggest a reduction in wind speed for many European countries, impacting wind power production [8,58], we decided to utilize historical weather data for the BWY scenario. The reason is that by incorporating climate scenarios in ReSTEP, the future generated power from sample wind turbines was reduced significantly, which was difficult to explain (please see our analyses in Appendix C.2). Therefore, it was decided to employ weather instead of climate scenarios. Nonetheless, we plan to develop a physics-aware deep learning model to assess the impact of RCP4.5 and RCP6.0 scenarios for future work [76]. An alternative approach would be to expand this study by incorporating multiple meteorological years, rather than focusing on extreme years [20]. Doing so would enhance the robustness of the results by accounting for inter-annual variability, enabling us to perform a more thorough risk-sensitivity analysis of the energy system toward the intermittency of variable renewable sources. However, this approach would require running the physics-aware simulation model over multiple years to generate spatially and temporally detailed power production profiles from wind turbines, which is computationally cumbersome. By disregarding spatial resolution, we conduct a sensitivity analysis over a wide variety of settings, in which the interplay between dispatchable bioenergy and variable

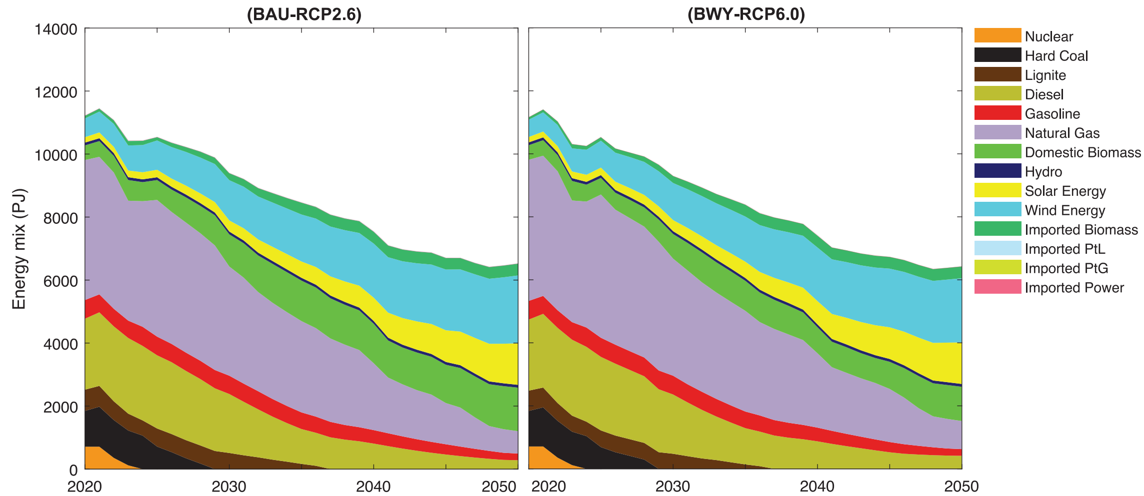

Fig. 9. The energy mix (in petajoule) from 2020 until 2050 under two contrasting scenarios. PtL: Power-to-Liquid, PtG: Power-to-Gas.

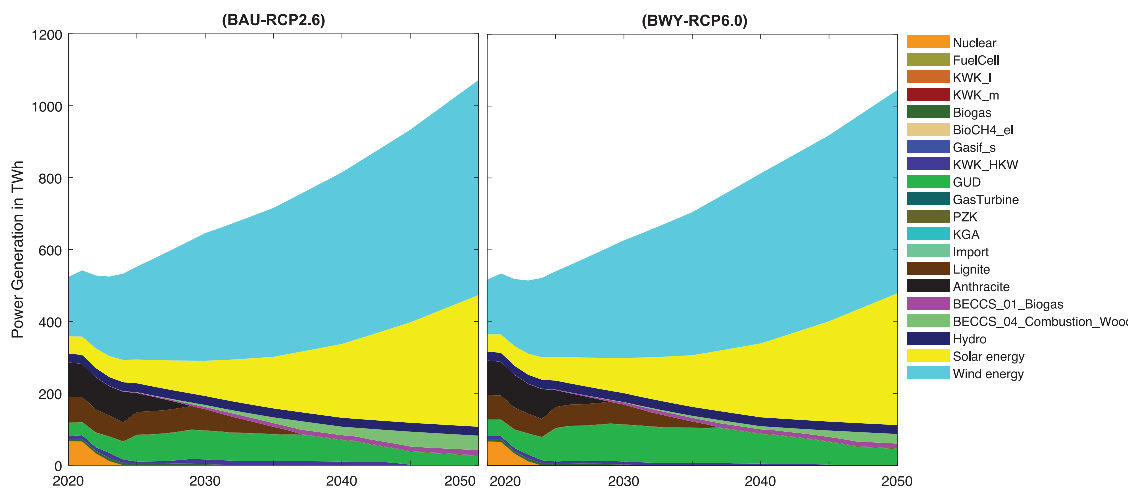

Fig. 10. The mixture of technologies in the power sector from 2020 until 2050 under two contrasting scenarios. GUD: Gas-and-steam, turbine power plants, KWK_HKW: Wood-fired power plant with steam turbine, PZK: Paper-and-pulp with CHP, KGA: Sewage sludge digestion with CHP, KWK_l: CHP burning wood, KWK_m: CHP burning rapeseed, Gasif_s: Gasification of wood.

renewable sources (i.e., solar and wind energy) is shown using the BENOPTex model. In Fig. 11, based on 40 weather years, we associate each time slice of the planning horizon with one of these categories: Average, worse, and best Variable Renewable Energy (VRE). Each setting in ternary plots is normalized relative to the maximum value of all settings. According to the results, bioenergy and VRE complement each other to the extent to which the cost-optimal solution switches to more bioenergy when we encounter the worse VRE scenarios more than 20% of times [77].

Finally, the impact of climate change on energy demand is disregarded to examine the upstream energy system better. Nonetheless, one may expect that higher temperatures will increase the energy demand, especially for space cooling.

4.2. Insights

Analyzing the results reveals that significant reductions in biomass production can profoundly affect the energy system. Variations in the composition of energy crops and residues can alter overall system costs and emissions profiles. Notably, the variability in weather conditions exerts a lower influence on the energy system. This resilience is largely due to the strategic distribution and sufficient capacity of wind turbines, which effectively mitigate most adverse impacts. The results underline the importance of maintaining a diverse portfolio of renewable options for building a resilient energy system.

Mid-term emission reductions will be driven by transitioning from coal to gas and electrifying the German energy system with renewable sources such as solar and wind energy. However, this transition may increase system costs in the mid-term due to investments in new technologies. In the long term, achieving climate targets could reduce system costs under moderate climate change impacts, whereas severe climate impacts may result in higher costs.

In addition, the findings highlight the significant role of the circular economy in achieving climate objectives. Results revealed multiple cascades that enhanced the adoption of innovative technologies, notably ethanol production via BECCS and its subsequent conversion to ethylene, a crucial component in plastic manufacturing. The interplay between these two NETs notably accelerated the uptake of BECCS. Additionally, a comparable synergy was identified between LULUCF practices, such as paludiculture production from wetlands, and BECCS. Therefore, policymakers should support concepts that can provide multiple benefits simultaneously, while being resilient against climate change. This is especially important as climate change and weather variability can have severe impact on Direct Air Capture (DAC), as another NET [78].

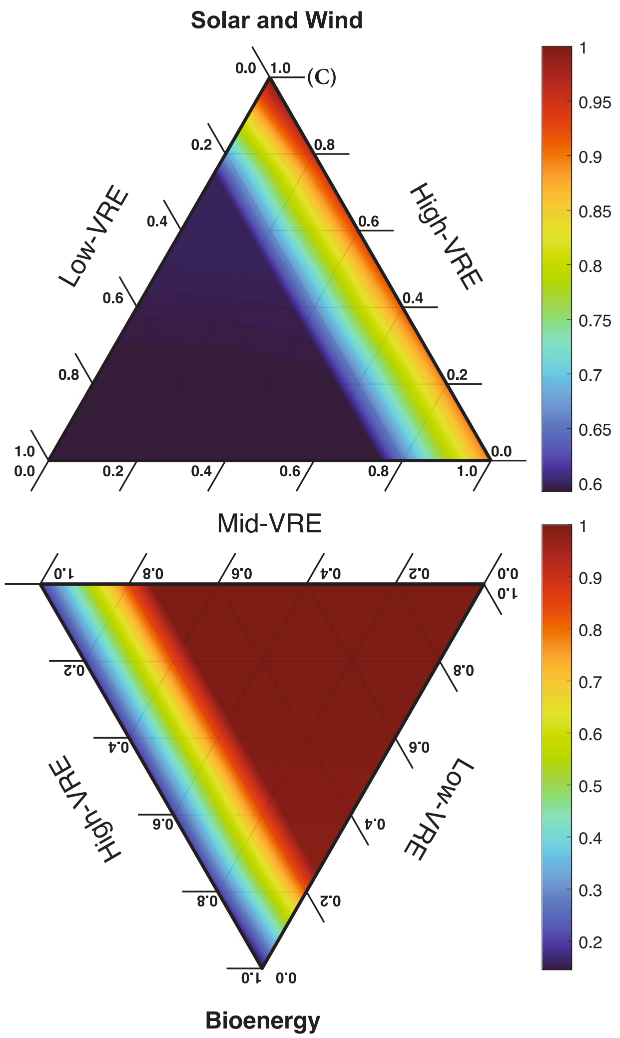

Fig. 11. The interplay between bioenergy and variable renewable energy (VRE) sources with 6 h time resolution under RCP2.6.

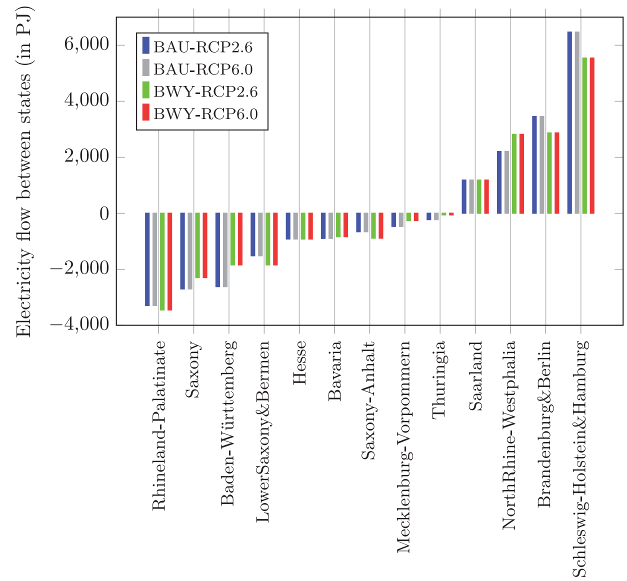

Fig. 12. The cross-state flow of electricity between 2020 and 2050 in various scenarios.

Model experiments that are less constrained show that Germany is expected to rely more on other neighboring countries for the supply and balancing of renewable electricity. Combining this piece of information with Fig. 12, we can see that electricity is needed in southern states (e.g., Rhineland-Palatinate and Baden-Württemberg). This signifies the importance of cross-border transmission lines with France, Austria, and Switzerland as well as inner-German north–south transmission capacities.

Hanski et al. [79] warned that climate change and severe drought can reduce the French nuclear energy sector's capacity to meet electricity demand, which may impact Germany's southern states. Thus, increased cross-border capacities are not only cost-optimal but also provide increased resilience to persistent drought periods.

5. Conclusion

Renewable sources, unlike fossil fuels, are vulnerable to climate change. Despite this, the reciprocal impact of climate change and the expansion of renewables in higher spatiotemporal details have not been thoroughly analyzed. Using the state-of-the-art model coupling framework, we investigate the combined effects of renewable energy expansion and climate variabilities on the German energy system and its possible impact on the neighboring countries. Our results show that the reduction in biomass availability due to climate variability is critical to the resilience of energy systems. Therefore, Germany should invest in climate-resilient energy crops in suitable regions, such as paludiculture in Lower Saxony. Although the bioenergy system can hedge against climate change by switching to more resilient energy crops, the severe shock may negatively impact the capacity of flexible bioenergy, making it more vulnerable to other disruptions, such as fluctuations in renewable electricity supply. Also, the findings highlight the significant role of the circular economy in achieving climate objectives. While the synergy between BECCS, nature-based solutions, and the chemical industry can enhance carbon removal efforts, achieving net-zero emissions by mid-century remains an ambitious goal that requires global collaboration [80]. Our analysis reveals a significant electricity demand in the southern states, where wind energy is ramping up more slowly, highlighting the critical role of cross-border transmission lines with France, Austria, and Switzerland, as well as the importance of strengthening north–south transmission capacities within Germany.

There are several promising directions for future research. One involves expanding the model framework both technologically and geographically to assess the impact of climate change on renewables, including solar power, across the EU. Achieving this will require simplifying the framework to ensure that the resulting models remain tractable and their outputs are easily interpretable. Also, the availability of critical raw materials for the expansion of renewables should be taken into account, as it can increase the system cost. Finally, we recommend that such analyses be repeated periodically with the most recent climate data projections to provide updated perspectives for investors and policymakers.

CRediT authorship contribution statement

Danial Esmaeili Aliabadi: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Niklas Wulff:** Writing – original draft, Formal analysis. **Reinhold Lehneis:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Mohammad Sadr:** Software, Data curation. **Sandra Gutjahr:** Software, Data curation. **Felix Jonas Reutter:** Formal analysis, Data curation. **Matthias Jordan:** Software, Data curation. **Paul Lehmann:** Writing – original draft, Resources. **Daniela Thrän:** Writing – original draft, Supervision, Resources.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly, Writefull (as part of Overleaf), and DeepL in order to translate and improve the readability of the manuscript. After using these tools, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Declaration of competing interest

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

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Appendix A. REMix

REMix provides the basis for analyzing energy system transformation scenarios in spatial and temporal resolution. Originally limited to the power sector, the framework has been continuously enhanced to include the flexible coupling to the heating and transport sectors to analyze the European electricity system [81].

The framework employs a multi-node approach, wherein nodes can be interconnected via various forms of transport infrastructure. Within each node, all units of a single technology are consolidated and managed as a unified entity. REMix utilizes a linear cost minimization strategy, aiming to optimize its objective function, which considers the annuities proportionate investment costs and fixed operation and maintenance (O&M) costs of endogenously added capacities, variable O&M costs of all assets, fuel costs, optional emission costs, and penalty costs for unsatisfied energy demand. The REMix framework is implemented in the General Algebraic Modeling System (GAMS) and in this study solved using Cplex. The construction of energy system infrastructures and their hourly operation over the course of a year are optimized integrally in one model run, with perfect foresight and from a macroeconomic planner's perspective.

Gils et al. [40] described the REMix model in detail for the power sector. The interested readers are invited to check Gils [82] for the heating sector, and Luca de Tena and Pregger [83] for BEVs and Gils et al. [84] for gas infrastructure modeling. The latest version of REMix was recently released under the BSD 3-Clause License [85].

Appendix B. Available land analysis for wind turbines

When combining REMix wind energy capacities in the MultipIEE optimization framework [86], we encountered the available land constraints in a few states (e.g., Schleswig-Holstein and Hamburg), indicating that the ambitious target for the expansion of wind turbines according to the German network development plan (the so-called Netzentwicklungsplan or NEP) in the B/C 2045 scenario does not consider the land-use constraints (e.g., nature-conservation regulation) of wind energy in their studies, thereby overestimating the available land. We overcame this problem by using Ryberg et al. [50] dataset by the MultipIEE team. Nonetheless, we should mention that this dataset does not utilize high-resolution data for settlements, which means it may overestimate the available land, considering the legal restrictions.

Deploying more potent wind turbines on the existing wind farms may assist us in reducing the land requirements. Using multi-rotor wind turbines can be a compelling option to increase the power density per unit land area [87,88].

The location of 403 wind farms in various states is shown in Fig. B.13.

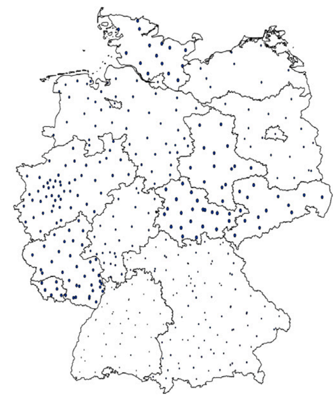


Fig. B.13. Optimal location of wind turbines in each state according to MultipIEE.

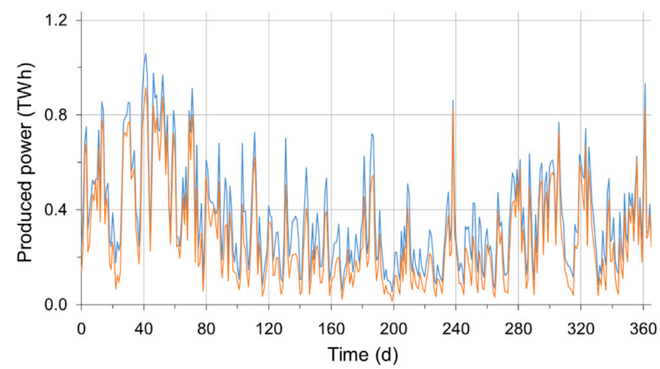


Fig. C.14. Measured feed-in pattern (orange line) and simulated wind power production (blue line) from onshore wind turbines in Germany for the year 2020 in daily resolution.

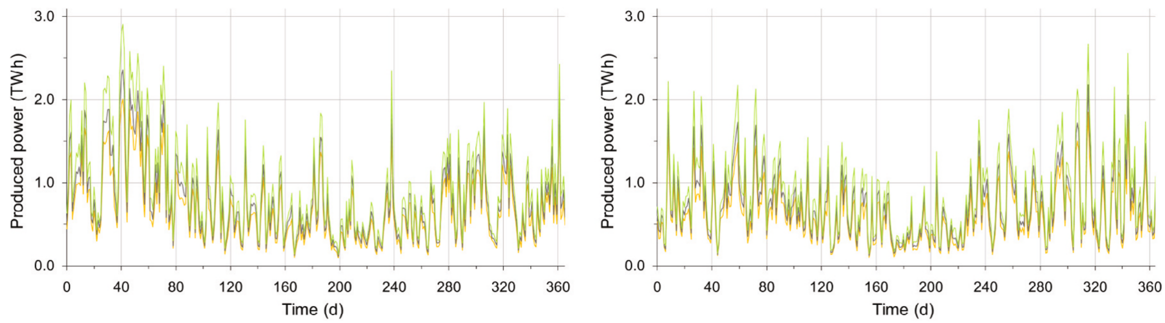
Appendix C. ReSTEP

C.1. Spatiotemporal analysis of onshore wind energy

The simulations are performed for 403 selected sites, where the installed capacity of each site is taken from the prior step (see Appendix B). The installed capacities are converted by the ReSTEP model into a corresponding number of identical wind turbines using an Enercon E-126 with a rated power of 4.2 MW and a hub height of 135 m [56]. This turbine type with its technical parameters represents a well-balanced compromise for the ReSTEP simulations both for the situation in 2020 and for the next decades.

Validated weather data play a key role in wind power calculations using numerical simulations, and their quality is essential for the accuracy of the simulation results [52]. Similar to the ReSTEP simulations presented in [41], this research also uses MERRA-2 weather data [55] provided by the publicly available Renewables.ninja web tool,[10] which delivers bias-corrected reanalysis data for Germany [89]. These weather data, which are retrieved separately for each of the 403

[10] www.renewables.ninja



(a) BAU (b) BWY

Fig. C.15. Simulated power production (BAU and BWY) from onshore wind turbines in Germany for the years 2030 (yellow line), 2040 (gray line) and 2050 (green line) in daily resolution.

sites based on their geographic center coordinates, have a temporal resolution of one hour.

After running the simulations for the year 2020, the resulting time series of the entire onshore wind turbine ensemble were spatially aggregated and compared with measured wind power feed-in data for the whole of Germany in order to verify the simulation results and to discuss the reasons for the existing deviations. To facilitate this verification, the measured and simulated time series were converted from hourly to daily resolution, as shown in Fig. C.14.

According to Fig. C.14, the simulated wind power production follows the measured feed-in pattern very well over the entire year. The frequently higher simulation results are mainly due to the fact that ReSTEP applies the same efficient wind turbine type for all sites and does not consider feed-in interruptions caused by capacity constrains in the power grids. Nevertheless, a Root-Mean-Square Error (RMSE) of 0.09% with respect to the annual power production and a Pearson correlation coefficient of 0.97, as defined in [41], indicate a high agreement of both time series also from a statistical point of view. Thus, the ReSTEP wind power model can be used to provide a realistic data basis for the scenario simulations over the next decades.

In order to show the patterns of the annual power production in Germany, the simulated time series were spatially aggregated and converted from hourly to daily resolution, as depicted in Figs. C.15(A) and C.15(B).

C.2. Climate versus weather data

To evaluate the impact of climate change on wind power production, we model a wind farm consisting of 48 individual Enercon E-126 wind turbines with a total capacity of 0.2 GW for a site in central Germany (near the town of Kronach). The simulation results for the weather data (MERRA-2) for the year 2020 were contrasted with the outcome of the climate-adjusted scenario (CORDEX regional climate projection with RCP2.6 [90]) for the years 2020, 2030, 2040, and 2050. The box plots in Fig. C.16 depict a downward trend in the daily power production of these wind turbines.

Unfortunately, attempts to estimate the wind power production using physical models faced challenges due to significant variability in climate scenarios and the current climate models' limitations in providing scenario-specific data with high spatial and temporal resolution [53]. Deep learning models might enhance the accuracy of wind power predictions in the future [76].

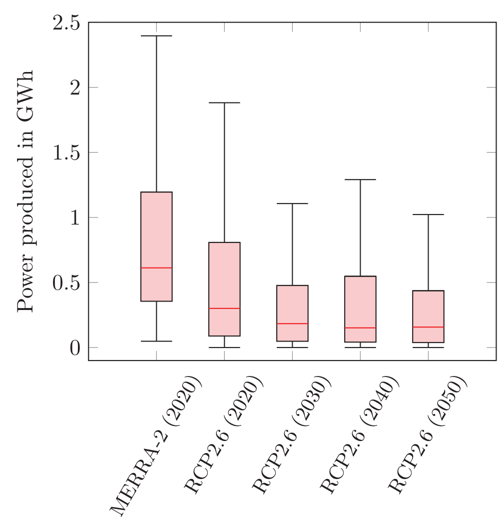


Fig. C.16. Simulation results for 48 wind turbines near Kronach under MERRA-2 and RCP2.6.

Appendix D. BENOPTex

D.1. Objective function

Eq. (D.1) defines the total system cost as an objective function in million Euros (Mil €), where the decision variables denoted in bold. For technology i, m^{opex}_{ti} accounts for its marginal cost (excluding feedstock inputs) at time t. The energy consumed in the technology as heat or electricity is represented by $\dot{m}^{th}_i$ and $\dot{m}^{el}_i$ in $\frac{\text{MWh}}{\text{PJ}}$ multiplied by its correspondent cost p^{el}_{ti} and p^{th}_t in $\frac{\text{Mil€}}{\text{MWh}}$. $\boldsymbol{\pi}_{t,i,s}$ is the production of output in PJ from technology i at time t for market (sector) s.

$$min \quad \mathbf{z} = (\mathbf{z}_1 + \mathbf{z}_2 + \mathbf{z}_3 + \mathbf{z}_4 + \mathbf{z}_5 + \mathbf{z}_6) - \mathbf{z}_7 \tag{D.1}$$

where:

$$\mathbf{z}_1 = \overbrace{\sum_{t,i,s} (m^{opex}_{ti} + \dot{m}^{el}_i \times p^{el}_{ti} + \dot{m}^{th}_i \times p^{th}_t + \dot{m}^{CO_2}_i \times p^{CO_2}_t) \times \boldsymbol{\pi}_{tis}}^{\text{Production costs}}$$

$$\mathbf{z}_2 = \underbrace{\sum_{t,i} (I^{+}_{ti} \times \boldsymbol{k}^{endo}_{ti})}_{\text{Investment cost}}; \qquad \mathbf{z}_3 = \underbrace{\sum_{t,i,f,c,r} (p_{tfcr} \times \dot{\boldsymbol{m}}_{tifcr})}_{\text{Utilized domestic feedstock cost}}$$

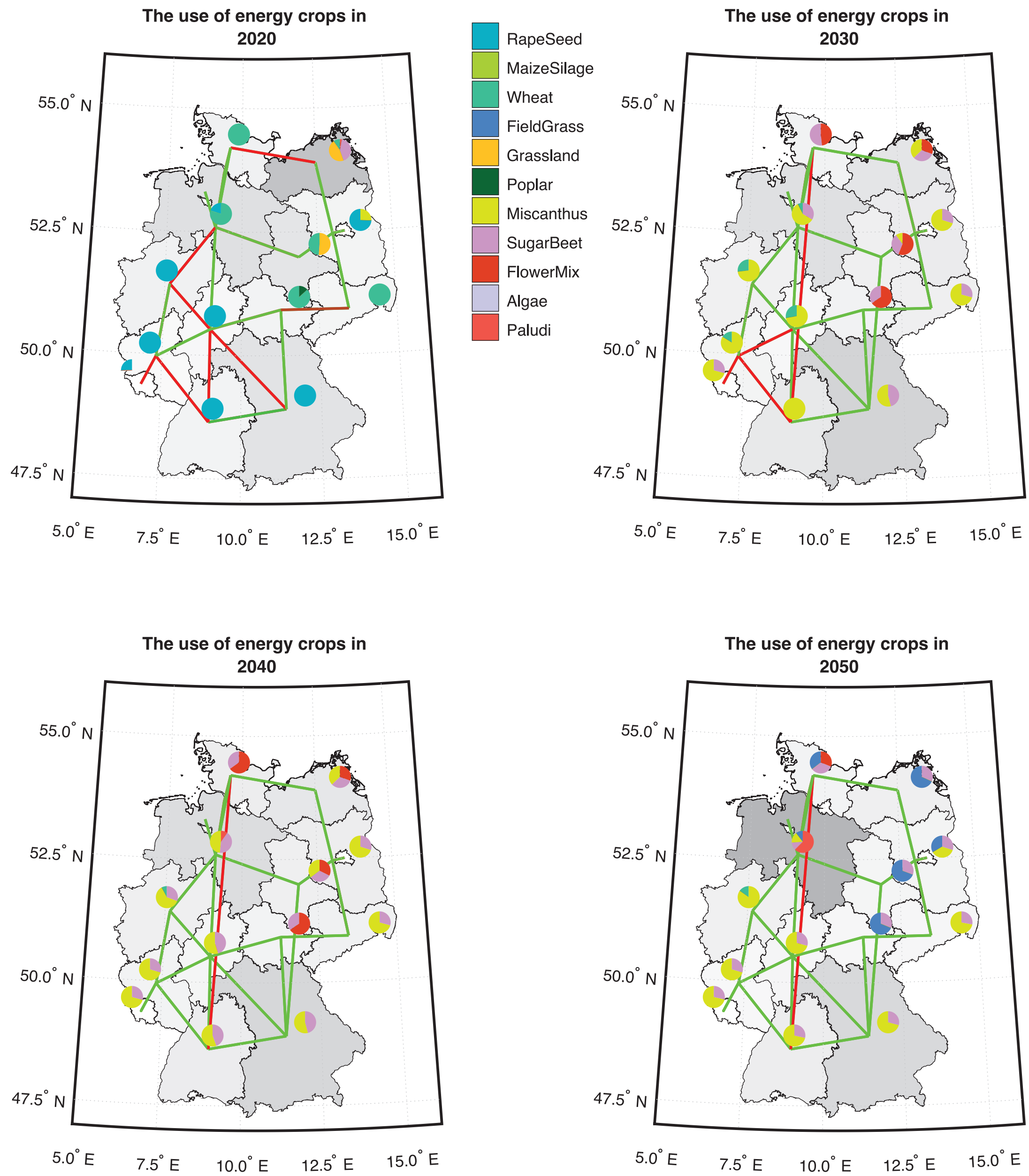


Fig. D.17. Energy crop production (from agricultural lands and wetlands) in each decade until 2050 and their impact on relieving congestion in the grid under the BAU-RCP6.0 scenario. The pie chart in each region shows the composition of energy crops by type.

$$\mathbf{z}_4 = \underbrace{\sum_{t,i,f,r} (p^{imp}_{tfr} \times \boldsymbol{m}^{imp}_{tifr});}_{\text{Cost of imported feedstock}} \qquad \mathbf{z}_5 = \underbrace{\sum_{d,t,i,r} (p^{\mathrm{CO_2}}_t \times \varepsilon^{FF}_{ti} \times \boldsymbol{\delta}^{FF}_{dtir})}_{\text{Penalizing the use of fossil fuels}}$$

$$\mathbf{z}_6 = \underbrace{\sum_{t} (\hat{p}^{\mathrm{CO_2}}_t \times \boldsymbol{m}^{\mathrm{CO_2}}_t);}_{\text{Carbon credit cost}} \qquad \mathbf{z}_7 = \underbrace{\sum_{t,i} (p^{\mathrm{CO_2}}_t \times \boldsymbol{\psi}_{ti})}_{\text{Revenue from storing } \mathrm{CO_2}}$$

Endogenously net installed capacity (minus decommissioned capacity) at time t for technology i showed by $\boldsymbol{k}^{endo}_{ti}$ in GW while the levelized investment cost showed by I^{+}_{ti} in $\frac{\text{Mil€}}{\text{GW}}$. p_{tfcr} represents the price at time t for feedstock f in category c (3 categories) for the region r in $\frac{\text{Mil€}}{\text{PJ}}$ and $\dot{\boldsymbol{m}}_{tifcr}$ describes the feed used in PJ. The imported cost comprises $\boldsymbol{m}^{imp}_{tifr}$, which is the price of imported feedstock in PJ multiplied by its price p^{imp}_{tfr} in $\frac{\text{Mil€}}{\text{PJ}}$ for feedstock f consumed in technology i in region r at time t. z_5 punishes those technologies that combust fossil fuels and emit CO_2 into the atmosphere. In z_6, for the years that the optimal solution surpasses the GHG targets, we are purchasing carbon credit from external partners with higher price than carbon price ($\hat{p}^{\mathrm{CO_2}}_t \geq p^{\mathrm{CO_2}}_t$) to compensate for the overshoot. Lastly, the revenue from storing CO_2 calculated based on the amount of CO_2 sequestrated and stored by technology i and the carbon price $p^{\mathrm{CO_2}}_t$ over time in $\frac{€}{t\mathrm{CO_2}}$.

D.2. Constraints

The extended bioenergy optimization model (BENOPTex) is an umbrella of standalone models – for instance for chemical [91], heat [92], and transport sectors [42] – that are developed in different projects to address different research questions. These island models are all linear optimization models with two objective functions: Maximizing GHG abatement and minimizing total system costs. By hard-linking different island models, we reviewed, revised and combined assumptions, constraints, and experts' views from various disciplines to provide an integral outlook of bioenergy/bioeconomy. The interested modelers

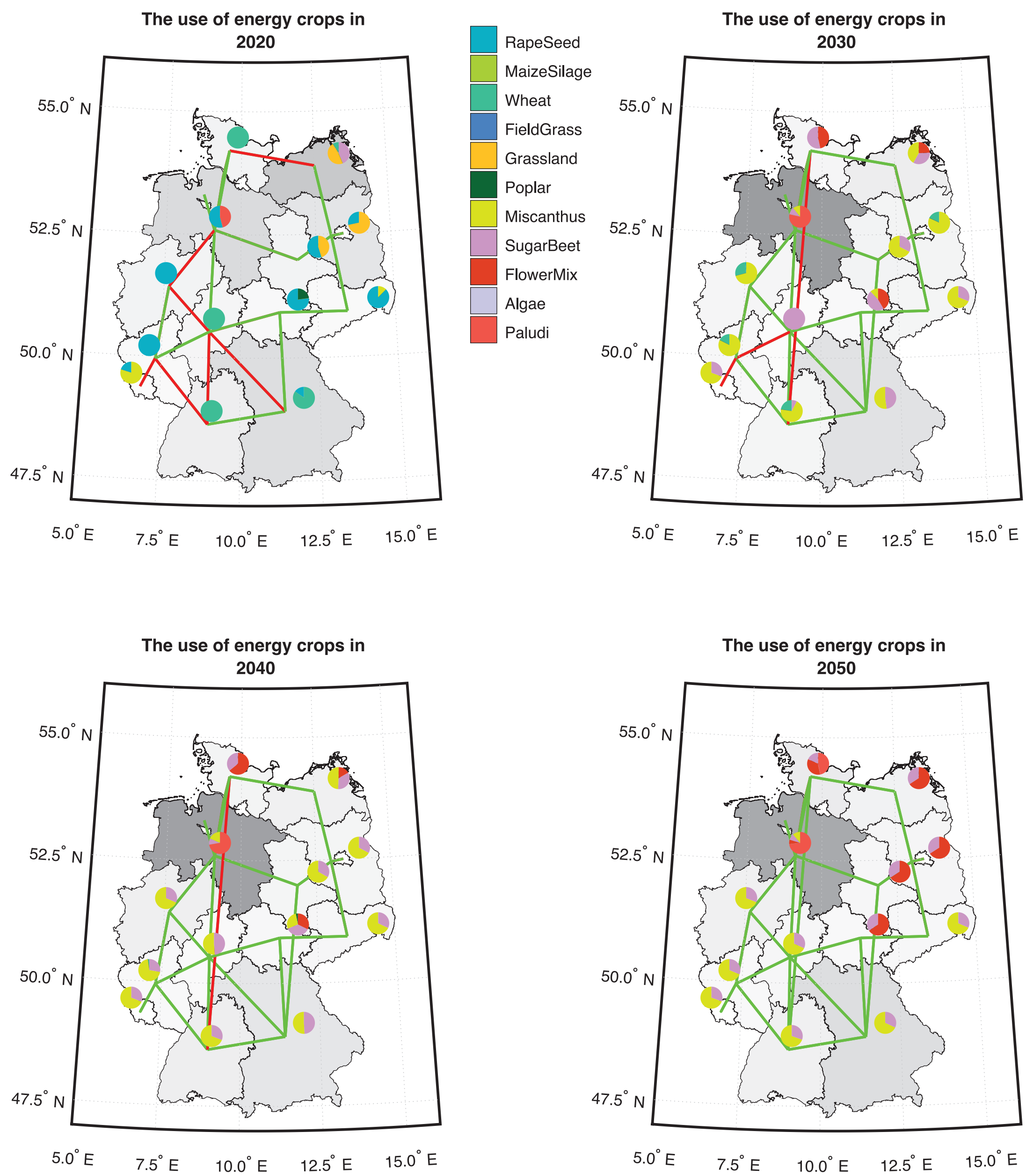


Fig. D.18. Energy crop production (from agricultural lands and wetlands) in each decade until 2050 and their impact on relieving congestion in the grid under the BWY-RCP2.6 scenario. The pie chart in each region shows the composition of energy crops by type.

are invited to read Esmaeili Aliabadi et al. [65] for RED constraints and Millinger et al. [42] for other generic constraints.

Also, the definition of CDR concepts is in accordance with Wollnik et al. [93,94], which were modeled in Sadr et al. [67] and Sadr et al. [95]. The social, economic, and ecological dimensions of these concepts are discussed in detail in Wollnik et al. [93].

D.3. Other results

Using information from previous steps, BENOPTex generated and solved an optimization model with an hourly temporal and NUTS-1 spatial resolutions for the following scenarios: BAU-RCP2.6, BAU-RCP6.0, BWY-RCP2.6, and BWY-RCP6.0. Running on a server with 6.0 TB memory and an Intel Xeon-E7 8867 CPU with 2.4 GHz, the Cplex solver found the optimal solution using the Barrier method. The least and most computationally challenging scenarios were BAU-RCP2.6 and BWY-RCP6.0 with over 15 and 50 h, respectively.

The results of BENOPTex model for the remaining three scenarios (i.e., BAU-RCP6.0, BWY-RCP2.6, and BWY-RCP6.0) are depicted in Figs. D.17, D.18, and D.19.

Data availability

Data exchanged between models has been cleaned, simplified, and can be found at https://git.ufz.de/esmaeili/remix-multipiee-restep-benoptex.git.

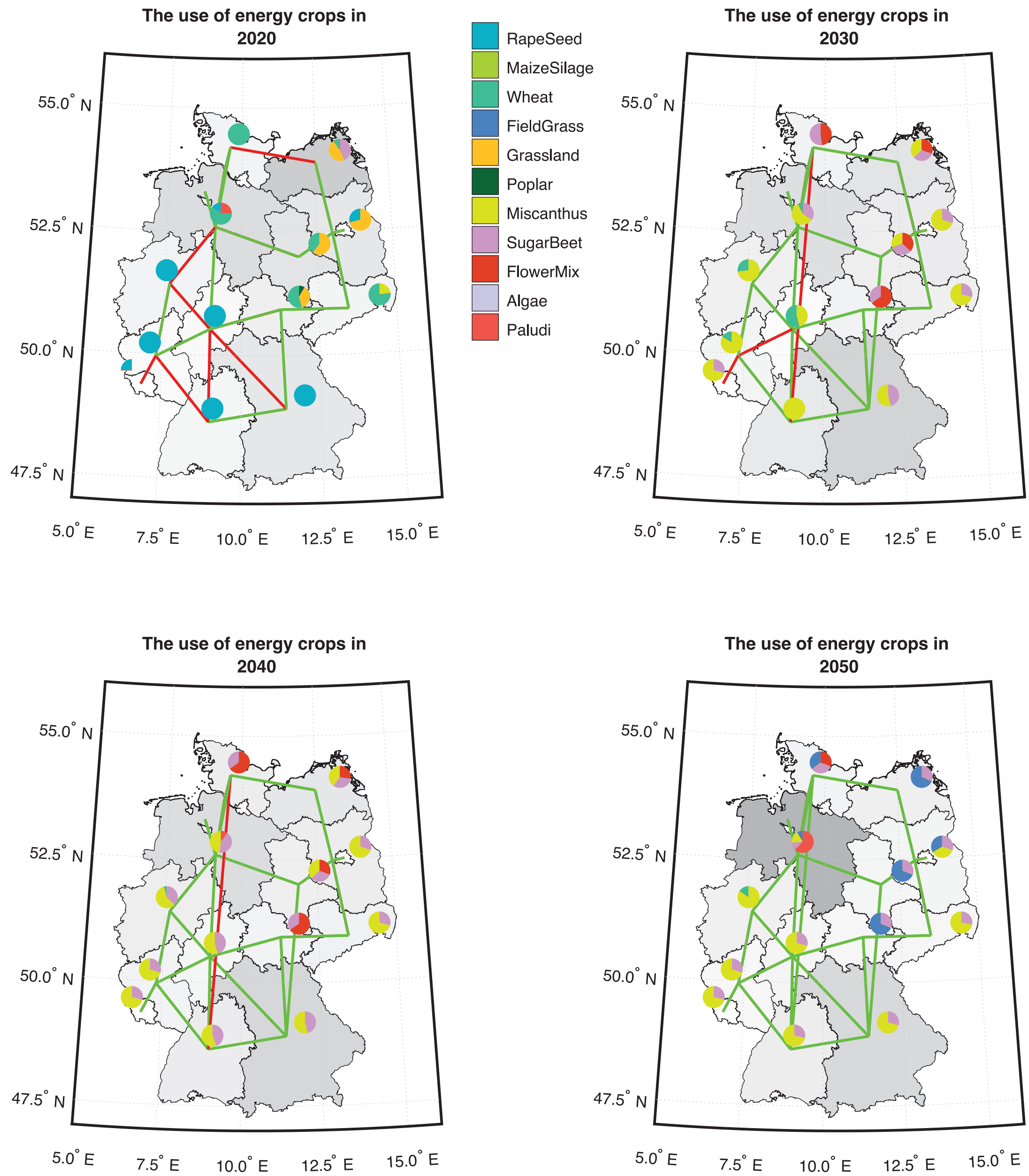


Fig. D.19. Energy crop production (from agricultural lands and wetlands) in each decade until 2050 and their impact on relieving congestion in the grid under the BWY-RCP6.0 scenario. The pie chart in each region shows the composition of energy crops by type.

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