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Perspective

Digital twins of the earth can take energy systems modeling to the next level

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SUMMARY

Digital twins of the Earth are an emerging field of research and development. Institutions like the European Centre for Medium-Range Weather Forecasts and the National Aeronautics and Space Administration have started ambitious initiatives to develop highly accurate digital replicas of the Earth system. These initiatives not only push the frontiers in global climate and weather modeling by making massive use of the largest supercomputers and AI but also set new standards in co-design and user engagement, allowing users to express needs and requirements right from the beginning of the developments. For the energy sector, Earth system digital twins bear great potential to overcome some of the major challenges in climate-energy modeling. In this perspective, we describe paths forward to bring the climate science and energy systems modeling communities closer together by leveraging the vast capabilities of Earth system digital twins, and we identify gaps, requirements, and recommendations for further developments.

INTRODUCTION

As a response to climate change, countries around the world have implemented ambitious targets for integrating renewable resources into existing electricity systems. In Europe, the European Commission (EC) has set up a series of packages and directives to foster the deployment of and investment in renewable energies, increase energy efficiency, electrify the transportation and heating sectors, support research and development, implement effective electricity market designs, and fight energy poverty. As a reaction to the Russian invasion of Ukraine and the energy crisis in Europe, the European Union (EU) has put the RePowerEU plan into force.[1] The goal of this is the independence of Europe from Russian fossil fuels by increasing the renewables target for 2030 from the previously agreed 32% to 42.5% with the aspiration to reach 45%. Other measures include the increase of energy efficiency, decarbonization of the industry, and diversifying energy supply. This includes 320 GW of additional solar photovoltaic (PV) capacity to be deployed by 2025 and almost 600 GW by 2030, recognizing the increasingly important role of PV in the European power supply.[2] To contribute to achieving this target, wind power installations should reach 425 GW by 2030.[3]

The increasing share of variable renewable energy sources in the electricity supply system increases the system's exposure to meteorological variability.[4] On the one hand, this variability makes the operation of the system more complicated. On the other hand, it sets new constraints for the design of the power system and defines the necessity to include state-of-the-art information about climate change in the decision-making processes in the energy sector.[5] Assets for the generation, transmission, distribution, or storage of electricity usually have lifetimes between 20 and 50 or even 100 years (e.g., high voltage overhead transmission lines). During this period of time, meteorological conditions can change significantly, depending on how climate change evolves. Consequently, the power system must be resilient to both meteorological events happening on short timescales and climate change effects to ensure the security of supply, meaning the access to electricity for everyone, everywhere, and at any time. A careful consideration of climate change in the planning process of electricity grids can additionally avoid or minimize costs for climate adaptation later on.

Indeed, grid operators (both transmission system operators [TSOs] and distribution system operators [DSOs]) are undergoing a rapid transition characterized by significant changes to their roles and the relinquishment of established processes.

- Many guidelines and regulations have been revised or are being updated; for instance, the revised Trans-European Networks for Energy (TEN-E) policy[6] and the updated cost benefit analysis implementation guidelines for the Ten-Year Network Development Plan (TYNDP) 2024.[7]
- Databases are currently being extended to include prospective meteorological information and the uncertainty introduced by climate change.[5] Workflows and methodologies are being updated to make use of these data (see, for instance, the updated methodology for the European Resources Adequacy Assessment (ERAA) 2024,[8] which will, for the first time, make use of the new Pan-European Climatic Database (PECD version 4)[5]).

To accommodate these changes, many actors have increased their research and development activities[9] and are seeking collaboration and exchange between the disciplines of energy and climate to "overcome the disconnect" between the two disciplines.[10–12]

At the same time, there are great efforts being made to develop very-high-resolution global earth system models (e.g., the EU-funded project nextGEMS[13]) and digital twins of the Earth, most prominently Destination Earth (DestinE),[14,15] funded by the EC; the Earth System Digital Twin[16] activities of the US National Aeronautics and Space Administration (NASA); and NVIDIA's Earth-2.[17] The core of these activities is the development of a highly accurate, very-high-resolution digital replica of the climate system combined with a system to forecast meteorological extreme events. These projects make extensive use of supercomputers,[18] machine learning/AI, and impact assessment with the aim of operationalizing climate projections and to implement a "digital twin of the Earth with and for humans."[19]

The aim of this perspective is to review current developments of Earth System Digital Twins (ESDTs) with respect to their potential contribution to improving energy systems modeling. Using grid planning and resource adequacy assessment as timely and representative operational workflows, we will systematically investigate how components of ESDTs can contribute to overcoming recent challenges in energy-climate modeling and foster the transdisciplinary exchange and collaboration between the energy systems and climate modeling communities. Last, we will derive recommendations for the further development of ESDTs to support the transition of energy systems.

ESDTs for energy systems modeling

Energy system models (EnergySMs) are suitable and widely used tools for investigating the energy transition and supporting decision-making processes both in industry and politics.[20,21] DSOs/TSOs use EnergySMs for their planning and adequacy assessment activities. Addressing the requirements defined by regulators, they periodically perform outlooks for the power system on the short, mid, and long term to assess the adequacy of the existing capacities for power generation, transmission, and storage[8] or for deriving long-term network expansion plans. To support evidence-based decision-making, system modelers need the most reliable and accurate information about the power system itself but also about its operation over time. As described above, the latter is strongly influenced by the spatiotemporal variability of renewable resources. In power system simulations, this is described by time series of the available generation potential for a given time and location normalized by the installed capacity, a model parameter often called capacity factor.[22] The databases for estimating capacity factors are compiled from different data sources, including reanalyses and climate simulations.[23,24] Currently used global reanalysis datasets do not have sufficient spatial resolution to capture local variation in wind speed.[25] While both reanalysis data and climate simulations can be adjusted with higher-resolution wind resource data,[26] such statistical downscaling is not a substitute for high-resolution weather modeling as performed by ESDTs. Hence, we expect that ESDTs will support energy systems modeling by providing better estimates of energy-related data through.

1. a more accurate and realistic representation of the variability of
   - the renewable resources and, hence, their potential to contribute to the future power supply in a highly renewable energy system;
   - the meteorological conditions affecting current electricity demand (e.g., for cooling and heating) as well as projected future patterns, taking into consideration the impacts of climate change; and
   - the meteorological variables necessary to characterize the availability and efficiency of conventional thermal power plants, like river flow, river water temperature, and relative humidity for cooling; and

2. a closer coupling of the climate and the EnergySMs, avoiding intermediate steps and allowing for the representation of feedback loops.
   Together with providing state-of-the-art meteorological data and modeling tools, this will
   - lead to a more accurate and reliable representation of the power system-atmosphere interaction (including uncertainties);
   - support grid operators in (1) fulfilling their policy-mandates (defined by national regulatory authorities [NRAs] at the country level or the EU Agency for the Cooperation of Energy Regulators [ACER] at the European level) and (2) making a valuable, pro-active contribution to achieving the policy objectives described above; and
   - increase the power systems' resilience against meteorological and climatological phenomena overall and reduced cost through better planning and operation.

ESDT components and their potential use in energy systems modeling

The core element of any ESDT is a global climate model with an unprecedented high resolution (grid spacing of 4–5 km

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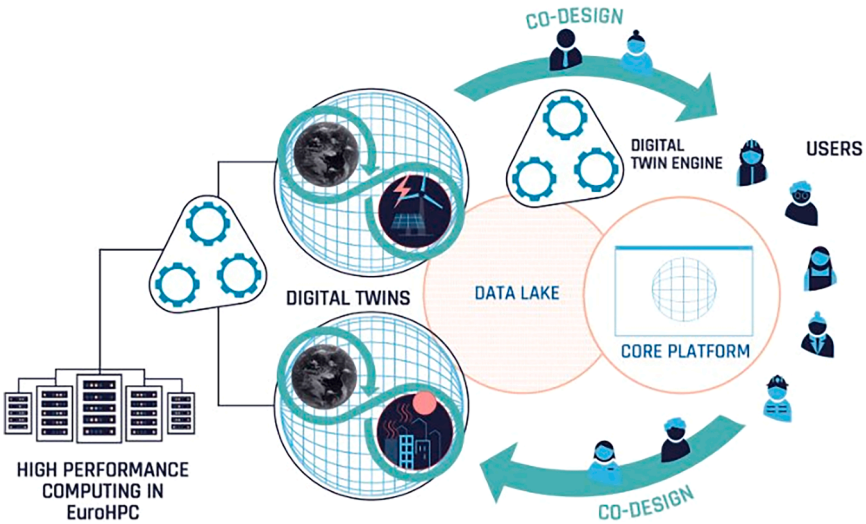

Figure 1. ESDT components

Shown is a schematic of ESDT components as implemented in DestinE, including the first two high-priority digital twins (see text for further details). Source: ECMWF.

horizontally). DestinE and NASA's ESDT additionally include a numerical weather prediction (NWP) model with grid spacings potentially below 1 km. After the final integration of these two models, ESDTs will, hence, have both weather and climate forecasting capabilities.[27] These integrated global climate and NWP models.

(for simplicity, we will use the term earth system model (EarthSM) in the remainder of the text) will be fed with the full wealth of earth science data and be run operationally; i.e., constantly over time. This will produce huge amounts of data, impossible to be stored permanently or downloaded and processed directly. This requires innovative approaches for both data assimilation (i.e., the input to the ESDT) and to handle their data output. While this may sound like an obstacle at first, it can enable more integrated, seamless, and novel approaches to climate-energy modeling.[28] To allow access to their data output without storing it for a longer time, the climate and weather models are embedded in their own ecosystem[14,29] (Figure 1). This ecosystem includes dedicated components for running the EarthSM alongside chosen impact sector models (such as EnergySMs or models for air quality and urban heat island effects), data handling, cloud computing, and tailored user services. We will illustrate this ecosystem using the example of the European DestinE initiative.[14]

High-resolution climate and weather predictions

One limiting factor of EarthSMs is their spatial resolution. The size of the grid cells determines which processes can be resolved explicitly and which need to be parametrized using empirical relationships. One possible example is tropical cyclones. Although the physical mechanisms influencing the development of such cyclones (cyclogenesis) and their intensification are well understood, they occur on spatial scales smaller than the grid spacing of conventional global EarthSMs. They need to be parametrized. New EarthSMs with a horizontal resolution below 10 km in the atmosphere can explicitly model cyclone lifecycles, especially a process called deep convection.[30] The same is true for convective processes leading to the formation of clouds. High-resolution global EarthSMs, as they are used for ESDTs,[31] are called cloud and storm resolving.[32] They can be considered fundamentally different from global climate models used, for instance, for the latest assessment report of the IPCC, which are also the basis for the newest version of the Pan-European Climate Database.[5] The new capabilities of the climate models used in ESDTs lead to a more accurate and realistic representation of weather phenomena.[30,33,34] As clouds and wind speed are the two major variables describing the variability of solar PV and wind power, data provided by ESDTS can, consequently, be a valuable input to EnergySMs.

Seamless model integration

In DestinE, the interface between the EarthSM and the impact sector model, here the EnergySM, is implemented as a data stream, the so-called generic state vector[35] (GSV; Figure 2). The idea is to provide chunks of the climate data in full resolution to downstream applications. The data chunks will be deleted/overwritten after a certain time. After that, only statistics of the data will be archived in long-time storage, a process called one-pass algorithm[36] in DestinE. On the one hand, this minimizes overall storage requirements by only storing relevant information. On the other hand, this allows for coupling the EnergySM with the EarthSM via the data stream. One can envision an operational mode where the EnergySM processes chunks of climate information as soon as they become available to produce relevant information about the operation of energy systems under the given meteorological conditions. By doing so, potential extreme situations could be detected early. This would allow activation of emergency plans and/or taking concrete safety measures to prevent major damage to infrastructure and people. In 2024, for instance, a severe summer storm toppled nine power pylons and caused damage to power lines and houses in the Belgian transmission grid.[37] So-called compound events (e.g., storms in combination with heavy rain and flooding) pose a particularly high risk for the power system. These events are expected to occur more often under future climate.[38] As a second flow of information, the carbon emissions from the energy system can be used as an input for further downstream models, like models for air quality and health (Figure 2).

Machine-learning and AI

ESDTs apply machine learning in several different ways and for different purposes. First, initializing a weather forecasting model requires the assimilation of large amounts of observational data to derive the actual state of the atmosphere. To produce the most accurate climate and weather forecasts, ESDTs aim to

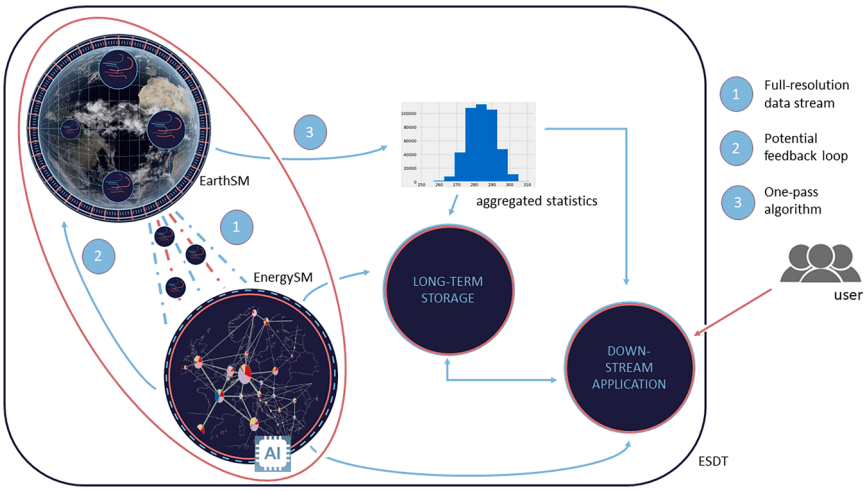

Figure 2. Coupling EarthSMs with EnergySMs

Streaming data from the EarthSM allows for a closer coupling of the EarthSM with the EnergySM, considering feedback loops and further downstream applications. Own figure using material from the ECMWF.

assimilate even more observations at an even higher resolution than classic NWP models. Often referred to as big data assimilation (BDA), this process can profit significantly from machine learning.[39] Second, probabilistic neural networks can be used to generate probabilistic weather forecasts from a single model run. This is becoming increasingly important as the resources required to produce one single forecast explode with increasing resolution of the EarthSM.[40] Third, and most importantly, in the context of energy system modeling, machine learning can support the seamless integration of the EnergySM with the EarthSM. As mentioned above, this integration requires the EnergySM to run in the data stream of the EarthSM. This means that the EnergySM must actually run faster than the interval between the delivery of two data chunks from the EarthSM. Applying machine learning models can avoid lengthy optimization runs and retrieve energy system simulations much faster.[41] Furthermore, machine learning models can be trained on the high-resolution climate data and, consequently, turn the ESDT data into valuable information for decision-making in the energy sector. Last, machine learning can be used to visualize the power system; more specifically, its mode of operation obtained from simulations, alongside with the climate data that drive the energy system operation. To demonstrate these aspects, several machine learning demonstrators have been set up on behalf of ECMWF.[42] As one of them, the DestinE ML Demonstrator Energy Systems will use a sophisticated physics-informed neural network approach[41] to translate climate information into decision support for the electricity sector. Focusing on performance and interactivity, the ML Demonstrator shall include the analysis of a variety of "what if" scenarios depicting the effect of different expansion strategies for the European power system on resource adequacy.[43]

Data handling and user access

The EarthSM and the EnergySM will, on the one hand, rely on a variety of datasets and, on the other hand, produce significant amounts of data themselves. Therefore, ESDTs need their own infrastructure for data handling (see data lake in Figure 1). This infrastructure is supposed to provide harmonized access to data generated by the ESDT and to facilitate access to external datasets used for data assimilation of the EarthSM (see the section "Machine-learning and AI") and/or the impact sector models. At the same time, computing infrastructure will allow near-data processing (i.e., processing data at the place where they are stored, reducing data movements) and distributed workflows for data analysis.

Users will access the whole ESDT ecosystem through different user services, apps for data access, visualization, and impact sector applications. In DestinE, this entry point is called the core service platform (Figure 1). We illustrate the role of this entry point using the examples of visualization and storylines. In the context of ESDTs, visualization refers to the interactive and dynamic representation and contextualization of real-time and simulated data that enable users to intuitively understand, monitor, and engage with the EarthSM. This also includes overlaying simulation and observational data as well as rendering data services. This can be done using immersive technologies such as virtual reality (VR) and augmented reality (AR) to experience climate-energy relationships and to raise stakeholders' awareness of the topic. In DestinE, dedicated activities have been planned for the use of immersive technologies for visualizing ESDT outputs (e.g., the Vision service). Storylines are guided, narrative-driven sequences of data visualizations and interactions that contextualize complex simulations and insights to support user understanding, exploration, and decision-making.[44] DestinE provides global kilometer-scale storyline simulations that reconstruct extreme weather events under past, present, and future climate conditions. By addressing "what if" scenarios, these simulations help users explore alternative climate realities, enhancing risk understanding and supporting adaptation strategies.[45]

Quality control and uncertainty quantification

Weather forecasts and climate projections always exhibit uncertainties and errors. At the same time, storm-resolving global climate models and kilometer-scale weather forecasting models, as they are used in ESDTs, are comparably new developments. Prototypes of these models have just been developed over the last years. In combination, this requires the implementation of thorough quality control and uncertainty quantification mechanisms. This includes a framework for the operational quality control of the EarthSM output,[46] approaches to derive uncertainty information for the weather forecasts (for instance, using machine learning; see section j), and multi-model ensembles to quantify the uncertainty in the climate scenarios. In DestinE, the latter is achieved by running three different global climate

models[47]: ECMWF's integrated forecasting system (IFS) coupled to two different ocean models and ICON, an open-source, high-performance framework for the prediction of weather and climate developed in Germany and Switzerland.[13]

Co-design and demonstration

The idea of incorporating participatory approaches into energy system modeling has been widely discussed in the literature, demonstrating multiple benefits of engaging stakeholders across different stages and activities related to the modeling process.[48–50] In particular, a broadly implemented stakeholder engagement activity has been found to achieve the following

- Improve the relevance of the model and its outputs by aligning them with practical needs of different users[51] (e.g., grid operators, policymakers, and researchers) and by incorporating knowledge from the users, which should ensure that applied scenarios or functionalities reflect real-world developments.
- Improve the quality of data and assumptions by allowing for the delivery and sharing of the most relevant data and/or challenging the existing assumptions with a more realistic view based on different types of knowledge and day-to-day operational experience. This should also support transparency, which increases the overall credibility of the modeling process and its results and outputs, leading to trust and co-ownership.
- Provide alignment with ongoing and planned policy, regulatory, and investment developments by efficient identification of potential implementation barriers.
- Lead to innovations through collaborative co-production, validation, and communication/demonstration activities.

This also holds true for co-design elements and demonstration activities of ESDT initiatives aiming to bridge the gap between climate data providers and the data users. In DestinE, the co-design with end users is given high priority. Several use cases demonstrate the capabilities of the different components for a wide range of impact sector models and user groups.[15] One of these use cases was the DestinE Use Case Energy Systems.[52] This use case was a unique effort, combining impact sector modeling with a thorough user engagement and co-design strategy. The core element was a demonstrator implemented in two open-source energy system modeling toolboxes (REMix[53] and pyPSA[54]). This demonstrator showcases the use of climate information in operational workflows of power system operators on the one hand and aims to contribute to overcoming some of the most severe challenges faced by energy system modelers in the context of incorporating meteorological data into their workflows on the other hand. The use case furthermore included a validation of the DestinE data with ground-based all-sky imager measurements[55] and satellite-based observations of clouds and wind speed, a sensitivity analysis, and a machine learning proof of concept applying the physics-informed neural network approach introduced by Li et al.[41] to the energy systems demonstrator. Last, a series of user engagement activities has been conducted to support the co-design efforts of DestinE. Finally, dedicated workshops and events organized by the three implementing agencies and/or their contractors are being conducted to establish close personal networks between the involved stakeholders. They provide an important platform for inter-disciplinary exchange and collaboration. From all these activities, important feedback is collected that can (and hopefully will) be considered for the further development of the ESDT.

CONCLUSIONS

ESDTs have the potential to take energy systems modeling for grid planning applications to the next level. The seamless integration of the ESDT and the EnergySM, together with the operationalization and leveraging of ML approaches, will make a significant difference in comparison to existing approaches. This, in the end, can support the further transformation of the European energy system and make a great contribution to reaching European climate targets. To achieve this, ESDTs must be more than "just another data store." In this paper, we exemplarily identified and demonstrated a potential path toward this goal for the energy sector. By combining access to a variety of energy-meteorological datasets, including operational state-of-the-art climate and weather simulations from the EarthSM, with energy system simulations on high-performance computer clusters, several recent challenges in energy-climate modeling can be addressed (Figure 3). The data from the high-resolution EarthSM can, for instance, be used to define more accurate and reliable scenarios for the future, ensuring the compliance of grid planning workflows with regulations; new approaches for data storage and processing together with machine learning approaches can foster the closer coupling of EarthSMs with EnergySMs; visualizations and storylines can contextualize, raise awareness, and enhance understanding of the complex climate-energy dependencies; and co-designing with selected key user groups can maximize the impact by improving relevance, data quality, and transparency and increasing innovation. Overall, this will facilitate reaching climate and policy targets by supporting European transmission and distribution system operators in fulfilling their policy-mandated contributions, increasing the climate resilience of energy system, and reducing cost.

To support decision-making, energy system modelers must be sure to use the most accurate and relevant information available. For the new-generation storm- and cloud-resolving global climate models used in ESDTs, this accuracy still needs to be proven. Although they have been found to lead to a better representation of tropical cyclones[30] and precipitation,[47] no dedicated validation for energy-related variables, especially with respect to their spatiotemporal variability, exists, to our knowledge. At the same time, the performance of energy system simulations is directly linked to the performance of the ESDT. Results of the power system simulations can only be reliable when the data used to set up the simulations are appropriate and have been proven to be of good quality, especially when the simulations are as sensitive to the data input as in the case of energy systems modeling.[4,56,57] A thorough data validation can, consequently, guide further developments and improvements of the ESDTs. Bringing the statistics of the historic simulations conducted by the ESDT as close as possible to those found in reference datasets definitely increases the reliability of ESDTs. Although validation is often hindered by poor or non-available

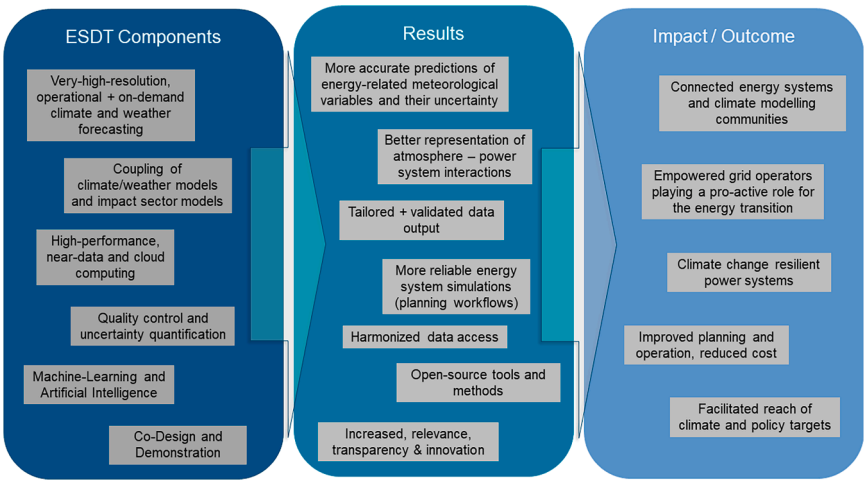

Figure 3. Impacts on energy systems modeling

Shown are ESDT components and their potential impact on energy systems modeling.

reference datasets, existing discrepancies should be explained and communicated transparently. At the same time, our analysis emphasizes that assessing and quantifying the uncertainty of the ESDT output through a multi-model ensemble is crucial. In future development of the twins, this uncertainty assessment should be extended, ideally by successively adding new climate models, similar to the approach applied for the most recent version of PECD version 4. Over the next years, this database will constantly be complemented with climate models from the Coupled Model Intercomparison Project (CMIP6).[5] These models all exhibit a smaller spatial resolution than the EarthSMs used in ESDTs. Hence, building a multi-model ensemble for the uncertainty assessment of ESDTs requires that more very-high-resolution climate models become available and new innovative approaches to seamlessly couple them to EnergySMs. Alternative approaches to quantify uncertainties currently under development (e.g., lagged ensembles[58]) can additionally support this or, in case further very-high-resolution climate models are not available, be used as an alternative approach to extend the uncertainty quantification.

Similar to the uncertainty assessment, quality control systems play a major role. Most importantly, the ESDT output should be compared to reference datasets used operationally among the grid system operators to increase the reliability and trustworthiness. This also emphasizes the importance of collaboration and exchange between different initiatives. To ease the data comparison, the approaches applied among the grid system operators for the reference databases should be adopted in the ESDTs. Additionally, the inclusion of dedicated energy-related metrics for assessing the quality of the climate simulations from an energy systems perspective in the quality control systems appears reasonable. In particular, we consider indices to quantify the spatial and temporal variability of the data important. Further metrics could focus on correlation patterns and the complementarity of the renewable resources, as this is an important feature of the renewables influencing power system operation and design.[59] Again, the results of quality control should be made transparent and easily accessible. Energy system demonstrators can support this by (1) identifying and visualizing differences in meteorological/climatological datasets and (2) linking these differences to the output obtained from energy system simulations. In the further development of ESDTs, this could be extended by establishing a live mode where the EnergySM is run in the data stream of the ESDT.

Overall, quality control and uncertainty quantification are crucial for increasing users' trust in the data and in fostering the uptake of the data. In the context of energy systems modeling, this is an important aspect, as decisions on which databases should be used for operational workflows in the energy sector are lengthy and complex processes, often monitored by public authorities. Consequently, an impact sector-specific validation of the ESDT output should be added to the quality control mechanisms. Further use cases to demonstrate the capabilities of the ESDT for the energy sector can complement quality control and help to increase the uptake of ESDT data and services. For the latter, data products provided by the ESDTs should, additionally, be tailored to the users' needs. For grid planning and/or adequacy studies, for instance, multi-year time series at sub-daily (ideally hourly) temporal resolution are required. When only statistics are made available, as described in Section j, this need would not be met. This re-emphasizes the importance of thorough co-design activities (see also Section j) and of aligning workflows and data processing chains with reference products like the PECD.

In the context of ESDTs, machine learning not only addresses the challenge of computationally expensive simulations, which has been identified as one of the major recent challenges of the energy systems modeling user community,[60] but can also enable coupling of ESDTs with an EnergySM (see Section j). A first proof of concept using the machine learning approach developed by Li et al.[41] has been conducted in the context of the DestinE Use Case Energy Systems. To further increase the users' trust in ML approaches, more use cases for demonstration are needed. ESDTs can provide the environments to conduct them. Additionally, some further developments of the ML approaches themselves are necessary to increase their applicability to operational user workflows.

In summary, initiatives for the development of ESDTS represent important platforms for interdisciplinary exchange between the energy systems modeling community and the climate sciences. Given the major challenges faced by modern energy

systems, it seems reasonable to use them to foster the transition toward highly renewable-based energy systems.

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AUTHOR CONTRIBUTIONS

Conceptualization, B.U.S.; project administration, B.U.S.; visualization, B.U.S.; writing – original draft, B.U.S., A.C., and A.K.; writing – review & editing, all authors.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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