BAMS
Meeting Summary

The Importance of Weather and Climate to Energy Systems

A Workshop on Next Generation Challenges in Energy–Climate Modeling

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Next Generation Challenges in Energy-Climate Modeling

What: Over 80 international participants, representing weather, climate, and energy systems research, joined two 4-h remote sessions to highlight and prioritize ongoing and future challenges in energy–climate modeling. The workshop had two primary goals: to build a deeper engagement across the "energy" and "climate" research communities, and to identify and begin to address the scientific challenges associated with modeling climate risk in energy systems.

When: 22–23 June 2020

Where: Online via Zoom, hosted by the University of Reading

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Energy systems across the globe are becoming increasingly sensitive to weather and climate variability. This sensitivity arises due to a combination of growing installations of renewable generation, as well as the electrification of the sectors within the energy system (e.g., heating buildings, resulting in increased temperature sensitivity). Not only does the increased weather sensitivity of the energy system amplify its exposure to present-day climate variability, but anthropogenic climate change may result in changes to the distributions and spatiotemporal covariability/evolution of meteorological variables relevant for both supply and demand in the energy system.

Recently, power system operations and energy system planning have shown a growing appreciation of the risks posed by climate variability, change, and uncertainty. The traditional approach in energy system modeling is to consider only a relatively small set (1–3 years) of "average" weather data to characterize weather and climate risk. However, the use of long-term climate datasets in energy system modeling is rapidly increasing. Power system dispatch and planning models can now consider a few decades of climate data, derived from historical meteorological reanalyses or global climate model (GCM) simulations. This practice is becoming more common in both the scientific literature and in industry. For example, the European Mid-term Adequacy Forecasts now use historical reanalysis data from 1982 to 2016 (ENTSO-E 2019).

Despite this growing attention, many scientific and technical questions remain to quantify and understand weather and climate risk in power systems. In particular, some sources of weather and climate uncertainty and their impacts are poorly addressed by current techniques. These include

- the impact of multidecadal climate variations on energy systems,
- reanalysis selection and calibration,
- the use of global climate models simulations and the need for postprocessing (e.g., bias correction, downscaling),
- error propagation in climate–energy decision modeling chains, and
- epistemic uncertainties of climate model and scenario choices.

Collectively, these issues are associated with a poor understanding of how weather and climate data can be ingested into complex energy system models to better understand and manage climate risk. The links between the “energy” and “weather and climate” research communities have historically been relatively weak. (For example, despite the fact that the workshop was advertised widely within the energy-meteorology community, results from the participant’s feedback survey show that fewer than 10% see themselves as experts in both energy and climate.) As a consequence, it is rare to find the scientific best practices of both communities fully embodied in any single study.

This workshop brought together an international group of leading researchers working at the interface between weather and climate science and energy applications. The aim was to stimulate discussion around the use of both historic and future climate datasets in energy system analysis and to discuss pathways for future collaborations toward establishing best practices in considering weather and climate risk in the study of energy systems.

Workshop structure

While planning for the workshop had begun before COVID-19-related shutdowns, the plan for an in-person workshop evolved radically in the few months before the workshop to be replaced by a fully virtual format. We designed a two-day structure, limited to four hours per day to straddle time zones for international participants. Over 140 applications were received to join the conference and places were offered to 107 participants with a mix of climate and energy specialists (this limitation was employed to enable more productive small-group discussions). Of these, 81 attended over the course of the two days. Participants were selected on the basis of their declared research interests (with an emphasis on the inclusion of early career researchers), and included representation from six different continents (see Fig. 1).

The first day focused on the use of historical-period data in energy climate modeling, with the aim to discuss the implications of using climate data to quantify current energy system risks. The second day focused on tools and techniques to investigate the impacts of a changing climate on the energy system.

Each day was organized with a set of three thought-provoking 8-min invited talks to set the stage for break-out group (BOG) discussions using Zoom’s break-out room feature. The talks gave diverse perspectives on the topics to be discussed. Each day featured one climate scientist, one energy systems researcher, and one scientist working at the interface of the two disciplines.

Each of the two BOGs per day were organized with a set of questions related to the topics of the initial talks. Each BOG included at least one member of the conference leadership team and a mix of weather/climate and energy/power systems specialists. The mix of people

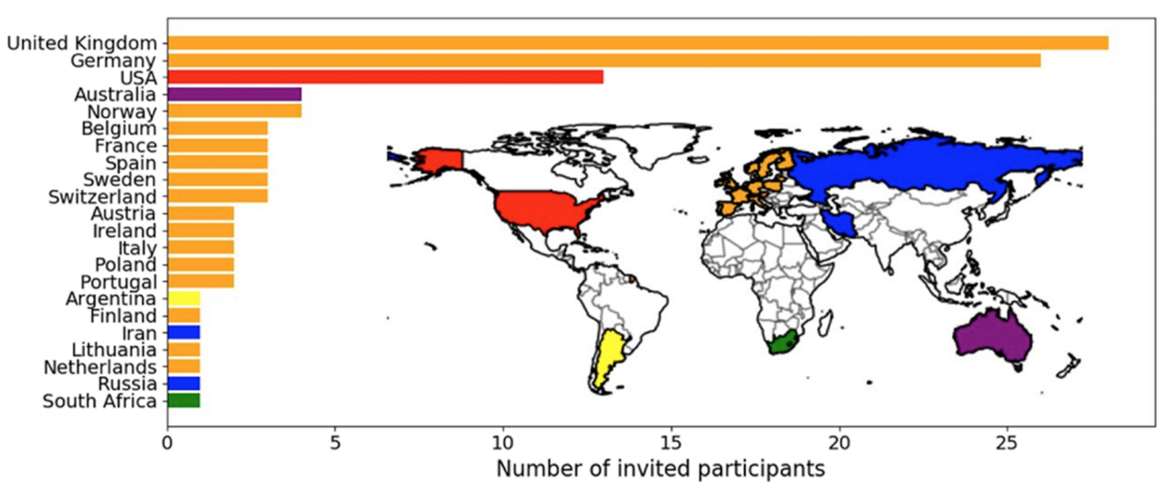

Fig. 1. A breakdown of the invited workshop participants based on their institutional email address included with their conference application.

changed each time participants were sent to break-out rooms to promote broader discussion and networking: in the first session, the division was based on participant research interests (to promote the development of a common language), while the second was purely random (to promote diversity of discussion and cross-fertilization of ideas). After each of the 45-min BOGs, participants rejoined a 30-min plenary session during which high-level conclusions from each group were presented. Each day finished with an open plenary session where other points of interest from within the day's discussions could be highlighted. Figure 2 summarizes the focus and discussion points of each day. The full meeting schedule and the consequent outputs are available from the workshop's website which is accessible from https://research.reading.ac.uk/met-energy.

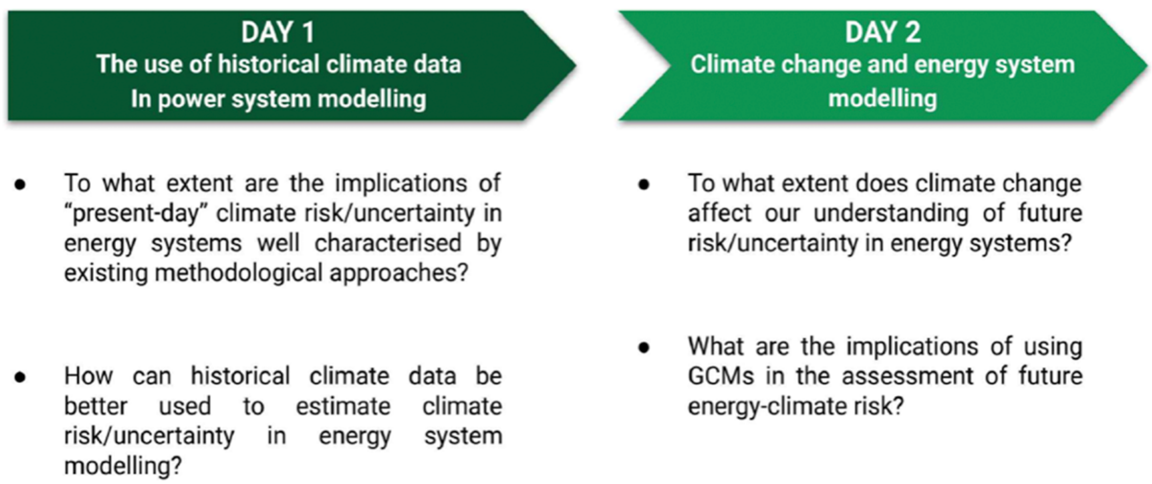

Fig. 2. Schematic that describes the topics and main discussion points of each meeting day.

Key outcomes and perspectives

Over the two days, a number of issues emerged from the climate and energy-modeling communities, which we discuss below. The overarching message from the workshop is that there is a mismatch in the methods and dialogue between the two communities concerned with quantifying climate risks. Increased collaboration would enhance the accuracy and usefulness of outputs to end-users.

A plethora of climate data. BOG discussions emphasized how energy researchers could and should incorporate meteorological risks. A common conclusion from the climate scientists was that the reliance on a "typical meteorological year" inadequately safeguards against the range of possible current and future climate risks that could stress energy systems (Bloomfield et al. 2016). The meteorological community has a wealth of resources at their fingertips if asked to quantify the risk of a particular event, or to understand the impacts of climate variability and change on a meteorological phenomenon. Atmospheric scientists would commonly base such assessments on multiple years of data which could range from 10 years (if using wind mast observations) to 40 years (the length of most modern reanalysis products) to hundreds of years (when using centennial reanalysis or ensembles of climate model simulations). These data, however, require multiple decisions to be made, including the climate model itself, spatiotemporal resolution, and appropriate time periods for study. The knowledge and technical skills to process these data are not always readily available to the energy-modeling community.

Keynote speaker Dr. Sofia Simões showed, as part of her talk, the provocative image of the data truck (see Fig. 3). This image emphasizes the mismatch in communication between the meteorological community's data supply, and the energy community's ability to ingest those datasets, especially when energy modelers must consider other uncertainties beyond weather and climate, such as societal choices, policy choices, etc. Some proposed solutions from the meteorological community included storyline techniques (e.g., Shepherd 2019) and subsampling techniques (e.g., Hilbers et al. 2019; Hoffmann et al. 2020). Improving the "data interface" between energy and climate science is clearly a major scientific and technical challenge.

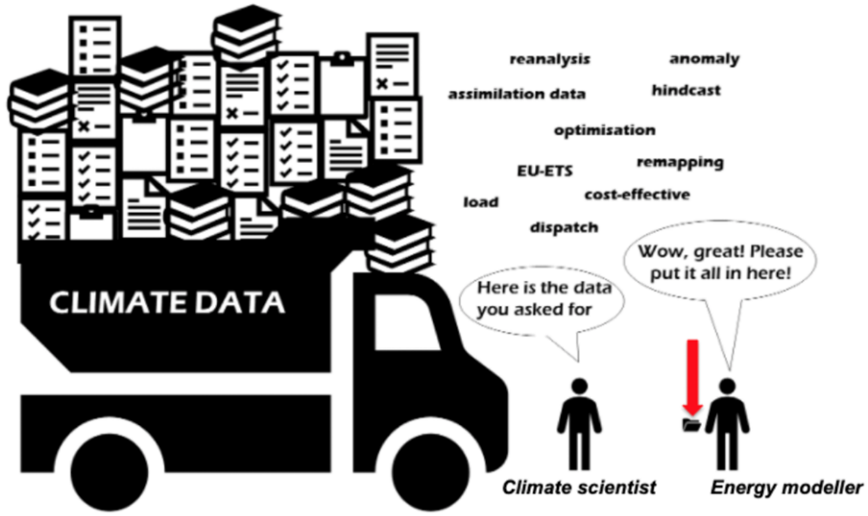

Fig. 3. The climate data truck analogy of the mismatch in data delivery (from climate scientists) to data requirements (from energy system modelers). Figure courtesy of Dr. Sofia Simões and the Clim2Power project (https://clim2power.com/).

Is this the right tool for the job? In addition to the apparent overabundance of climate data, energy system modelers lack guidance for selecting which gridded atmospheric product is most appropriate for a given purpose, as well as for adequately post-processing that data (e.g., downscaling, bias correction) before using it as an input into an energy system model.

Consecutive 10-min to hourly gridded meteorological input data over a period of at least a year is often sought for the weather-dependent components of most energy system models, though the specific requirements depend on the application (e.g., Deane et al. 2014; Poncelet et al. 2016). These input data are not available in a coordinated way in many countries, despite a substantial effort from the climate community to provide datasets. Discussion itemized the different datasets currently available from which suitable energy variables could be derived including European reanalysis-based proof-of-concept climate services products:

- CLIM4ENERGY—http://clim4energy.climate.copernicus.eu;
- Clim2Power—https://clim2power.com/;
- ECEM—www.wemcouncil.org/wp/european-climatic-energy-mixes/;
- EMHIRES—https://ec.europa.eu/jrc/en/scientific-tool/emhires/;
- Renewables.ninja—www.renewables.ninja/;
- S2S4E—https://s2s4e.eu/, https://researchdata.reading.ac.uk/272;

and raw climate model output including

- regional climate model output from EURO-CORDEX—www.euro-cordex.net/ and
- global climate model output from CMIP6—https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6 and PRIMAVERA—www.primavera-h2020.eu/.

The organization of a coordinated comparison of these climate-based demand and renewable generation products was enthusiastically identified by users and developers as a highly valuable outcome from the workshop, and is at the planning stages at the time of this report.

The prospect of precalibrated high-spatial (sub-50 km) and temporal (hourly) resolution reanalysis and climate model data were desirable to the energy modeling community. However, providing this is nontrivial, with the most appropriate method to perform these calibrations a subject of much scientific debate (Ho et al. 2012; Maraun 2016; Cannon et al. 2020). Whichever technique is applied, participants agreed that the covariances of meteorological variables must be preserved for the resulting climate data to be useful within energy modeling simulations, in agreement with previous assessments (e.g., Jones et al. 2017). For example, a wintertime blocking ridge situation over Europe brings both increased energy demand (due to low temperatures) and decreased power supply (due to low wind power generation). Such covariances between temperature and winds should ideally be preserved, though the choices and implications of a given methodology are not trivial (e.g., Dekens et al. 2017; François et al. 2020).

Ever-increasing quantities of high-frequency and high-resolution climate data are likely to further exacerbate the challenges associated with the data volume. Even with multidecadal "off the shelf" products that provide time series of demand and renewable generation, the task of simulating multiple years of energy system operation can lead to large computational constraints, due to the complexity of the modeled systems. To be able to ingest more or higher-quality climate data, energy modelers must compromise on the representation of the energy system, for instance, by reducing the resolution or constraining technological choices. Furthermore, such derived energy time series might not be sufficient for the experimental design required for some energy applications. For example, national time series of demand and renewable generation are unsuitable if the user wishes to model regional energy system characteristics in markets with international integration like Europe.

Similarly, energy system models require expert knowledge about the proposed system to ensure they are initialized and integrated reliably. Climate scientists would encounter a similarly large volume of issues to those discussed above if they were to try to implement an energy system model (for instance, when having to define technical parameters of the infrastructure involved, making cost assumptions, or implementing how operational decisions are considered in these models). This need for extra insight further highlights that prolonged thoughtful collaboration between these two disciplines is essential.

What is the truth? High-quality, open-access energy system observations (i.e., feed-in measurements, system design data, etc.) for model validation are not widely available. These data must be of high spatial (e.g., national or regional level), high temporal resolution (e.g., subdaily). Quality-controlled energy system observations are particularly needed in developing countries, where the available data quality is poor or nonexistent.

The use of reanalysis climate data as an input to create energy variables was the research topic of many workshop participants. However, energy modelers were generally unaware that climate reanalyses are subject to biases and limitations compared to local observations, and may therefore require calibration for many applications. At the same time, point-based observations are also subject to errors, and when only low-quality observed data are available it might be preferable to resort to reanalysis-based energy products, which have some desirable qualities such as physical consistency between variables and spatial coherence.

Conversely, the climate science community was generally less aware of the range of conditions that can impact the interpretation of energy data as well as weather and climate. For example, a wind power time series would not just be impacted by local wind speeds, but also factors such as maintenance outages, plant degradation, price sensitivity, curtailments, and other interventions by energy network operators.

Climate models and reanalyses are evaluated based on a different set of variables compared to those energy system models require as input. While temperature and precipitation fields are useful to assess demand and hydropower potential, the energy models also require input fields of hub-height wind speeds (approximately 100 m, which can vary considerably from observed 10-m wind speeds) and incoming direct and diffuse solar radiation. While these fields are available from both reanalyses and climate models, their quality has not been rigorously established.

Uncertainty is key, but not just climate uncertainty. Future energy modeling studies face a number of different sources of uncertainty, beyond weather and climate. The sources of variability in energy systems are very broad: weather and climate simply add to the unknowns driven by socioeconomic choices, population growth, political decisions, generation costs, market incentives, technological innovation, and other external factors (e.g., mass migration and land use competition with agriculture and transport). As such, while climate uncertainty is undoubtedly important to energy system planning, it should nevertheless be recognized that the magnitude of its impact may be modest by comparison to these wider issues.

To develop robust energy–climate modeling strategies it would therefore be advantageous to compare the relative contributions of these different sources of uncertainty, and to better understand how they propagate through the complex modeling chains involved. Such analysis may help to identify where appropriate simplifications to the modeling process can be made (e.g., the substitution of "future" climate data for purely "historic" analysis), and the limitations they produce.

Are we speaking a common language? The interactive nature of the workshop allowed for learning opportunities for both communities about the common jargon of energy and climate modeling. This need for translation arose in the first BOG where participants were asked to name "climate risks relevant for the energy sector." Depending on whether the groups were predominantly climate scientists or energy modelers, the type of responses were very different. However, all groups gave answers from the climate–energy interface of the modeling (see Fig. 4).

Other points of divergence included some confusion from the energy community about whether historical climate model simulations included observations from the historical period like a reanalysis does (or even what the term "reanalysis" meant). The concept that "historical" climate model output does not represent "real years" was not obvious to many of the attendees without a meteorological background. Some particular words that disrupted the dialogue were "transient" and "projections." Confusion from the atmospheric science perspective included the differences between "energy" and "power" system models (which is often used to refer to just electric energy generation), and the differences between "demand-side" versus "supply-side" uncertainty.

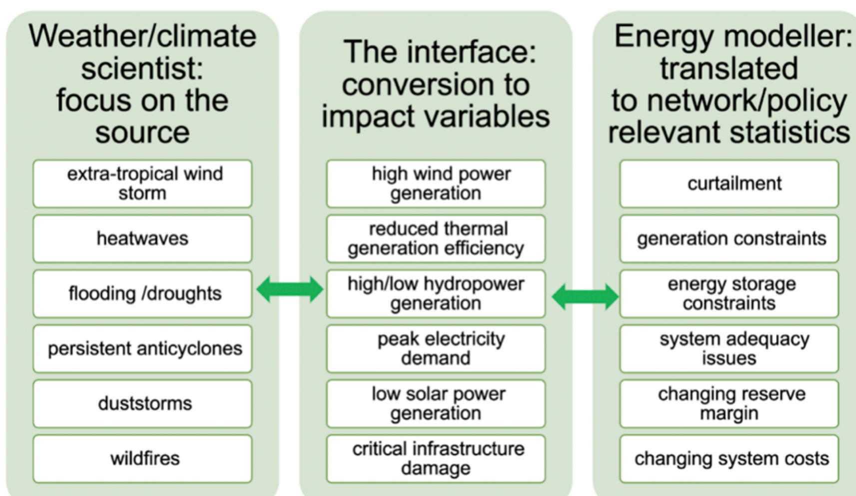

Fig. 4. Samples of identified climate risks related to the energy sector depending on the participant's research interests.

Extending collaboration beyond academia. The need for enhanced collaboration was a key theme throughout the workshop, but not just within the present (predominantly academic) participant group. Regional and national utilities, transmission system operators, energy traders, and policy-makers should be involved in the modeling chain to improve the quality and usefulness of the final output and suggest an emphasis on the most relevant sources of uncertainty. Interaction with policy-makers could also be particularly important for scenario definition, as this collaborative design could help rule out some near-future scenario developments and simplify the modeling design.

Despite the fact that this collaborative and interactive approach, often referred to as co-production or co-design, has become quite popular in recent years in the context of climate services, it is still generally ambiguous (e.g., Goodess et al. 2019). The idea of co-production of useful climate information is often pursued quite loosely, without strict definitions, frameworks, or strategies (e.g., Vincent et al. 2018). Future collaborations in the climate–energy interface could benefit from stronger and formal interactions with social scientists to maximize the usefulness of the outcomes.

Future plans. Participant surveys revealed consistently positive feedback for the workshop, which has resulted in the commitment to provide a follow-up meeting in approximately one year's time. The virtual conference experience allowed for very diverse participation (see Fig. 1) and significantly higher attendance than would have been possible at an in-person meeting. The organizing committee is keen to repeat this format. The workshop was particularly well attended by early career researchers helped by the low travel/funding barrier.

Engagement with other communities such as OPENMod (Open Energy Modeling Initiative, https://openmod-initiative.org/) and the Open Energy Ontology (https://openenergy-platform.org/ontology/) was discussed within the session plenaries to increase the climate science involvement in dictionary-style products currently under development, with comments that an energy-meteorology dictionary would be particularly useful.

The need for more cross-disciplinary training was discussed multiple times within the workshop. A particularly useful outcome would be guidelines for best practices when using climate data, and which datasets are optimal for specific purposes. An energy–climate summer school was also suggested as a mechanism for capacity and resources building. The goal of such a summer school could be not just to educate participants, but to amplify its impact by generating educational resources. For example, one summer school project could funnel the energy, enthusiasm, and expertise of participants into building a curriculum for developing multidisciplinary practitioners, who are fluent both in weather/climate science and energy system modeling. This curriculum could include short educational videos and a webinar series. All of the previously discussed activities promote opportunities for networking and future project collaboration.

Summary

The challenges emerging from the workshop highlight the need for increased interaction. Weather and climate scientists must first begin to understand how climate information is used by energy researchers in practice, ensuring that the data provided can interface with the tools and techniques being used. This understanding requires atmospheric scientists to investigate how the processes involved in energy modeling relate to the impacts of weather and climate, rather than focusing on the climate itself. In parallel, energy scientists should seek to develop a better appreciation of climate uncertainty, addressing its importance for both historical and future simulations. A key step is therefore to develop the tools and understanding required to quantify the effects of climate uncertainty in highly complex energy systems, and to understand the importance of climate relative to the contributions from other sources of uncertainty.

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Data availability statement. The full meeting schedule and the consequent outputs are available from the workshop's website which is accessible from https://research.reading.ac.uk/met-energy/.

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