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PERSPECTIVE

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A shifting climate: New paradigms and challenges for (early career) scientists in extreme weather research

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Abstract

Research on weather and climate extremes has become integral to climate science due to their increasing societal relevance and impacts in the context of anthropogenic climate change. In this perspective we examine recent changes and evolving paradigms in the study of extreme events, emphasizing the increasingly interdisciplinary nature of research and their societal implications. We discuss the importance of understanding the physical basis of extreme events and its linkages to climate impacts, highlighting the need for collaboration across multiple disciplines. Furthermore, we explore the challenge of big climate data analysis and the application of novel statistical methods, such as machine learning, in enhancing our understanding of extreme events. Additionally, we address the engagement with different stakeholder groups and the evolving landscape of climate services and private-sector involvement. We conclude with reflections on the risks and opportunities for early career researchers in navigating these interdisciplinary and societal demands, stressing the importance of meaningful scientific engagement, and removing barriers to inclusivity and collaboration in climate research.

KEYWORDS
big data, climate impacts, climate services, early career scientists, extreme event research, machine learning

1 | INTRODUCTION

Research on weather and climate extremes has become a fundamental part of physical climate science, involving their modeling, predictions, study of their dynamic drivers, detection of changes, and attribution to causes. Different types of extremes are expected to shift in intensity, frequency, and duration due to climate change, and already demonstrate regional trends, including increases in heat extremes, heavy precipitation, and agricultural droughts (e.g., fig. SPM.3 in IPCC, 2021).

Over recent decades, climate researchers have made significant advancements in providing a physical understanding of extreme events. This is owed much to theoretical groundwork in dynamic meteorology (e.g., Hoskins & Karoly, 1981), sophisticated climate model archives like those from the Coupled Model Intercomparison Project (CMIP, Eyring et al., 2016), a variety of observational,

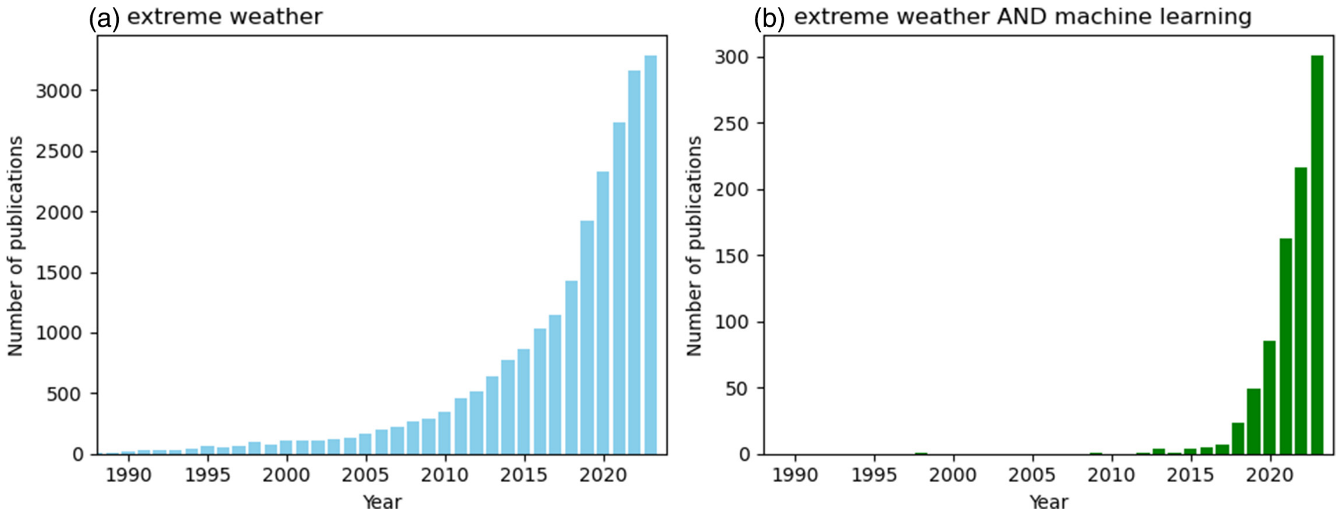

FIGURE 1 Increase in articles on extreme event research. (a) Number of articles in Web of Science from 1988 to 2023 including at least one of the terms (searched for in title, abstract, author keywords): Extreme weather, weather extreme(s), weather and climate extreme(s), weather hazard(s), climate hazard(s). (b) Same as (a), but with the additional constraint of containing at least one of the terms: Machine learning, deep learning, artificial intelligence. Note that the different scales of the *y*-axes. Data accessed on June 14, 2024.

remote sensing, and reanalysis products (e.g., Funk et al., 2015; Hersbach et al., 2020), statistical methodologies like extreme value theory (e.g., Katz & Naveau, 2010), and collaborative efforts (e.g., the core activities of the Word Climate Research Programme [WCRP]). These advancements are also reflected in increasing numbers of publications on weather extremes (see also Figure 1a), including the emergence of new subfields such as the study of extreme event attribution (Diffenbaugh et al., 2018; Jézéquel et al., 2018; Otto, 2017), compound events (Zscheischler et al., 2020), and event-based storylines (Sillmann et al., 2021).

The reason why research on the physical basis of extreme events (hereafter, simply referred to as physical climate science) is developing, is not only the observed increasing trends in extremes, but also the associated growing scale of impacts on society, ecosystems, and the economy (with research on these topics hereafter simply referred to as climate impact science). As such, understanding and predicting how extreme weather will change under different greenhouse gas emission scenarios is particularly critical for adaptation and mitigation planning. Moreover, such research is crucial to provide evidence-based information on expected losses and damages to support decision-making, as well as to contribute to liability and compensation questions in the context of climate change (Zhang et al., 2024).

Despite all mentioned advancements, there are still noticeable knowledge gaps regarding the physical basis of extreme events (Titley et al., 2016). This is particularly evident from the limited availability of data and literature, notably in regions of the Global South (e.g., fig. SPM.3 in Huggel et al., 2016; IPCC, 2021; Otto, 2023), where models often perform poorly even in simulating basic climatology (e.g., Bergner et al., 2022; Romanovska et al., 2023). Other key challenges include adequately reproducing processes that happen at smaller scales than the current horizontal resolution of state-of-the-art climate models (e.g., Davis, 2018), to constrain uncertainties in regional climate model projections (Shepherd, 2014), understanding and modeling the role of vegetation and biodiversity in modulating extreme events (Findell et al., 2024), overcoming discrepancies between physical reasoning and statistical practice (Kretschmer et al., 2021; Shepherd, 2021), as well as meaningfully evaluating extreme event predictions (Lerch et al., 2017).

These prevalent research gaps present significant opportunities to advance physical climate science and enhance its relevance to society. Working Group 1 of the Intergovernmental Panel on Climate Change (IPCC, https://www.ipcc.ch/working-group/wg1/) plays a pivotal role in offering scientific insights to tackle climate challenges on a global scale. Moreover, climate scientists operate in a context where "Climate Action" stands as a critical Sustainable Development Goal of the United Nations, with many other goals also intersecting with climate change issues. These are just two high-level examples of how physical climate science is closely linked to societal needs and impacts. Recent discussions have highlighted the importance of recognizing how social values influence research, impacting, for instance, choices in attribution studies and climate service developments (Pulkkinen et al., 2022; Rodrigues & Shepherd, 2022).

In this perspective piece, we discuss how extreme event research has rapidly evolved in recent years due to societal and technological shifts, affecting research questions, data, methods, and target groups, with more transformations anticipated. We here focus on the atmospheric climate science community, and document some of these key shifts we have witnessed since we entered the field about a decade ago, acknowledging that these changes might also apply to other research activities. We further stress that our observations, shaped by our positions at research institutions in Western Europe and the United States, are particular to us and not representative of the broader field. In this perspective, we reflect on the early career scientist (ECS) perspective and argue that while these changes introduce new risks, they also offer exciting new opportunities (for a common ECS definition see e.g., https://egu.eu/awards-medals/ecs-definition/). In particular, we tackle questions related to the above reflections. What can we contribute as physical climate scientists to the continuously evolving field? How can we better train, prepare, and support ECSs in addressing interdisciplinary research? What do we need, and what is needed from us?

2 | NEW PARADIGMS AND CHALLENGES

2.1 | Linking to climate impact research and social science

Extreme weather events have societal interest as they are susceptible to causing high impacts both in the short- and long-term (e.g., Vigdor, 2008), with the United Nations Framework Convention on Climate Change (UNFCCC) highlighting the existence of noneconomic losses on individuals (loss of life, health, or mobility), society (e.g., loss of territory, cultural heritage, indigenous or local knowledge, or societal or cultural identity), and on the environment (e.g., loss of biodiversity or ecosystem services).

Physical climate science alone cannot fully assess these impacts or comprehend their causation as it primarily addresses hazards. However, impacts arise not just from hazards, but also from exposure and vulnerability (Simpson, Mach, et al., 2021), and the most extreme weather events are not necessarily leading to the biggest impacts and vice versa (Tschumi & Zscheischler, 2020; van der Wiel et al., 2020). This calls for interdisciplinary work (Mahecha et al., 2024; Pisor & Jones, 2021), especially against the backdrop of a nonstationary climate, where hazards are changing, and exposure and vulnerability are too. Interdisciplinary research is particularly urgently needed in the Global South, where vulnerability is often greater than the Global North, and where there is a relative scarcity of such studies, further contributing to climate injustice (Callaghan et al., 2021; Otto et al., 2020; Pulkkinen et al., 2022).

Yet, there are more and more successful examples of interdisciplinary studies on extreme events, combining climate science with disciplines like hydrology, ecology, as well as social sciences such as geography, economics, or anthropology (Byers et al., 2018; Choksi et al., 2021; Júnior et al., 2021; Steinke et al., 2023). For example, Smiley et al. (2022) applied climate science attribution methods to a hydrological flood model and socioeconomic data to evaluate social inequities in climate change attributed impacts of Hurricane Harvey. Verschuur et al. (2021) showed that climate change made the 2007 Lesotho-South Africa drought more likely, contributing to crop failure and thereby to food insecurity in the region. Bastos et al. (2020) used different vegetation models to assess the influence of the 2018 heat wave and drought in Europe on ecosystem productivity. At a global scale, Byers et al. (2018) investigated the overlap between climate hotspots including some extreme event metrics with vulnerability indices. Climate scientists have also propelled extreme weather event research as useful for society, be it for raising awareness when a high-impact event happens (Van Oldenborgh et al., 2021), adaptation planning (Hov & Cubasch, 2013), or climate litigation (Stuart-Smith et al., 2022; Wetzer et al., 2024).

While collaboration with social sciences is encouraged, it may suffer from inadequate integration and differing research focuses (Pisor et al., 2023). In the case of extreme event attribution, information may also result in a so-called "climatization" of natural disasters, by putting the emphasis on the hazard and the responsibility on emitters, and eluding the roles of vulnerability and exposure, and hence the responsibility of local stakeholders in potential maladaptation (Grant et al., 2015; Lahsen & Ribot, 2022). The need for contextualizing is further exemplified in the debate regarding the informativeness (or rather lack thereof) of extreme event research for loss and damage (King et al., 2023; Noy et al., 2023).

The interdisciplinary space around extreme weather research thus appears plural and burgeoning. For ECSs, interdisciplinary research can present both an opportunity and a risk. On the one hand, an ECS wishing to conduct interdisciplinary work will have to become familiar with two or more different communities and literatures, with different epistemologies and values. This tends to slow down the publication process, which is key to getting recognition, funding, and new career positions. On the other hand, it allows them to explore spaces that are not already populated by many senior scientists, opening space for pioneering work relevant for society. Researchers able to navigate on the interfaces between different research communities, and particularly between physical climate science and social science, should hold some keys to overcome big challenges regarding climate action, especially around adaptation. Increased collaborations between physical climate scientists —who are eager to share their findings and put them in a decision-making context—and experts in cognitive science, law, philosophy of science, and science and technology studies are therefore needed. This requires better support and interdisciplinary training for ECS to minimize current obstacles, as well as guidance and funding from federal agencies.

2.2 | Applying novel methods and tools

Along with increasing opportunities for interdisciplinary work with climate impact scientists, we are also witnessing a new frontier for the application of statistical algorithms in climate science. Nowhere is that more apparent than in the adoption of artificial intelligence (AI) and machine learning. A recent review on just some of these advances in climate science can be found by de Burgh-Day and Leeuwenburg (2023), with limitations with respect to extreme events further discussed, for instance, by Watson (2022) and Lafon et al. (2023).

While examples of machine learning applied to predicting meteorological phenomenon have existed for decades (e.g., Barnes Jr. & Frankel, 1990; Chisholm et al., 1968; Marzban & Stumpf, 1998), this field has seen a particularly fast expansion in the last few years. In 2023, around 9% of all articles on weather extremes listed in *Web of Science* included machine learning applications, in contrast to less than a handful of publications on that topic only 10 years earlier (see Figure 1a,b). Both the American Geophysical Union and American Meteorological Society have recently launched new journals to target submissions that make use of AI methods (AGU Newsroom, 2023; Camporeale et al., 2024; McGovern & Broccoli, 2022). Moreover, in just the last year alone, several machine learning-based models have been introduced that demonstrate skill that is already comparable to traditional numerical weather prediction (Bi et al., 2023; Chen et al., 2023; Kurth et al., 2023; Lam et al., 2023, see also fourth paradigm/challenge). Despite an increasing number of summer schools, workshops, short courses, online tutorials, and open-source code packages being offered each year around the topic of machine learning (Abadi et al., 2016; Chase et al., 2022; Chase et al., 2023; Hedström et al., 2023; McGovern et al., 2023; Pedregosa et al., 2011), ECSs may struggle to keep up-to-date with the sheet scope of machine learning terminology, literature, and coding libraries, while simultaneously advancing their research in physical climate science (Jain et al., 2022).

The increasing use of machine learning in climate research raises also new ethical questions, particularly concerning its "black box" nature and issues with reproducibility (Gibney, 2022; McGovern et al., 2019). It is therefore crucial to enhance machine learning models with explainability and interpretability to foster user trust, especially for evaluating physical mechanisms behind extreme events and for use in regional climate services or policymaking where transparency is essential (Bommer et al., 2024; Mamalakis et al., 2022; Parker & Lusk, 2019). In the United States, this has led to the formation of the AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES), devoted to researching ethical issues regarding the use of machine learning methods in Earth science (McGovern, Bostrom, et al., 2022; McGovern, Ebert-Uphoff, et al., 2022). Moreover, the development of open-source tools and benchmark datasets for model validation (Rasp et al., 2024; Watson-Parris et al., 2022) and explainable AI (Alber et al., 2019; Flora et al., 2024; Hedström et al., 2023) is underway to address these concerns. However, the lack of ground-truth data, particularly for extreme events, complicates the application of machine learning in climate science, where the utility of such applications often hinges on the context and underlying values (Pulkkinen et al., 2022).

We also recognize that it is not just the use of deep learning that has grown. Frameworks bridging atmospheric and climate science with statistical methods have expanded immensely over the past decade, forming the basis for extreme event attribution (e.g., Diffenbaugh et al., 2017; Singh et al., 2014; Sippel et al., 2020; Swain et al., 2020). New popular techniques of analysis further include storyline approaches (Mindlin et al., 2020; Shepherd et al., 2018), such as applying numerical weather prediction models for attribution (Leach et al., 2021) and ensemble boosting for targeting unforeseen extreme events (Fischer et al., 2023; Ragone et al., 2018; Sippel et al., 2024). Moreover, causal inference and causal discovery methods are now used to study the climate system (Kretschmer et al., 2016; Kretschmer et al., 2021; Runge, Bathiany, et al., 2019; Runge, Nowack, et al., 2019), emergent constraint relationships between different climate models have been further evaluated (e.g., Hall et al., 2019; Sanderson et al., 2021; Simpson, McKinnon, et al., 2021), and forms of downscaling are now applied to resolve regional information at finer spatial resolutions (e.g., Ekström et al., 2015; Xu et al., 2019). All these methods require substantial data science knowledge and experience, along with robust physical reasoning during their application (Kretschmer et al., 2021; Shepherd, 2021).

ECSs interested in pursuing interdisciplinary connections between computer science, statistics, and climate science, face similar challenges to those linking with climate impact science. There are substantial differences in publishing norms and expectations between fields, posing the risk of ECSs having less time to focus on the involved physics (Jain et al., 2022). For example, machine learning papers are more likely to be published as preprints (e.g., on arXiv) and short conference papers (e.g., at NeurIPS) compared with the long-form scientific journals standard in climate science. While we urge users of these new methods to carefully and critically consider their purpose, usefulness, strengths, and weaknesses, we stress their potential to advance the field, if applied meaningfully. They offer a plethora of exciting opportunities, and ECSs equipped with strong data analytical skills, will play a major role in this transformation. Therefore, we highlight the importance of training, recognizing, and rewarding the successes of the next generation of scientists tasked with addressing Earth system science problems using machine learning advancements, as much of this work will require extensive data science and coding (Ebert-Uphoff et al., 2019; Jain et al., 2022; McGovern & Allen, 2021). Achieving this in the Global South presents additional challenges, as resources, including access to GPUs, are more limited, underscoring the need for targeted support and investment in these regions (Dike et al., 2018).

2.3 | Analyzing big climate data

Climate science has become a (big) data problem with different products serving to answer different questions (see Figure 2 for an overview of common data types). Studies assessing extreme climate and weather projections typically use CMIP-type datasets and require evaluations of multiple models for high-impact publications. Large ensembles are essential as internal variability can sometimes surpass model uncertainty in climate extreme predictions, particularly for compound events (Bevacqua et al., 2023; Deser et al., 2020). Additionally, high-resolution datasets are critical because extremes may be overlooked in coarser datasets (e.g., Davis, 2018; Liu et al., 2023), which has led to advances in high-resolution global climate models (e.g., Chang et al., 2020), nested and variable model grids (Harris & Lin, 2014), and regional climate modeling (e.g., Giorgi & Gutowski Jr, 2015). Climate impact data are powerful resource for understanding the links between weather and impacts, with datasets available at global (de Bruijn et al., 2019;

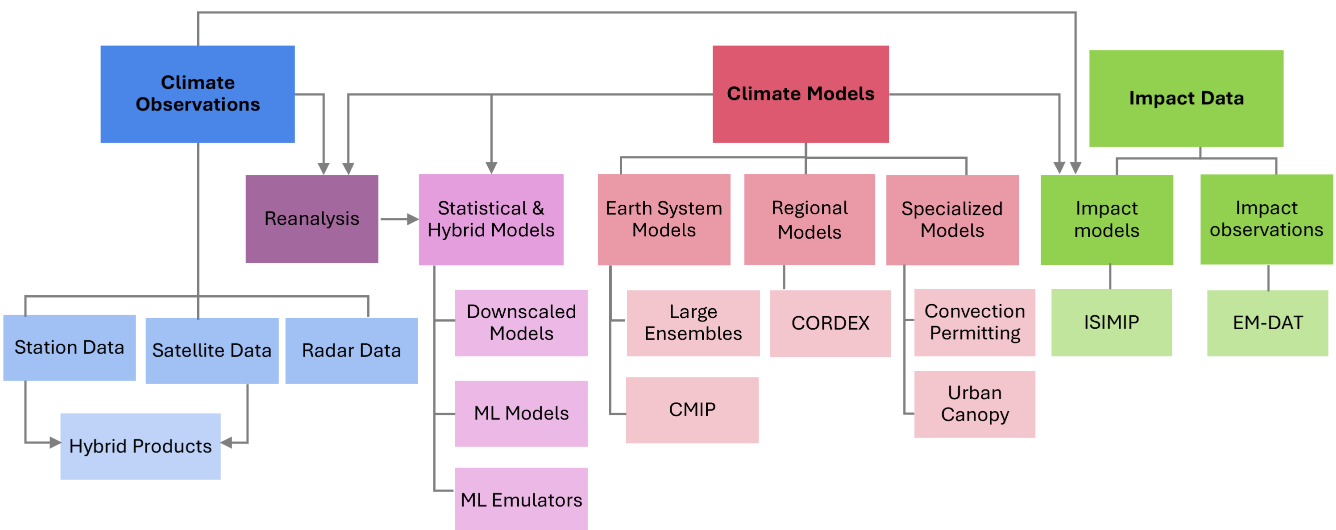

FIGURE 2 Overview of the major data categories used in extreme event research. Shown are observations (in blue), climate models (in red) and impact data (in green), with reanalysis data (in purple) and statistical and hybrid models (in pink) further indicated. The arrows in the schematic indicate typical data flow between data categories, while the nondirected links connecting the boxes indicate dependencies and examples of data types. Note that this overview is not fully comprehensive, with the IPCC Sixth Assessment Report (Working Group 1, Chap. 10, figs. 3 and 5), for example, showing a larger scope of models and datasets used in climate research. The purpose here is to illustrate the variety of data products, including "big," computationally heavy products such as large ensembles and CMIP. (CMIP, Climate Model Intercomparison Project; CORDEX, Coordinated Regional climate downscaling experiment; EM-DAT, Emergency Events Database; ISIMIP, Inter-Sectoral Impact Model Intercomparison Project).

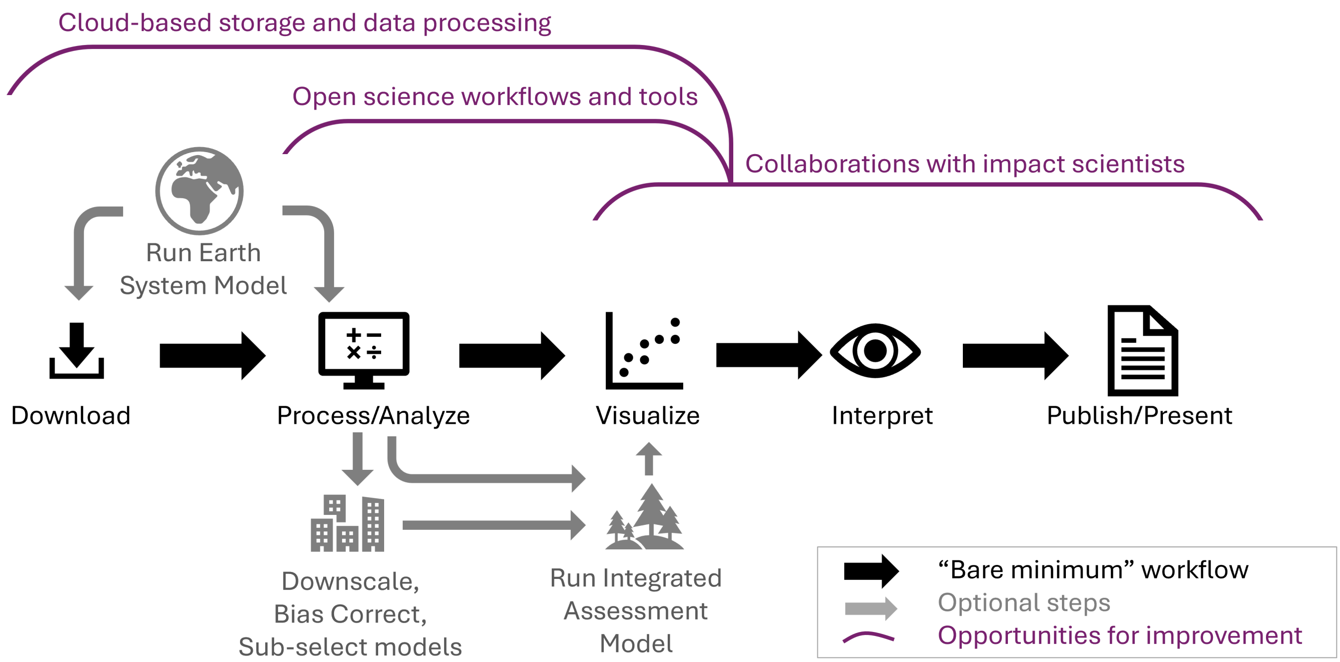

FIGURE 3 Typical climate science workflow in extreme event research and opportunities for improvements. The "bare minimum" workflow (shown in black) from downloading data to publishing results, is often extended by additional steps (shown in gray) including running an Earth System or Integrated Assessment model with optional processing steps. Along with this workflow, different opportunities for improvement are indicated (in purple).

Guha-Sapir et al., 2017), regional, or national scales (Gourley et al., 2013; Hall et al., 2015), covering multiple disasters (Hilker et al., 2009) or specific types of events (Artés et al., 2019).

Researchers hence rely on modeling centers to make their output public, or on public or private computational support for climate simulations, which may not always be straightforward. Once they can access or run these climate simulations, another hurdle may appear due to the size of the very large datasets (on the order of petabytes, *O*[PB]) that need to be accessed, downloaded, analyzed, and visualized (see Figure 3 for a typical workflow). As an example, the upcoming CMIP7 archive is expected to exceed 20 PB (Robinson et al., 2020). Additionally, specialized skill sets, or software may be needed to analyze variable resolution or specialized grid model output. As the access to internet/connectivity, computing and data storage resources differ across countries and institutes, this creates an uneven playing field and can shape the ECSs' success in their scientific impact (Jain et al., 2022). In particular in the Global South, access to high-performance computing including storage is more limited, with direct implications for publishing in high-impact journals.

Against this background, proposals for a reduced set of climate models to operate similarly to global weather forecasting models are gaining traction, potentially freeing resources for more impactful climate research (Jakob et al., 2023; Stevens, 2024). Efforts to merge weather and climate modeling are underway, such as at ECMWF, with calls for similar initiatives at other global modeling centers (Randall & Emanuel, 2024). Moreover, the use of AI and machine learning, for example, to emulate high-resolution processes in climate models, is reducing the need for intensive computational approaches like dynamical downscaling (Jones et al., 2024; Schneider et al., 2024). Centralized or cloud computing efforts (e.g., pangeo, OPeNDAP, Google Earth Engine) have also allowed more streamlined analysis, allowing scientists to analyze data in situ, and enable assessment of multiple model outputs and ensembles in one location (e.g., Robinson et al., 2022, see also Figure 3), with "compute-near-the-data" also planned for the Next Generation Earth System Grid Federation (ESGF2). Some modeling centers have also established diagnostics packages that can be easily used to assess various metrics of climate data, including climate extremes (e.g., Phillips et al., 2014). Additionally, partially due to open data and science publishing policies, researchers are now more often sharing workflows that have been used in published articles, reducing some of the hurdles that other researchers keen to apply their methodologies may have in assessing some of the datasets (Erdmann et al., 2022).

For ECSs, there are several emerging opportunities to challenge and improve the status quo. For example, "Fresh Eyes on CMIP", a WCRP working group led by ECSs, is bringing new perspectives to the development of future CMIP datasets. Given that it takes time to make results broadly usable (e.g., through software and tutorials) and is often undervalued by the academic system, greater support from research institutions and modeling centers is important. Necessary steps include training workshops (e.g., McGovern et al., 2019), simplified user interfaces (e.g., Lombardozzi et al., 2023), unrestricted access to publications and datasets, and ensuring easier access for Global South scientists to HPC. Importantly, these should be integrated by all research institutions, not just dedicated institutes like ICTP or IIASA. Ultimately, ECSs have the potential to lead and invest in some of these modeling and analysis efforts and may be able to make larger scientific contributions as simulations and datasets become more efficient.

2.4 | Engaging with different stakeholder groups

As anthropogenic climate change and its impacts affect everyone—albeit in varying ways—the number of stakeholders in physical climate science is increasing. These stakeholders include decision-makers in politics and industry, lawyers, water managers, indigenous communities, nonprofit organizations, and the general public.

For example, the recognition of extreme weather events as presenting societal and financial risks has spurred interest from multinational finance and insurance companies like MSCI, AXA-Climate, and Citadel which now have departments dedicated to quantifying climate risks (Fletcher, 2023). Additionally, tech giants like Huawei Cloud, Google DeepMind, and NVIDIA are developing machine learning-based weather forecasting technologies (Bi et al., 2023; Chen et al., 2023; Kurth et al., 2023; Lam et al., 2023). These companies offer attractive employment opportunities to ECSs in climate science due to cutting-edge research, quicker decision-making, more permanent contracts, and often higher salaries than academia. On the other hand, independent academic research remains vital in the context of climate justice, as companies may prioritize business interests over public interest (Keele, 2019). Condon (2023) argues that "actionable and transparent information about our climate-changed future is a public good that the private sector cannot be depended upon to provide equitably or reliably." Looking forward, a greater integration of academic and corporate research is likely (e.g., through scientific collaborations, joint workshops, nontraditional funding sources), necessitating discussions on forms of engagements, with key challenges around transparency and equity.

In recent years, climate services have surged, showcasing successful collaborations between climate scientists and various stakeholders (White et al., 2022). Climate researchers also increasingly collaborate with policy institutes (e.g., Climate Analytics) and national agencies (e.g., Copernicus) on extreme weather and climate change questions. Despite encouragement from funding agencies to provide actionable climate information and engage with decision-makers, challenges arise due to differing stakeholder needs and scientific methodologies (Bruno Soares & Buontempo, 2019; Findlater et al., 2021; Nissan et al., 2019). Coproduction is promoted (Vincent et al., 2018), yet it takes time to yield results, and might lead to gray literature rather than journal papers (something that is again not valued in academia, at least in our domain). Moreover, the scope of community-engaged research is likely too narrow for high-impact publications, mirroring challenges in interdisciplinary research. In particular, working with indigenous communities is crucial (Makondo & Thomas, 2018; Reyes-García et al., 2024) but takes time and can lead to unethical practices if not done carefully (Orlove et al., 2023). Translating scientific results into action is further complex and can sometimes harm the communities it aims to help (Klein et al., 2022; Vaughan et al., 2018; Vaughan et al., 2019). For example, Webber and Donner (2017), argue that in the Pacific islands, the development of climate services may divert limited adaptation resources available in these countries from other actions. They also point out that the commercialization of climate services leads to optimizing profit over the needs of the users. ECSs may work with "boundary" organizations that have deep and ongoing relationships with different communities and are sometimes a part of their own academic institution. For example, the University of California Cooperative Extension in California, establishes and maintains essential ties with agricultural entities and tribal communities across the state, and has been found to increase the impact of academic research hours on the creation of societally relevant knowledge (Chatterjee et al., 2018).

Nuanced science communication is also increasingly crucial. Whereas in the past climate scientists mainly defended the existence of anthropogenic climate change and the scientific consensus around it, they are nowadays frequently asked to comment on the role of climate change in extreme weather events in near-real time. This shift happened alongside the establishment of scientist-led fast-track attribution initiatives like World Weather Attribution (Philip et al., 2020) and the recent Climameter (Faranda et al., 2023). However, succinct media statements usually lack the space to convey the complexities and uncertainties inherent in these attribution questions. Consequently, scientists face a dilemma—they may be labeled as 'activist' and 'alarmist' on the one hand or

FIGURE 4 Integration of Science and Activism. Climate protests on 20 September 2019 in Berlin, Germany, featuring a banner from the activist group Scientists4Future stating "We provide the facts. Time to act!" along with a figure of the "climate stripes" (https://showyourstripes.info/). The protests in Berlin were part of a series of climate protests around the world that day, just a few days before the United Nations Climate Action Summit in New York (e.g., Kaplan & Dennis, 2019).

accused of downplaying the significant risks of climate change on the other (e.g., Brysse et al., 2013; Showstack, 2019). While social media offers a platform for disseminating more intricate findings, online engagement presents challenges, particularly for marginalized groups, and may not be fully appreciated by the scientific community.

Finally, activist groups such as "Fridays for Future," "Extinction Rebellion," or "Last Generation" frequently cite scientific findings in their advocacy efforts. In the case of "Scientists for Future" and "Scientist Rebellion," academics themselves engage in activism (Hagedorn et al., 2019, see also Figure 4). Arguably, the increasing visibility of climate activism has become a key reason for young people to enroll in climate science-related studies in the first place, highly motivated in finding climate solutions. However, activist groups also critique the scientific community for its inertia and lack of urgency in communication, further underscoring how these emerging forms of climate activism might also influence scientists.

Overall, given the various stakeholder interactions in climate science, there is a growing need for more training and support for ECSs on this matter. Successful collaborations highlight the potential for impactful research but also reveal challenges such as differing stakeholder needs, the complexity of science communication, and the integration of interdisciplinary efforts. Additionally, more collaborations between researchers across institutions, particularly with those in the Global South, require concrete actions to facilitate these partnerships. Research institutes and funding agencies can play a critical role in addressing these challenges by providing interdisciplinary training and career development programs, offering mentorship and networking opportunities to help ECSs navigate both academic and industry career paths. Encouragingly, funding agencies are partly beginning to understand, value, and support co-produced research endeavors (e.g., NASA's "Earth Science to Action" strategy), which could pave the way for academic institutions to also recognize these achievements beyond peer-reviewed publications.

3 | CONCLUSIONS AND OUTLOOK

The expected effects of human-caused climate change, coupled with recent academic, technological, and social shifts, have led to fundamental changes in climate science, including the establishment of extreme event research. These changes imply that young scientists entering the field nowadays are formed in a remarkably more interdisciplinary environment than it was even a decade ago. While fundamental and theoretical climate research on extreme events is still needed, especially for types of events and regions with little certainty regarding expected changes, we believe that our research should continue to become more interdisciplinary—be it in the form of linking to climate impact science and working with social scientists, by applying novel machine learning and big data techniques, or through stakeholder interactions.

For ECSs, we argue that these changes overall present a high-risk, high-reward situation. While they provide an opportunity to craft a distinctive research profile with cutting-edge work directly relevant for society, they also pose challenges in developing deep expertise and establishing oneself within a specific community. Consequently, there is a risk that traditional evaluation metrics used by (disciplinary) appointment committees and funding agencies may not adequately reflect scientific excellence, impact, and creativity (e.g., Bromham et al., 2016). This exacerbates the existing issue in academia of limited permanent faculty positions and the absence of mid to long-term career planning.

Therefore, supervisors and PIs need to be aware of the risks associated with interdisciplinary work, especially for ECSs, and should provide support in navigating them. This could involve allocating sufficient time and resources for training and offering joint supervision with scientists from other disciplines to bridge domain differences. As interdisciplinary work often requires more time and may result in fewer publications, funding agencies, and universities must reconsider how they measure scientific success. For example, interdisciplinary PhD programs should allow more time for graduation, and funding schemes should differentiate between disciplinary and interdisciplinary applications in their evaluations. Moreover, training and infrastructure are of imminent importance to support ECSs, including international training workshops, cloud-solutions, and open science practice (see also Figure 3). The new generation of scientists should push for new metrics, and to rethink the values by which academia is currently led.

ECSs should also have a greater voice in established international research networks to shape processes and discussions. Initiatives like the Young Earth System Scientists community (YESS), or Fresh Eyes on CMIP are therefore crucial for advancing as a research community and deserve more visibility among ECSs as well as scientists at later career stages. Finally, it is imperative to dismantle barriers that particularly hinder researchers from the Global South, such as reducing publication costs, providing comprehensive travel and visa support for scientific conferences, facilitating easy data access, and fostering capacity building and open collaborations (Connors & Chavelli, 2023; Tandon, 2021).

The numerous scientific challenges we face, coupled with the societal importance of our endeavors, should ignite our enthusiasm, and drive us to action. ECSs are uniquely positioned to transform the field of climate science, given their specialized training and invaluable skills crucial for providing climate information. With robust support and acknowledgment from supervisors, research institutes, and funding agencies, ECSs can lead the charge in addressing climate challenges and help to limit climate injustices. It is essential to include diverse voices and recognize the role of values in climate science, ensuring that a wide range of perspectives and ethical considerations inform our work, which might depend on context and user. This optimistic outlook emphasizes the vital role ECSs play in advancing climate science and underscores the importance of meaningful engagement, introspection, and institutional backing within the field.

AUTHOR CONTRIBUTIONS

Marlene Kretschmer: Conceptualization; writing—original draft; visualization; project administration. **Aglaé Jézéquel:** Conceptualization; writing—original draft; visualization. **Zachary M. Labe:** Conceptualization; writing—original draft; visualization. **Danielle Touma:** Conceptualization; writing—original draft; visualization.

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CONFLICT OF INTEREST STATEMENT

The authors serve as guest editors for the ASL special collection "Novel data science approaches to evaluate weather and climate extremes."

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Web of Science. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of Web of Science.

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