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Report: Broadening Access to Climate AI Innovation

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Executive Summary

for Climate Researchers, Affected Communities, and Policymakers

Climate knowledge is not a single issue, because the climate affects every aspect of every society, of every life. Considering how artificial intelligence (AI) can be leveraged for developing new approaches to extreme weather events, therefore, is not a single issue either, but warrants broad engagement across disciplines and communities.

The Broadening Access to Climate AI Innovation workshop convened climate scientists, AI experts, climate activists, policymakers, and representatives from communities impacted by extreme weather events. Through interactive sessions, participants examined how climate and extreme weather events are evolving under climate change and how AI is reshaping research and forecasting in this domain. Discussions centered on dismantling structural barriers to community participation in AI innovation and emphasized the importance of community-driven AI transparency. Following the workshop, five cross-cutting takeaways emerged, extending insights from existing literature while revealing new directions for future research:

1. Redefining Extremes
2. AI Uncertainty as an Opportunity for Engaging a Fuller Spectrum of Climate Knowledges
3. Explainability as a Foundational Dimension of Climate AI
4. Reconfiguring Climate Expertise
5. Institutional and Infrastructural Conditions for Responsible Innovation

This report concludes by proposing a new, multifaceted research agenda. Rather than presenting a singular path forward, the takeaways highlight the multiple and intersecting dynamics shaping the integration of AI into climate science, policy, and public life—underscoring the importance of cross-disciplinary research and stakeholder-driven collaboration. They suggest that future progress in the field of AI-driven climate science will depend as much on social and institutional innovation as on AI advancement.

The project is based at the University of Virginia and is directed by Dr. Mona Sloane (Data Science and Media Studies), Dr. Antonios Mamalakis (Data Science and Environmental Sciences), and Dr. Charity Nyelele (Environmental Sciences), and Ava Birdwell (graduate student researcher). It is funded by the Environmental Institute at the University of Virginia.

Plain Language Summary

Artificial intelligence (AI) is a new tool being used in climate science. It can study very large sets of data, find patterns, and help predict extreme weather like floods, fires, or heat waves. This can give people and communities more time to prepare. But there are also challenges. AI decisions or predictions can be hard to explain and data and the models built with them may exclude different groups' perspectives. To talk about these opportunities and problems, a workshop brought together scientists, policymakers, community leaders, and advocates. Participants agreed that the future of climate AI is not only about better technology but also about fairness, trust, and shared knowledge.

Five main lessons came out of the workshop:

1. Redefine extremes – Extreme events should be defined by their real impacts on people and places, not just numbers.
2. Use uncertainty – Uncertainty in AI should be seen as a way to bring in new ideas and voices, not only as a weakness.
3. Explainability matters – AI needs to be open and clear in different ways for different users, from scientists to local communities.
4. Share expertise – Communities most affected by climate change should help shape the questions, models, and solutions.
5. Change institutions – Universities, funders, and governments must support long-term, cross-community, and cross-discipline work.

The report calls for a new approach: build systems where communities can share their experiences with extreme weather, talk openly about risks and uncertainties, and design AI tools together. AI can then be used not only to predict the future, but also to create fairer and stronger climate solutions for everyone.

AI, Climate Science, and Stakeholder Knowledge

AI systems[1] are increasingly used in climate science to advance climate and weather forecasting. For example, climate AI models are used in a variety of environmental settings such as wildfire detection[2], extending drought and flood prediction lead times[3], modeling tropical cyclones[4] and forecasting localized weather events with longer lead times[5]. In addition, AI can be used to enhance operational forecasting systems by improving both speed and accuracy[6], while also increasing the computational efficiency of producing large-scale climate projections[7]. AI has also been used to downscale large-scale climate model outputs to fine-scale regional levels, aiding local adaptation strategies and predicting climate characteristics in future scenarios[8]. AI models are advantageous in this way, because they can handle extremely large datasets[9] and find patterns, particularly nonlinear ones[10], whereas traditional methods in climate science (such as methods that use the laws of physics, such as the conservation of mass and conservation of energy, to simulate the Earth system as well as some statistical methods) may struggle to capture this complexity.

However, extreme weather events, expected to only increase with climate change, have major effects on communities. This drives the necessity and desire to understand, predict, prepare for, and mitigate extreme events on a more localized level. The question remains whether AI innovations can meaningfully support community-based climate prediction. Here, three key areas of challenges remain: methodological challenges pertaining to AI use in climate science; governance, ethics and justice challenges; and challenges in explainable AI (XAI) efforts, including AI transparency and trustworthiness[11].

First, AI in climate science faces challenges related to uncertainty and generalizability[12]. Even though AI can assist in quantifying or reducing uncertainty in some contexts e.g., uncertainty arising from physics-based climate model parameterizations[13], it carries sources of epistemic or aleatoric uncertainty. These stem from the limited historical record combined with the rarity and irregularity of extreme events, and the inherently chaotic nature of the climate system[14]. Generalizability refers to a model's ability to perform well beyond the spatio-temporal scope of its training data[15]. As the climate changes, AI models trained on historical data may struggle to capture emerging patterns. Moreover, studies are often geographically limited to areas with available ground and observational data, complicating the reliability of the AI model output to regions or events that lie outside the training dataset. To improve accuracy, interpretability, and trustworthiness, researchers increasingly advocate for hybrid approaches that combine physical modeling with machine learning[16].

Second, serious questions around the social implications of AI systems in climate science remain unanswered, specifically with regards to data and AI governance, ethics, and justice. Data and AI governance questions pertain to unresolved issues of data ownership and sovereignty whereby communities may provide climate science critical data, but are excluded from the climate science process or do not see benefit from it. To address this, efforts have been made to identify processes that align with open science protocols (i.e. protocols that aim to make scientific research and its outcomes freely accessible through practices like data sharing and preregistration[17]) while also upholding the rights of Indigenous Peoples. In this context, the implementation of the CARE Principles for Indigenous Data Governance (Collective benefit, Authority to control, Responsibility, Ethics) is especially important when navigating complex research governance and funding structures[18]. Ethical questions around appropriate and fair prioritization in AI deployment surface when AI systems inadvertently prioritize certain regions or demographics while neglecting others[19]. Globally, there is unequal opportunity for climate change forecasting, insufficient awareness of climate change risks and opportunities to reduce them, and discrepancies in the ease of introducing innovations (i.e. clean or green energy) to mitigate climate change[20]. Another concern is that AI models inherit biases present in the training data, for example, historical data reflecting systemic inequalities in energy access or pollution exposure can lead to potential unfair or discriminatory outcomes that disproportionately benefit certain groups over others[21]. Relatedly, justice questions in AI-driven climate science pertain to the unequal distribution of extreme weather harms that are experienced disproportionately by already marginalized and vulnerable communities[22]. Additionally, AI use can significantly contribute to greenhouse gas emissions, posing a paradox when using AI to combat climate change[23]. AI data centers, particularly in the United States, are often located in rural and poorer communities who experience spikes in electricity costs and increased drought risk in already heat-stressed regions[24] due to escalating water demand to cool the data centers.

Third, XAI efforts have gained prominence in addressing AI's "black box" nature (i.e., the fact that AI models' prediction making processes are often not transparent, comprehensible, or physically-meaningful to the user[25]). XAI methods have been applied to make AI models more interpretable in an effort to gauge trust[26]. This approach has become well-known in climate science to foster confidence in predictions and help scientists gain insights into specific climate tasks[27]. For example, XAI methods in climate science have helped detect the link between human impacts and temperature changes[28] and contributed to heat wave attribution[29]. Despite this very progress, important issues remain. First, no optimal XAI method exists for all prediction tasks and AI models[30] and there is a plethora of XAI tools proposed in the literature. Consequently, AI explanations may exhibit “inter-method” variability, that is applying many different XAI tools to generate explanations, potentially confusing the user. Recent works have proposed methods for addressing this issue by focusing only on desired explanation properties (such as robustness, faithfulness, and randomization[31]) or by combining outputs from multiple XAI methods to construct a unified, optimal explanation[32]. However, such a unifying approach does not address the issue that different users have different explainability needs and desires, depending on their different knowledge profiles: different communities and users from different backgrounds seek inherently different types of insights from an explanation[33].

At the intersection of these challenges, there is potential for holistically leveraging AI in climate science in the public interest. Here, XAI can serve as a point of departure: XAI has been called upon as a tool to not only foster trust with stakeholders, but as a means of improving stakeholder engagement and decision making in environmental policy and sciences[34] and to help align AI solutions with the knowledges and preferences of those communities who are and will be affected by extreme events[35].

Taking this as a cue, the goals of the Broadening Access to Climate AI Innovation workshop was to bring into conversation otherwise disconnected areas of expertise on climate science, AI and XAI, and stakeholder knowledge, and to seed sustainable networks that yield new and independent projects on AI, climate science, stakeholder engagement, and policy.

Five Take-Aways

As the climate science AI field matures, there is consensus that technical innovation alone is not enough. A transformational shift toward inclusivity, transparency, and co-ownership of AI innovations will better help society respond to a changing climate. Here, five take-aways emerge that shape the technical development of climate science AI and its broader societal role. These take-aways can help catalyze changes in how environmental knowledge is generated, validated, and applied vis-à-vis the potentials of AI.

01. Redefining Extremes

Statistical definitions of “extremes” may be insufficient for capturing the real-world impacts of climate hazards. Understanding “extremes” requires local context: in practice, the impact of a climate event often depends not on its rarity in statistical terms, but on its intersection with localized socioeconomic vulnerabilities, infrastructure resilience, and institutional capacity. Thus, the definition of “extreme” is contingent—not only on climate data, but also on historical, cultural, geographical, and political contexts.

Take-Away: Climate science AI approaches must define and integrate impact-based and context-sensitive thresholds for “extremes”, rather than relying solely on traditional climate data. AI has the potential to support this reframing through spatial downscaling (increasing the spatial resolution at which forecasts become available), risk clustering (grouping together patterns in weather or environmental conditions that tend to lead to similar types of impacts or risks, for example, clustering storm systems that often result in urban flooding), and localized impact prediction, but only if its development is informed by interdisciplinary and community-based knowledge.

02. AI Uncertainty as an Opportunity for Engaging a Fuller Spectrum of Climate Knowledges

Rather than treating AI uncertainty solely as a limitation to be minimized, emerging work in climate AI increasingly conceptualizes it as a unit of inquiry, providing an opportunity to engage a fuller spectrum of climate knowledges and implications. For example, approaches such as probabilistic modeling (integrating probability and uncertainty into forecasting), ensemble learning (building and training multiple models), and counterfactual simulation (exploring “what if” weather scenarios to build resilience) can be used not only to quantify uncertainty but to develop conversations with multiple stakeholder groups and explore its implications for risk management and scenario planning, as well as governance.

Take-Away: Uncertainty in climate science AI approaches can be used as a cue to develop interdisciplinary collaborations and dialogues with stakeholders. The development and use of new climate science AI tools can serve as prompts for deliberation across domains, fostering contingency-aware decision-making that is grounded in stakeholder knowledge, and inviting the inclusion of perspectives outside of climate science specifically that may operate with different forms of evidence and reasoning.

03. Explainability as a Foundational Dimension of Climate Science AI

The role of explainability in climate science AI is not ancillary but constitutive, because it is central to both the credibility and the usability of model outputs. In practice, however, explainability is situated: what is adequate for a climate scientist may be insufficient or unsuitable for a policymaker or a frontline community. As such, explainability is not only a technical feature but also a sociotechnical relationship, shaped by context, audience, and stakes.

Take-Away: The stakes of explainability are raised with AI applications in climate science, given its role in guiding predictive decision-making for weather and climate, and the often-contested nature of environmental research results. New approaches, therefore, should not reduce explainability to a single metric or output, but find ways to express and leverage explainability as a multidimensional communication tool. This includes the traceability of inputs and knowledge, the interpretability of model behavior, and the communicability of model design and results to diverse stakeholders/audiences. Communities and decision-makers need to understand how AI tools work and where their limits lie. Different kinds of clarity are needed, and different users need different forms of explanation.

04. Reconfiguring Climate Expertise

The absence of situated and historical knowledge of local actors raises important questions about power and epistemic authority in climate prediction. Histories of marginalization and institutional architectures structure research agendas, data governance, and funding priorities. To address this issue, engaging local communities as part of improving both the contextual accuracy and the ethical orientation of AI applications, including data and model governance concerns, is key.

Take-Away: Climate science AI approaches ought to mandate engaging communities in problem definition, model co-design, transparency requirements, and interpretation of outputs—particularly to those who bear the greatest burdens of climate risk and extreme weather events. The reconfiguration of expertise in this context involves a shift from viewing communities as users or recipients of climate knowledge to recognizing them as co-producers of insights and solutions right from the beginning of climate science projects. Such a reconfiguration ought to build on inclusive language and communication that can bridge divides and build nonpartisan support for climate agendas and avoid further polarization in the climate and AI discourse. Emphasizing storytelling, advocacy, lived experience, and language that resonates across divides alongside data and models is critical to not only connect with people's lived experiences and identities, but for building shared understanding and trust in climate discourse and science.

05. Institutional and Infrastructural Conditions for Responsible Innovation

Current institutional arrangements–academic reward structures, funding mechanisms, computational resource access, and data sharing policies–are often poorly aligned with the collaborative demands of impactful climate science AI. Short project cycles and siloed disciplinary funding can discourage the sustained partnerships needed for co-production or longitudinal impact assessment, negatively influencing the trajectory of climate science AI innovation.

Take-Away: The institutional infrastructures of climate science AI must ensure temporal alignment between the long-term orientation of climate science and climate knowledge and the operational environments in which climate science innovation can occur. Incentive and support structures should be set up to create this type of alignment and encourage and sustain interdisciplinary collaborations between different experts, including experts outside of the academy. Emerging institutional models—such community data trusts and interdisciplinary research centers—can provide useful templates.

A New Knowledge Agenda

AI for climate is about relationships, not just data, but the intersection between climate modelling with AI, XAI, and stakeholder knowledge remains under-researched. Valuable knowledge exists outside academia, including among farmers, youth activists, elders, and local officials which can strengthen AI climate modeling, but these communities are disconnected.

The disconnect manifests in multiple ways: in discipline-bound epistemologies, problem definition and articulation, prioritization of issues, communication style, and the absence of platforms to engage. Building climate AI tools and actions that are more relevant, trusted, and effective requires breaking down siloed approaches and building relationships and trust across disciplines, sectors, and communities.

As there is no clear path forward to address the issue of this disconnect, a new knowledge agenda can serve as a generator and catalyst for innovation in AI-driven climate science. A knowledge agenda is a purposeful plan that identifies the most important questions, topics, types of knowledge, and forms of knowledge production the climate science and AI field should focus on. It helps coordinate efforts, set priorities for research and collaboration, and makes sure what is learned is meaningful and used in practice.

This new agenda must center on reimagining how environmental knowledge is produced, shared, and applied in a world shaped by compounding climate risks and social disparities. Both climate scientists and the general public require not just better models, but better ways of understanding what counts as climate knowledge, who gets to shape it, and how it is used in public life.

Build Participatory Knowledge Infrastructures

AI has the potential to support a more impact-sensitive approach, but only if it is developed in partnership with communities, local institutions, and interdisciplinary researchers. One important direction here is the creation of participatory infrastructures for data collection. A long-term, open-access platform where individuals and communities can report their experiences with extreme weather events (such as floods, droughts, heatwaves or wildfires) could serve as a powerful tool for transforming the data landscape. For example, the Local Environmental Observer (LEO) Network in the Arctic, started as a grassroots Alaskan movement by the Alaska Native Tribal Health Consortium (ANTHC) with funds from the US Environmental Protection Agency (US EPA). As a network and a tool, started in 2009, LEO affords local observers and topic experts the opportunity to share knowledge about unusual animal, environment, and weather events[36]. Infrastructures such as LEO amplify local and potentially previously unheard perspectives on the impacts of environmental change on our shared ecosystems and biodiversity. Inspired by projects like LEO, constituents of participatory infrastructures focused on severe weather data could record when and where an event occurred, its perceived severity, their coping mechanisms, and the impacts it had on their lives, alongside optional demographic and contextual information. Different forms of data could be considered: oral histories, objects, photographs, and more. Maintenance and governance of this platform would be stakeholder-driven, and funded through public interest technology investments. Over time, this type of system could accumulate a rich, human-centered dataset that captures the social, psychological, and infrastructural dimensions of climate events. Such data could eventually be used to train large language models or other AI systems capable of recognizing patterns and forecasting risks based not just on atmospheric data but on lived experience. These models could be co-developed with communities, and co-owned and -maintained. This would help shift climate modeling from a narrow focus on meteorological anomalies to a broader, more grounded understanding of disruption and vulnerability while ensuring fair data and AI governance.

Communicate Uncertainty

Uncertainty is a core feature of both climate science and AI modeling, and rather than treating it solely as a limitation to be minimized, it can be leveraged as a productive force in scientific and policy processes. In climate forecasting, uncertainty arises from incomplete observations, model simplifications, and the chaotic nature of the climate system. AI introduces additional uncertainties, such as sensitivity to training data, model opacity, and limited generalizability to novel conditions. Knowledge production in climate science AI should prioritize developing pipelines that are designed to qualitatively describe and quantify types of uncertainties, identify and surface the associated sources, and ultimately communicate such uncertainties to relevant communities and stakeholders explicitly to present a range of plausible outcomes rather than single-point forecasts. This can assist risk management, contingency planning, and the identification of where further data or analysis is needed. Moreover, communicating uncertainty transparently can foster interdisciplinary and community dialogue, since different stakeholders often have distinct risk tolerances, evidence standards, and decision criteria. Making uncertainty visible can promote trust, highlight knowledge gaps, and open space for collaboration and deliberation, especially when navigating high-stakes and value-laden climate decisions.

Expand Explainability

The role of explainability is similarly central. As AI systems are integrated into climate science, the question of what can contribute to making a model output more trusted becomes complex. Traditional climate models rely on physically interpretable relationships, while AI-based systems often operate as black boxes. The assumption that a single metric or visualization can make such models "explainable" across all contexts is incorrect. Instead, explainability must be understood as context-specific and relational. What counts as a good explanation for a researcher may not be adequate for a policymaker or a community leader. Future XAI research should prioritise the usability of explanations and explore new approaches to explainability that reflect these differences, combining technical interpretability with clarity, and linking model behavior to tangible local concerns. Such work should advance both the algorithm design and include participatory evaluation of what types of explanation are most useful and meaningful in different settings.

A forward-looking knowledge agenda for climate science AI cannot be limited to questions of accuracy or efficiency. It must also ask: Who is defining the problems? Whose knowledge is being incorporated? Who benefits from the solutions? And how can AI be used not just to predict future weather events, but to shape more just, transparent, and inclusive pathways forward? These are not only ethical questions, they are scientific ones, essential to building robust and socially meaningful climate AI systems.

Background: Workshop Summaries

Session I: AI, Weather, and Extreme Events
Moderator: Antonios Mamalakis
Presenters: **Kate Marvel**, Research Physical Scientist, NASA Goddard Institute for Space Studies; **Pierre Gentine**, Professor of Earth and Environmental Engineering, Columbia University; and **Tom Beucler**, Assistant Professor of Environmental Data Science, University of Lausanne, Switzerland

This session explored how extreme weather events are changing under climate change, and where AI is transforming forecasting, prediction, and helping to solve climate change issues.

Kate Marvel discussed the challenges of extreme event attribution, with a focus on drought attribution. She highlighted both scientific and other motivations for attributing extreme events to human activities; for example, improving our understanding of Earth system responses, but also for risk prevention, media communication, raising climate change awareness, and legal accountability. She outlined two major challenges: we don't know the "noise" (natural variability) or the "signal" (human influence) in our climate system. We rely on climate models, yet many models disagree on future projections. Kate discussed two approaches to data: machine learning and Bayesian inference. Machine learning is powerful with abundant training and testing data, but struggles to capture uncertainty. She concluded by proposing a challenge to the traditional way of generating research as a climate scientist and moving forward, utilizing the opportunity we have with new technologies to ask questions in an extremely tailored and stakeholder-driven way.

Pierre Gentine explored how climate models struggle to capture the magnitude and frequency of weather extremes, particularly for precipitation. Traditional coarse-resolution models often underestimate extremes, posing risks for preparedness and adaptation. Higher-resolution models, similar to those used in weather forecasting, better simulate these events. Pierre emphasized that unresolved small-scale physical processes are a major source of uncertainty. To address this, he discussed using neural networks to represent processes like convection and embedding them into climate models to reduce bias and improve the simulation of extremes. He concluded by raising the question of how can AI be used to predict changing extremes when machine learning systems are typically trained on past, non-extreme data and struggle with shifting distributions?

Tom continued the discussion by focusing on the use of AI to enhance high-resolution climate imagery and forecasting. He echoed Pierre's concern about generalization - AI models trained on past data may break under new, extreme climate conditions. He asked whether we can make empirical downscaling techniques (statistical and machine learning) more robust to climate change, using wind gust prediction as an example. He pointed to the promise of combining physical understanding and extreme value theory with machine learning to improve predictions where data are sparse. He also emphasized the growing accessibility of neural weather models, which can be run efficiently once trained. He ended with questioning the role of academia and how can scientists deliver information from AI models that stakeholders trust?

The broader discussion touched on defining “extreme” events and how varied definitions affect both research and communication. The group agreed that natural variability - or "noise" - in the climate system presents a persistent challenge. Jeannie emphasized the desire to understand the agricultural impacts of extreme weather on vulnerable communities like farmworkers. Erin, from a disaster management perspective, echoed the potential for advances in modeling to improve preparedness. Susan added that understanding local implications - such as how extreme weather might cause power outages - is crucial, particularly for low-income populations. AI-powered downscaling was highlighted as an exciting advance that enables end-to-end predictions and direct stakeholder engagement. Ultimately, participants reflected on the power of machine learning as a “counterfactual” and using the technology to imagine unprecedented extremes and what our future in a changing climate might look like.

Session II: Stakeholder Engagement in AI-Driven Climate Solutions
Moderator: Charity Nyelele
Presenters: **Pooja Tilvawala**, Founder and Executive Director, Youth Climate Collaborative; **Bob Inglis**, Executive Director, republicEn; former US Representative for South Carolina’s 4th Congressional District; and **Riley Taitingfong**, Postdoctoral Researcher, Udall and Native Nations Institute

This session focused on addressing barriers to stakeholder participation and exploring ways to ensure broad participation when integrating AI into climate solutions.

Pooja opened the session with an interactive activity focused on climate science, AI, and stakeholder engagement. From the discussion questions and examples she shared, several key insights emerged: the climate and technology policy spaces are often filled with jargon-heavy language; there is limited stakeholder input during early stages of policy development; and the need for meaningful youth engagement. Key challenges to integrating AI into climate work include disparities in internet access, language and literacy barriers, and limited public understanding of technological tools.

There is also concern that AI could exacerbate existing inequalities in regions most affected by climate change. Additional issues raised included access to funding, the energy demands of AI systems, biases in training data, and the need for greater transparency and trust. A significant gap was noted in the availability and awareness of AI tools that support equitable climate solutions. Moreover, frontline communities are often excluded from the design of these tools, and valuable co-production approaches are often underutilized because of the additional time and resources they require. Pooja highlighted the importance of working directly with affected communities, drawing on lived experience and personal stories, and using advocacy to elevate marginalized voices. Concerns were also raised about the environmental footprint of AI technologies themselves.

Bob shared his perspective from a policy, government, and climate skepticism background. One of his main points was that the language used in climate conversations often excludes right-of-center individuals, hindering the ability to successfully address and advocate for climate solutions. He spoke about "solution aversion," where people resist climate policies because proposed solutions are not framed in a way that aligns with their values. This highlighted the importance of inclusive, values-based communication - especially when incorporating AI into climate science and political landscapes.

Riley commented on AI in the climate science space from an Indigenous stakeholder and rightsholder perspective, using references and examples from the Indigenous data sovereignty movement. She emphasized that Indigenous Peoples have unique and deep knowledges about the environment through land stewardship, data collection, and data recording over millennia. At the heart of the Indigenous data sovereignty movement is ensuring the Indigenous Peoples to whom Indigenous data relate are determining how those data are used and shared, according to their own principles. She notes research findings that climate studies are more extractive of Indigenous knowledge rather than involving community engagement or collaboration[37]. One framework she offers is CARE (Collective benefit, Authority to control, Responsibility, and Ethics)[38] as well as detailing some inspirational examples of co-developing in the climate science and AI space. She also highlights the concern to make AI systems sustainable and circular in the risk of contributing to climate change with the energy and water requirements of AI. She concludes with thoughts on how to move forward, including reiterating thinking about sustainability, operating in the jurisdictions of Indigenous Peoples, importance of data sharing agreements, designing models from the ground up, culture of consent, and data governance.

The broader discussion revolved around how to engage diverse stakeholders in a relevant way, including those from a conservative viewpoint. Misinformation was identified as a concern, especially the risk that AI and LLMs can amplify partisanship by creating different sets of facts that can undermine collective climate action. Commonalities were found between farmworkers and indigenous communities, who both see the need for equitable solutions and entering into relationships where both farmworkers and indigenous voices are equally heard. Sunandan commented on the opportunity to expand how we design AI with multiple knowledge systems and the impact this can have on the perception of climate change or other issues. Ultimately, integrating diverse knowledge systems and rethinking/challenging how models are created will lead to a more inclusive and holistic climate AI field.

Session III: AI Explainability and Climate Science Innovation
Moderator: Mona Sloane
Presenters: **Philine Bommer**, Doctoral Researcher, ATB Potsdam, Germany; **Emily Gordon**, Postdoctoral Fellow, Stanford Data Science; **Zachary Labe**, Climate Scientist, Climate Central Inc.; and **Kirsten Mayer**, Project Scientist, National Center for Atmospheric Research (NCAR)

This session brought together ideas from the previous two sessions and discussed the importance of explainable and transparent AI in climate research.

Kirsten began the session by talking about how explainability and XAI has been used on the sub seasonal to seasonal timescale to explore sources of predictability. She explained her work using neural networks to examine whether model confidence could act as a proxy for identifying these periods of enhanced predictability. Layer-wise Relevance Propagation (LRP) (an XAI tool) was used to determine if confident predictions reflected physically meaningful phenomena; it is used to visualize what parts of the input data the model used in its predictions. She found that higher confidence correlated with higher accuracy, suggesting these periods could be considered forecasts of opportunity, or a “signal” in the chaotic earth system. Kirsten concluded with the provocation that while XAI has potential, it is not yet useful to the broader climate forecasting community until it is actually incorporated into improving forecasts.

Emily explored the challenges of decadal climate prediction. She highlighted key obstacles including limited observational records, complex interactions between oceanic, atmospheric, and land processes, and the difficulty of separating internal variability from anthropogenic climate change. Emily shared her own research addressing these problems using machine learning. She used models trained on simulated climate data to predict transitions in the Pacific Decadal Oscillation (PDO) and assess the contribution of internal variability to future warming predictions. Techniques like LRP and permutation importance testing help interpret machine learning models, and reveal that even under high climate forcing scenarios, internal variability still plays a role in prediction skill. Emily also highlighted results where machine learning models trained on global climate models (GCMs) can skillfully predict real-world observations without additional training. Emily concluded by questioning the need for a full, set description or definition of AI explainability or a more holistic, adaptive approach that works for a broader set of stakeholders.

Philine presented a broad overview of their work focused on targeted explainable AI (XAI) for climate science. They emphasize that XAI can help address four major needs in climate modeling: model validation, targeted model improvement, knowledge deduction, and model understanding. She highlighted these needs are critical for applications such as extreme weather forecasting or long-term climate prediction, but also to ensure models are grounded in physical principles and deliver results that people can trust. XAI builds trust by making model decisions transparent and interactive, allowing users to test how changes in input or policy might affect outcomes. However, challenges remain, including model diversity, task-specific explanation goals, and the complexity of choosing suitable XAI methods. To address this, Philine highlighted her creation of a plug-and-play Colab tool to explore different XAI techniques. Philine concluded by advocating for a human-in-the-loop approach, facilitated by using XAI tools in climate and weather forecasting to show reasons for decision making and open opportunities for targeted attributions.

Zack's presentation focused on the use of machine learning and XAI for climate change detection, attribution, and communication through climate services. He discussed the Climate Ready Nation initiative from NOAA; a system that provides information like weather forecasting but for climate data. He shared his work with artificial neural networks and XAI tools to identify and learn unique information for different climate scenarios. He highlighted the fact that these climate "fingerprints" can be used to detect when rapid climate mitigation efforts start influencing global conditions. The importance of regional information and two-way stakeholder engagement was emphasized. He notes that AI and climate science must collaborate with local communities to provide trusted data. He ends on the challenge of uncertainty and black box approaches to stakeholder understanding climate model information.

The discussion started off with a consensus on the lack of a clear definition of "explainability". The meaning varies based on the user and the context and can lead to confusion as to what XAI is accomplishing and fragmentation within the XAI field itself. Another challenge raised was user bias when interpreting and using these XAI methods; scientists should keep in mind their physical bias and consider using more than one method.

Questions were raised about the usefulness of XAI or AI at all when simple statistical tools such as compositing often suffice and has XAI actually helped scientists produce new knowledge or simply confirm what is already known. However, there were counterpoints made emphasizing the computational efficiency and flexibility of AI. For example, the ability to advance high resolution climate modeling, ability to integrate different data sources and communities, and the newness of the field, and highlighting perhaps unexpected patterns that prompt further human-led research. Ultimately, XAI holds potential for scientific and societal value, yet its use should be evaluated in specific contexts.

Reflection session
Moderator: Jonah Fogel
Panelists: **Susan Kruse**, Executive Director, The Community Climate Collaborative; **William Chapman**, Project Scientist, National Center for Atmospheric Research; **Erin Coughlan de Perez**, Research Director and Dignitas Professor, Tufts University; and **Jacob Rigby**, Assistant Professor, Department of Computer Science, University of York

This reflection session aimed to consider lessons learned, new insights, and future directions.

Across the three sessions, participants explored how AI can support climate science and action, while grappling with scientific, ethical, and collaboration challenges. Participants discussed how to meaningfully integrate AI into climate solutions by aligning those models with the lived realities of communities on the ground. A major theme was the importance of involving stakeholders, especially local communities, early in the development process to ensure tools are usable for said communities, relevant, and trustworthy. This engagement also helps to advance efficient, local climate action. Yet, this raises questions about roles and responsibilities: while some climate scientists are eager to engage, others argue this work lies outside the expertise of climate scientists and may be better suited to intermediaries or boundary organizations with the right training and support. Several panelists highlighted the need for structural changes in how science is performed and how funding works to enable this kind of interdisciplinary, user-centered work. The sessions also emphasized that AI should not be treated as a one-size-fits-all solution, it must be applied thoughtfully and in partnership with those most affected.

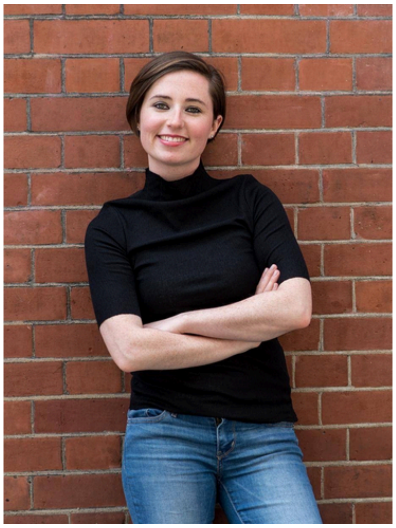
Overall, the conversations reflected an energized, interested, and hopeful community. The climate AI field is still in the early stages and the workshop highlighted some of the challenges faced as well as the urgent need and promise to forge inclusive access to climate AI innovation.

Team and Participants

Ava Birdwell is a graduate student at the University of Virginia in the McIntire School of Commerce, with a Biotechnology concentration. She completed her undergraduate degree in Environmental Sciences at UVA. Ava is committed to creating and inspiring positive environment change with community impact. She is dedicated using a variety of tools to address environmental challenges, including research, business, AI, education and advocacy. Ava is the graduate research assistant for the project: Broadening Access to Climate AI Innovation in the Sloane Lab.

Dr. Antonios Mamalakis is an environmental data scientist interested in exploring data science tools like statistical and Bayesian analysis, machine/deep learning, and explainable AI to solve challenges in environmental applications. Among others, these challenges include improving predictive skill of hydroclimate and extreme events, understanding climate teleconnections and predictability, advancing climate attribution and causal discovery, etc. Prior to joining UVA, he worked as a research scientist at Colorado State University, where he pioneered the investigation of the fidelity of explainable AI tools for applications in the geosciences. Some of his papers have garnered international attention and have been highlighted by publishers. Examples include "A new interhemispheric teleconnection increases predictability of winter precipitation in southwestern US," published in Nature Communications; "Zonally contrasting shifts of the tropical rain belt in response to climate change," published in Nature Climate Change; and "Underestimated MJO variability in CMIP6 models," published in Geophysical Research Letters. Antonios serves as an Associate Editor for the AMS journal "Artificial Intelligence for the Earth Systems." Mamalakis holds a Ph.D. in Civil and Environmental Engineering from University of California, Irvine, and a M.Sc. in the same major from University of Patras, Greece.

Dr. Charity Nyelele, an Assistant Professor of Environmental Sciences at the University of Virginia (UVA), bridges the gap between social and ecological sciences to address issues at the nature-people interface, particularly on biodiversity, climate change, and ecosystem services. Her current research is on forested systems, primarily in urban areas, evaluating the effects of planning and management strategies on ecosystem service demand and supply, trade-offs and synergies among services, climate resilience, and priority areas for forest restoration. She is also interested in the science-policy interface and was an Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services (IPBES) fellow on the Nexus Assessment, generating the scientific knowledge to inform global policy action on issues related to biodiversity, water, food, health and climate change. Charity, a Fulbright alumna, earned her PhD in Environmental Science from the State University of New York, College of Environmental Science and Forestry (SUNY-ESF). Prior to joining UVA, she was a post-doctoral researcher in the Department of Earth System Science at the University of California, Irvine.



Dr. Mona Sloane is an Assistant Professor of Data Science and Media Studies at the University of Virginia (UVA). As a sociologist, she studies the intersection of technology and society, specifically in the context of AI design, use, and policy. At UVA, she is a Faculty Co-Lead in the Digital Technology for Democracy Lab at the Karsh Institute of Democracy, Affiliated Faculty with the Department of Women, Gender and Sexuality, and Faculty Affiliate with the Thriving Youth in a Digital Environment (TYDE) research initiative. She also convenes the Co-Opting AI series and serves as the editor of the Co-Opting AI book series at the University of California Press as well as the Technology Editor for Public Books. Mona's growing research group Sloane Lab conducts empirical research on the implications of technology for the organization of social life. Its focus lies on AI as a social phenomenon that intersects with wider cultural, economic, material, and political conditions. The lab spearheads social science leadership in applied work on responsible AI, public scholarship, and technology policy. More here: monasloane.org.

Alice Alpert, Senior Scientist, Environmental Defense Fund

Dr. Alpert leads an initiative to characterize and address chokepoints in realizing the potential of climate mitigation technologies in the Office of the Chief Scientist, at the Environmental Defense Fund (EDF). She also works closely with the Methane, Climate, and International Cooperation work streams, leveraging international scientific climate assessments and institutions to support climate change mitigation. Dr. Alpert previously served in the U.S. Department of State for nearly 6 years in the Office of Global Change including supporting Special Presidential Envoy for Climate John Kerry and Special Envoy for Climate Change Jonathan Pershing. She represented the United States at the Intergovernmental Panel on Climate Change throughout its 6th Assessment Cycle. She was the lead U.S. negotiator for the Global Stocktake process of the Paris Agreement and the Periodic Review under the United Nations Framework Convention on Climate Change. She also served as the U.S. focal point to the Climate and Clean Air Coalition and head of delegation to the Arctic Council's Expert Group on Black Carbon and Methane. She was instrumental in the development and launch of the Global Methane Pledge at COP27 in 2021.

Tom Beucler, Assistant Professor of Environmental Data Science, University of Lausanne, Switzerland

Dr. Tom Beucler's broad interests span atmospheric physics, deep learning, climate informatics, and environmental fluid dynamics. He combines statistics, theory, numerical simulations, and observational analyses to improve the understanding of meteorology and climate, and to guide the development of operational models of storms and clouds. Tom previously served as an assistant project scientist in atmospheric science affiliated with the University of California, Irvine, and Columbia University. He collaborated with Michael Pritchard and Pierre Gentine to integrate deep learning and atmospheric physics, helping to develop the first operational neural-network representation of storms and clouds in climate prediction models. During his PhD, Tom worked at the Lorenz Center at MIT with Timothy Cronin and Kerry Emanuel to investigate the dynamics of storms, radiation, and their interactions with atmospheric water in the Tropics.

Philine Bommer, Doctoral Researcher, Data Science in Bioeconomy, ATB Potsdam, Germany

Philine is interested in Deep Learning, Explainable AI, scientific data evaluation and environmental science. She is working towards developing explainable AI solutions, which are targeted towards the application in scientific data analysis. Her work focuses specifically on environmental and climate science. In these fields she assesses the application of XAI solutions to gain new scientific insight in climate and how to develop XAI methods to enable the transparent application of AI.

Ann Bostrom, Weyerhaeuser Endowed Professor in Environmental Policy, Evans School of Public Policy and Governance, University of Washington

Dr. Bostrom researches risk perception, risk communication, and decision-making under uncertainty, with a focus on mental models of hazardous processes. Her projects include interview, survey and experimental research on perceptions, communication and decision making about climate change, earthquake early warning, and extreme weather forecasts and warnings. Dr. Bostrom is the Weyerhaeuser endowed Professor of Environmental Policy at the Daniel J. Evans School of Public Policy and Governance, University of Washington. She earned her PhD. in Policy Analysis from Carnegie Mellon University, her M.B.A from Western Washington University, and her B.A. in English from the University of Washington.

Natalie Burls, Associate Professor; Director, Climate Dynamics Program, University of George Mason

Dr. Natalie Burls's research is focused on improving our understanding of the key processes determining Earth's climate and climate variability on a variety of timescales: seasonal; decadal; and longer geological scales. In particular, Dr. Burls is interested in the climatic role of ocean general circulation, ocean-atmosphere interaction and cloud dynamics. Her research efforts acknowledge that, to fully understand, model and predict changes in climate characteristics that have a large impact on society, a fully coupled ocean-atmosphere perspective is needed – one that accounts for changes in important variables such as the thermal structure of the slowly-adjusting ocean. Natalie endeavors to accompany complex simulations of climate phenomena with simple models capturing the essential dynamics required to explain unanswered questions within climate science. Dr. Burls received her PhD in Physical Oceanography from the University of Cape Town in 2010. From 2011 to 2014, she worked as a postdoctoral associate in the department of Geology and Geophysics at Yale University. Dr. Burls joined George Mason as an assistant professor in January 2015.

Sunandan Chakraborty, Program Director, Undergraduate Artificial Intelligence. Associate Professor of Data Science, Luddy School of Informatics, Computing, and Engineering, Indiana University Indianapolis

Sunandan Chakraborty focuses on data science for social good. He applies computational models that leverage vast data sets to a broad spectrum of problems in social and environmental science, agriculture, health, and other fields. He draws on diverse data sets (news, social media, images, etc.) and uses tools such as big data analytics, machine learning, information extraction, and time series analysis to compile information and discover knowledge that can lead to solutions. Before coming to the Luddy School, Dr. Chakraborty worked with Jennifer Jacquet as a Moore-Sloan postdoctoral researcher at the NYU Center for Data Science. Their award-winning research explored the problem of illegal online wildlife trading, utilizing complex digital text analyses. Dr. Chakraborty was part of the Big Data Group and the Center for Technology and Economic Development while earning his doctorate. He did his research under the supervision of Lakshminarayanan Subramanian at the Courant Institute of Mathematical Sciences of New York University.

William Chapman, Project Scientist, National Center for Atmospheric Research

Dr. William Chapman is broadly interested in the processes that inform weather and climate predictability. Currently, Will is an ASP Post-Doctoral Fellow at the National Center for Atmospheric Research and a Post-Doctoral Researcher with the Multiscale Machine Learning in Coupled Earth System Modeling project (M2Lines). His work focuses on examining regional climate model biases through data assimilation increments and developing online corrections using modern machine learning methods. Will recently graduated from the Scripps Institution of Oceanography, where his dissertation centered on improving the understanding of North American West Coast weather predictability using Deep Learning techniques and the theoretical study of long-range weather predictability. He is particularly interested in numerical weather prediction post-processing and leveraging large ensemble simulations to identify forecast windows of opportunity. Currently, he is developing methods and schemes to enhance extreme weather event predictability at subseasonal timescales. His Ph.D. advisor team included Dr. Shang-Ping Xie and Dr. Marty Ralph, and he is a team member at the Center for Western Weather and Water Extremes.

Erin Coughlan de Perez, Research Director and Dignitas Professor, Friedman School of Nutrition, Tufts University. Senior Advisor, Red Cross Red Crescent Climate Centre

Erin bridges science, policy, and practice in her research on climate risk management around the world. She focuses on extreme events, exploring how droughts, floods, heatwaves, and other climate shocks can be anticipated before they happen. Erin works with humanitarian teams to develop early action protocols to avoid disaster impacts, and she researches the adoption and effectiveness of climate change adaptation measures. Erin comes to the Feinstein Center from the Red Cross Red Crescent Climate Centre, where she built a global climate science team and led the first Forecast-based Financing pilots in the Red Cross Red Crescent Movement. Erin retains a senior advisor position at the Climate Centre, to maintain links to humanitarian operations around the world. Erin was formerly an Associate at Columbia University. Erin is also a lead author of the Intergovernmental Panel on Climate Change (IPCC) 6th Assessment Report. Her chapter is Decision-Making Options for Managing Risk, as part of the Working Group II on Impacts, Adaptation, and Vulnerability. Erin received her Ph.D. from Vrije Universiteit Amsterdam, her M.A. in climate and society from Columbia University, and her B.S. in environmental science and international development from McGill University.

Noah Diffenbaugh, Kara J Foundation Professor and Kimmelman Family Senior Fellow, Stanford Doerr School of Sustainability

Dr. Noah Diffenbaugh studies the climate system, including the processes by which climate change could impact agriculture, water resources, and human health. Dr. Diffenbaugh has served the scholarly community in a number of roles, including as the inaugural Editor-in-Chief of the peer-reviewed journal Environmental Research: Climate, and as Editor-in-Chief of Geophysical Research Letters from 2014-2018. He has also served as a Lead Author for the Intergovernmental Panel on Climate Change (IPCC), and has provided testimony and scientific expertise to Federal, State and local officials. Dr. Diffenbaugh is an elected Fellow of the American Geophysical Union (AGU), a recipient of the James R. Holton Award and William Kaula Award from the AGU, and has been recognized as a Kavli Fellow by the U.S. National Academy of Sciences. He is currently the Kara J Foundation Professor and Kimmelman Family Senior Fellow in Stanford's Doerr School of Sustainability, and the Olivier Nomellini Family University Fellow in Undergraduate Education. Dr. Diffenbaugh leads the Climate and Earth System Dynamics Group at Doerr where their research takes an integrated approach to understanding climate dynamics and climate impacts by probing the interface between physical processes and natural and human vulnerabilities.

Jeannie Economos, Coordinator of pesticide health and safety, Farmworker Association of Florida. Co-coordinator of Lake Apopka Farmworker Memorial Quilt Project

Jeannie has worked for over 20 years on issues of the environment, environmental justice, indigenous and immigrants' rights, labor, peace, and social justice. From 1996-2001, she worked for the Farmworker Association of Florida as the Lake Apopka Project Coordinator, addressing the issues of job loss, displacement, and health problems of the farmworkers who worked on the farmlands on Lake Apopka prior to the closing of the farms in 1998. Since 2007 she has been the coordinator of the pesticide health and safety program of the organization, which includes annually training over 500 farmworkers in Florida on their rights and protections in the workplace and how to protect themselves and their families from pesticide exposure. She is also engaged in local, state, national, and international coalitions and collaborations related to farmworker rights and health and safety, pesticide reduction, sustainable agriculture, and food sovereignty. She is currently co-coordinator of the Lake Apopka Farmworker Memorial Quilt Project whose purpose is to raise awareness about the impacts of pesticides on the former farm workers on Lake Apopka.

Jonah Fogel, Research and Engagement Program Manager, UVA Environmental Institute

Dr. Jonah Fogel leads the UVA Environmental Institute's core seed funding programs, performance management system, and student engagement programs. He works closely with students, faculty, and university administration facilitating research development activities that attract extramural research funding, create relationships, and increase institutional competitiveness. Jonah works regularly with a wide variety of internal and external partners translating research through outreach and training activities. Jonah holds a PhD in Natural Resource Management, a Master's of Landscape Architecture, and a BS in Hydrogeology. He's taught at a graduate level and has extensive experience in public administration, land use planning, and solar energy policy.

Pierre Gentine, Maurice Ewing and J. Lamar Worzel Professor of Earth and Environmental Engineering, Columbia University. Director, Learning the Earth with AI and Physics (LEAP) NSF Science and Technology Center

Dr. Pierre Gentine and his group investigate the multiscale nature of the continental hydrologic and carbon cycle, with observations (remote sensing and in situ), models and machine learning. He is a Professor in the department of Earth and Environmental Engineering and in the department of Earth and Environmental Sciences at Columbia University. He is director of the National Science Foundation Science and Technology Center "Learning the Earth with Artificial intelligence and Physics" and a director of the Graduate Program in Earth and Environmental Engineering. Dr. Gentine received his undergraduate degree from SupAéro, in France. He earned his PhD in Civil and Environmental Engineering at MIT in 2010. He joined the faculty at Columbia in 2010 as an instructor in applied mathematics and then as a tenure track assistant professor in Earth and Environmental Engineering in 2011.

Bob Inglis, Executive Director, republicEn.org

Bob Inglis is the Executive Director of republicEn.org, a growing group of conservatives who care about climate change. He served in the U.S. Congress from 1993 to 1999 and again from 2005-2011, a Republican representing Greenville-Spartanburg, South Carolina. On leaving Congress Inglis went full-time into promoting free enterprise action on climate change, launching a 501(c)(3) educational initiative now based at George Mason University and known as republicEn.org. For his work on climate change Inglis was given the 2015 John F. Kennedy Profile in Courage Award. He appears in the film Merchants of Doubt, in the Showtime series Years of Living Dangerously (episodes 3 and 4), and has given TED Talks on political courage and on his metamorphosis on climate change. Inglis was a Resident Fellow at Harvard University's Institute of Politics in 2011, a Visiting Energy Fellow at Duke University's Nicholas School of the Environment in 2012, and Resident Fellow at the University of Chicago's Institute of Politics in 2014.

Lydia Jennings, Assistant Professor of Environmental Studies, Dartmouth College

Dr. Lydia Jennings (she/her) is an environmental soil scientist. Lydia, citizen of the Pascua Yaqui Tribe (Yoeme) and Huichol (Wixáritari), earned her Bachelors of Science from California State University, Monterey Bay in Environmental Science, Technology and Policy. She completed her Ph.D. at the University of Arizona in the Department of Environmental Sciences, with a minor in American Indian Policy. Her research interests are in soil health, environmental data stewardship and science communication. Lydia is a 2014 University of Arizona NIEHS Superfund Program trainee, a 2015 recipient of National Science Foundation's Graduate Research Fellowship Program, a 2019 American Geophysical Union "Voices for Science" Fellow, a 2020 Native Nations Institute Indigenous Data Sovereignty Fellow, and a 2021 Data Science Fellow. Lydia was a Presidential Postdoctoral Fellow at Arizona State University (School of Sustainability) and Research Fellow at Duke University (Nicholas School of the Environment) prior to her current role as an Assistant Professor in Environmental Studies at Dartmouth College.

Susan Kruse, Executive Director, Community Climate Collaborative (C3)

Susan has been advocating for environmental protection and justice for 25 years. After launching the Allegheny Defense Project in her native Pennsylvania in 1994, Susan helped to found the National Forest Protection Alliance and joined the staff as the Eastern Field Coordinator. She led their federal legislative efforts to protect national forests before ultimately serving as the organization's executive director. In 2006, Susan pursued her passion for philanthropic work and became the Director of Development for the Legal Aid Justice Center in Charlottesville, Virginia. After 10 years of growing Legal Aid's development program and becoming a major gifts specialist, Susan returned to environmental work in 2016 to join Appalachian Voices as their Director of Philanthropy. Excited to merge her passion for the planet and the community she loves, Susan became C3's executive director in 2019. She was appointed to Virginia's Clean Energy Advisory Board for a three-year term by Governor Ralph Northam in 2019, and she was named in Virginia Business Magazine's list of 100 people to meet in 2022 as an Impact Maker in Virginia. Susan is a graduate of Clarion University in Pennsylvania.

Zachary Labe, Climate Scientist, Climate Central Inc.

Zachary Labe is an atmospheric scientist trying to disentangle the signal from a lot of noise in the Earth system. His research interests coincide with identifying patterns of climate change from climate variability using data-driven methods. Dr. Labe also spends a lot of time thinking about improving science communication and accessibility through storytelling with engaging visualizations. He received his Ph.D. in 2020 from the Department of Earth System Science at the University of California, Irvine. His thesis focused on using observations and global climate model experiments to identify linkages between Arctic climate change (especially due to sea-ice loss) and the extratropical large-scale atmospheric circulation. Dr. Labe completed postdocs in the Atmospheric and Oceanic Sciences Program at Princeton University and the Department of Atmospheric Science at Colorado State University on research related to explainable artificial intelligence (XAI) methods as a new method of detecting regional patterns of climate change and variability. He completed an undergraduate degree at Cornell University and received a B.Sc. in Atmospheric Sciences in 2015.

Xiaoyue Li, Traditional Knowledge Consultant, Wildlife Conservation Society

Dr. Xiaoyue Li is an environmental anthropologist specializing in Indigenous knowledge systems and climate adaptation. She currently serves as a Traditional Knowledge Consultant at the Wildlife Conservation Society and will join Southern Methodist University as an Assistant Professor of Anthropology in Fall 2025. Her research explores how traditional ecological knowledge interfaces with contemporary climate challenges, with a focus on Indigenous climate monitoring systems and wild food resources. Through fieldwork across multiple Indigenous communities including the Akha and Nuosu peoples in Asia and the Tanalana in Madagascar, she investigates how traditional knowledge systems can inform climate adaptation strategies and enhance conservation outcomes. Her work bridges diverse knowledge traditions to create more effective and equitable climate solutions. Dr. Li has contributed to major international assessments including the IPCC 6th Assessment Report and the IPBES Assessment of Sustainable Use of Wild Species. Previously, she worked as a research consultant at the American Museum of Natural History's Center for Biodiversity and Conservation and Integrated Natural Resource Management at USAID. She also held a postdoctoral position at the Universitat Autònoma de Barcelona and worked as research consultant for UNESCO's Man and the Biosphere Programme. She earned her Ph.D. in Applied Anthropology from Oregon State University in 2017.

Madhav Marathe, Executive Director, Distinguished Professor of Biocomplexity, Professor of Computer Science

Dr. Marathe is a passionate advocate and practitioner of transdisciplinary team science. His areas of expertise include digital twins, network science, artificial intelligence, multi-agent systems, high-performance computing, computational epidemiology, biological and socially coupled systems, and data analytics. Currently, Madhav Marathe is an endowed Distinguished Professor of Biocomplexity, Executive Director of the Biocomplexity Institute, and a tenured Professor of Computer Science at the University of Virginia. His prior positions include Professor of Computer Science and Director of the Network Dynamics and Simulation Science Laboratory within the Biocomplexity Institute of Virginia Tech and a team leader of research and computing in the Basic and Applied Simulation Science Group, Computer and Computational Sciences Division at the Los Alamos National Laboratory. He is a Fellow of the American Association for the Advancement of Science (AAAS), Society for Industrial and Applied Mathematics (SIAM), Association for Computing Machinery (ACM), and Institute of Electrical and Electronics Engineers (IEEE). Dr. Marathe has published more than 500 articles in peer-reviewed journals, conferences, and workshops. Mentoring and training next-generation scientists has been his lifelong passion.

Kate Marvel, Research Physical Scientist, NASA Goddard Institute for Space Studies

Kate Marvel is a climate scientist at Columbia University and the NASA Goddard Institute for Space Studies. She studies climate forcings (things that affect the planet's energy balance) and feedbacks (processes that speed up or slow down warming). Her work has contributed to understanding that observational estimates of the Earth's sensitivity to greenhouse gases are probably biased low and that human influences are already apparent in global drought patterns, cloud cover, and in the timing and amount of regional rainfall. She received a PhD in theoretical physics from Cambridge University and has worked at Stanford University, the Carnegie Institution, and Lawrence Livermore National Laboratory. Kate writes the Hot Planet column for Scientific American and essays for On Being and Nautilus Magazine. She’s given talks in places as diverse as comedy clubs, prisons, and the TED main stage.

Kirsten Mayer, Project Scientist, National Center for Atmospheric Research (NCAR)

Dr. Mayer's research interests include S2D predictability, tropical-extratropical teleconnections, large scale climate variability, machine learning, and eXplainable and Interpretable Artificial Intelligence (XAI/IAI). As a Project Scientist I at NSF NCAR in the Climate and Global Dynamics Laboratory, she researches how explainable and interpretable machine learning algorithms can be used to enhance (our understanding of) Earth system predictability. She obtained her PhD and MS in Atmospheric Sciences at Colorado State University in 2022 and 2019 respectively, focused on the application of neural networks to subseasonal to seasonal predictability in present and future climates. She received her B.S. in Atmospheric & Oceanic Sciences at the University of Wisconsin, Madison in 2017.

Karen McKinnon, Associate Professor of Statistics and the Environment, University of California Los Angeles

Karen McKinnon studies large-scale climate variability and change, with a particular focus on connections to high-impact weather events. Her most recent work is modeling and understanding internal variability in surface temperature and precipitation, the predictability of extreme events, and the joint behavior of temperature and humidity in a changing climate. She is interested in developing novel statistical and computational methods to optimally gain insight from historical observations, climate model simulations, and the paleo proxy record, as well as linking climate science insights to actionable changes. Before joining UCLA in November of 2018, Karen was an Applied Scientist at Descartes Labs, and an Advanced Study Program post-doctoral fellow at the National Center for Atmospheric Research. She received her PhD in 2015 from Harvard, working with Peter Huybers. Her work on predictability of heat waves has been covered by news outlets including the New York Times, Fox News, and the Washington Post.

Jacob Rigby, Assistant Professor, Department of Computer Science, University of York

Dr. Jacob Rigby joined the Department of Computer Science at the University of York as a lecturer, specialising in Human-Computer Interaction in September 2024. Previously, he was a postdoctoral researcher at the University of Bristol, working on multiple projects investigating how to deliver climate and weather information to different users in East Africa. Jacob gained his doctorate in HCI at University College London, focusing on emergent video consumption behaviours. This included a placement as a research assistant at the Interactive Technologies Institute in Madeira, Portugal. Before that he completed an MSc in research and BSc in computer science at the University of Durham. Dr. Rigby's current research interests include: Human-computer interaction, climate and weather services, ICT/HCI for development, climate change adaptation, immersive media.

Riley Taitingfong, Luce Foundation Postdoctoral Researcher, University of Arizona Native Nations Institute

Riley Taitingfong (CHamoru) is a researcher and educator working on issues of environmental justice, Indigenous self-determination, emerging technologies, and community engagement. She completed her PhD in Communication at the University of California San Diego, where her project focused on Indigenous governance of genetic engineering technologies known as gene drives. Riley is currently a postdoctoral researcher with Udall and the Native Nations Institute, working on the implementation of CARE Principles of Indigenous Data Governance within data repositories. As a CHamoru researcher, Riley is committed to building cross-movement solidarity among Indigenous communities from Oceania to Turtle Island.

Pooja Tilvawala, Founder & Executive Director of Youth Climate Collaborative

Pooja is a rising leader in climate justice and intergenerational equity. As the Founder and Executive Director of Youth Climate Collaborative, she creates pathways for youth worldwide to realize their full potential in climate leadership. Her team has supported thousands of youth with programs that increase their access to climate mental health resources, housing and passes to attend life-changing convenings, media training to effectively communicate their climate stories, technical support to accelerate their initiatives, and more. She is also the Founder and CEO of Jaali, a soon-to-launch digital social impact platform, which leverages AI to connect changemakers of all ages with each other, funders, and opportunities to advance their action, democratize information sharing, and strengthen collaboration for the Sustainable Development Goals. In addition, in 2023 she co-founded the Entertainment + Culture Pavilion, and has since co-organized over 230 events across 7 cities to mobilize a global movement for culture-based climate action. Further, she helps design climate grant programs, advises organizations on youth engagement and strategy, and is conducting innovative research to create a guidebook of intergenerational decision-making models to encourage their wide adoption across sectors.

Rebecca Young, Director of Programs, Farmworker Justice

Rebecca joined Farmworker Justice in Washington, DC in 2010 and currently serves as the Director of Programs. Rebecca engages farmworker communities across the country and finds continued inspiration for her work through the stories the farmworkers and their families so willingly share. Through her work in program management and training and curriculum development, Rebecca works with promotores de salud (health outreach workers) on health content areas like pesticide safety, heat stress prevention, and HIV/AIDS awareness to name just a few. Her work in these areas is steeped in the philosophy of popular education which allows for participants of a wide variety of educational, cultural and linguistic backgrounds to understand and interact with training content in a meaningful and memorable way. Prior to joining Farmworker Justice, Rebecca worked seven years at a language school and bookstore/cafe that catered to after-school projects for kids and literacy projects for women. Rebecca holds a MA in Sustainable Development and Social Justice from the School for International Training and Bachelor of Arts in Anthropology and English from Bowdoin College.

Endnotes

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