Data Brief

Assessing the Global Research Landscape at the Intersection of Climate and AI

Author
Joanna Lewis
Autumn Toney
Xinglan Shi

CSET CENTER *for* SECURITY *and* EMERGING TECHNOLOGY

November 2023

Table of Contents

Introduction

Artificial Intelligence (AI) has the potential to revolutionize approaches to climate change research by rapidly advancing problem solving and formulating solutions. Scholars have begun to analyze the potential role that AI could play in addressing global climate change, both through improving our scientific understanding of the causes and impacts of climate change and by helping to develop solutions.[1] There are increasing applications of how AI and machine learning can be used to improve the accuracy of climate system modeling,[2] fill time series data gaps,[3] estimate emissions inventories,[4] refine climate scenario projections[5] and assess climate impact,[6] as well as develop systems for low carbon technology deployment through power, transportation and building system optimization.[7] While we have a general sense of the scope of climate change research undertaken,[8] and studies have previously laid out the potential for AI to improve climate research and enable the achievement of global sustainable development goals,[9] no studies to date have taken a systematic and comprehensive approach to characterizing the way in which AI is intersecting with climate change research at a large scale.

This Data Brief aims to address this information gap by mapping the production of research publications at the intersection of climate change and AI to understand how AI methods are being applied to climate[*] related research. As China and the United States emerge as the largest sources of research being conducted at this intersection, we dig deeper to explore the role of Chinese research institutions and funders in the context of global climate research using AI methods, and how China's applications in climate research compare to those being used in the United States.

Key findings include:

- Chinese research institutions lead the world in publication output and observable research funding at the intersection of climate and AI, followed by the United States.
- The EU-27, UK, and India follow China and the United States in climate research publications generally, while India, the EU-27, and South Korea follow China and the United States in research publications on climate and AI.
- Climate change research areas such as climate modeling, climate impact, and energy technologies make use of a wide range of AI techniques, whereas other areas such as transportation and energy trends have fewer AI implementations.

[*] Throughout this report "climate" and "climate change" are used interchangeably.

- There appear to be publication gaps in certain climate research areas where AI tasks and methods are not as widely used and where there may be useful applications. Exploring these gaps is a proposed area for future research.
- The U.S. is more involved in global collaboration efforts among the research clusters in the climate and AI research domain than China.

As a result, the findings of this research can directly inform U.S. innovation policy, climate policy and security policy, all of which are increasingly interconnected. In addition, China's activities at the intersection of AI technology and climate change technology have direct national security implications for the United States. [10] Both sectors, AI and climate technologies, have been identified as key areas of strategic competition between the United States and China.[11]

Background

AI simulations and machine learning are being integrated into weather and climate modeling, including emulating and forecasting weather patterns and climate processes with greater consistency, data efficiency, and improved generalization.[12] AI is used in flood risk modeling frameworks to increase the performance and accuracy of prediction methods.[13] Using neural networks for weather and climate modeling has improved agriculture and crop yield predictions under a range of climate scenarios,[9] and machine learning algorithms have been applied in areas such as monitoring soil quality, managing crops, and modeling evapotranspiration, rainfall, drought, and pest outbreaks.[14]

AI algorithms are increasingly being used for improving the efficient management natural resources. For example, combining deep learning with statistical techniques could create more useful assessments of the impact of deforestation on rising carbon emissions in metropolitan areas.[15] In addition, machine learning approaches are being applied in developing renewable energy materials,[16] including in concrete and steel production to improve supply chain optimization for heavy industries.[17] AI frameworks have been applied to minimize water consumption and emissions from oil and gas reservoirs, while other research has demonstrated methods using machine learning in assessing the carbon footprint of buildings. [18]

Many studies have used AI methods in renewable energy research and demonstrated the increasing number of use cases for integrating AI into renewable energy systems. AI techniques are becoming a key tool in deploying data-integrated renewable energy networks,[19] estimating and forecasting solar radiation resources,[20] and wind energy resources,[21] as well as in micro-grid management.[22] Additionally, AI has been shown to be a powerful tool to assess and develop carbon markets and generate more accurate carbon price models, including dynamic carbon pricing mechanisms,[23] and more robust comparison models for carbon price forecasting. [24] Such methods have been applied to studies of emissions trading schemes including in China[25] and the UK.[26]

The use of AI to further climate change research is also reflected in policy. For example. the Chinese government has issued explicit guidance on the use of AI in climate research in the “Meteorological Science and Technology Development Plan (2021-2035)” issued by the Ministry of Science and Technology and Chinese Academy of Sciences in March 2022.[27]

Identifying Climate Change and AI Research in CSET's Map of Science

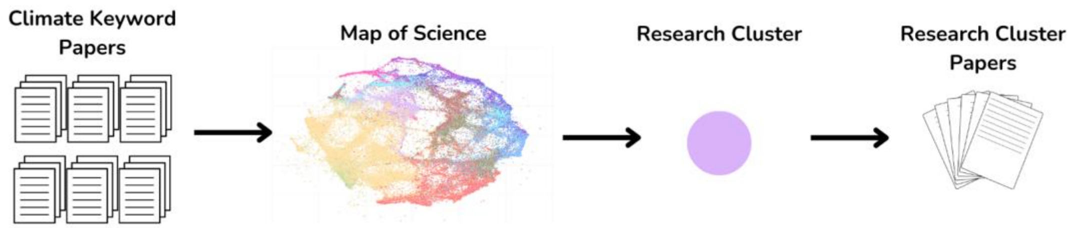
In order to map the production of research publication at the intersection of climate change and AI, we use the CSET merged corpus of scholarly literature,[28] which includes Digital Science's Dimensions, Clarivate's Web of Science, Microsoft Academic Graph, China National Knowledge Infrastructure, arXiv, and Papers with Code. CSET's Map of Science provides more than 120,000 research clusters derived from citation relationships within this merged corpus.[29] Research clusters are groupings of scholarly documents based on citation links, not on topic similarity or author networks; thus, research clusters are groupings of scientific publications that address similar research questions. Each research cluster includes a set of research publications and aggregated metadata generated from the constituent publications, such as, key areas of research (fields and topics), key researchers in the field, and key funders.

We perform our analysis by identifying climate change related research papers via a keyword search, linking the publications to their research clusters, and then analyzing research clusters of interest.

Figure 1 illustrates our data collection pipeline, starting with a set of keyword publications and ending with a set of research clusters and their member publications. Each dot in the map of science represents a research cluster and is colored by its broad area of research.

This data collection pipeline enables us to find research clusters of interest by locating climate change research publications in the Map of Science. We can then look at a subset of research clusters of interest and analyze aggregate statistics from their member papers. We generated a scientific research corpus of climate change literature using a regular expression search in English and Chinese, including terms for climate change, global warming, carbon emissions and low carbon (see Appendix for full list). If a publication contains one of the terms in its title or abstract it is included in our climate change publication set.

Figure 1. Data Collection Pipeline Using CSET's Merged Corpus and Map of Science



Source: Author's rendering of high-level process

Linking the climate change publications to research clusters, we identify 2,351 research clusters with 5% or more concentrations of climate change keyword publications to generate a set of climate-related clusters.[30] Next, we further scope our research clusters of interest by identifying clusters with high percentages of AI-related publications. We use the AI percentage from the Map of Science, which identifies the concentration of AI-related publications in a given cluster[31]. AI relatedness in English language publications is classified using a model trained on arXiv publications,[32] and Chinese-language publications are classified using a regular expression query.[33] By selecting research clusters that have both 5% or more concentrations of climate change related publications and AI-related publications we identify 111 research clusters to analyze from the starting set of 2,351 climate change clusters.

Figure 2 displays the full Map of Science and the two subsets (climate change and climate change and AI) of research clusters we identify highlighted within it.

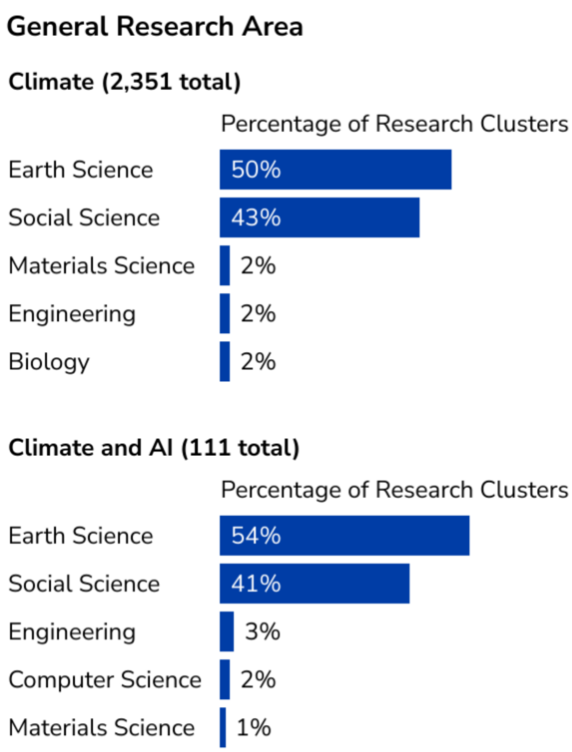
Figure 2. Climate Change and Climate Change AI Research Clusters Highlighted in the Map of Science

Source: CSET Map of Science

Characterizing the Climate and AI Research Landscape

In order to contextualize the landscape of climate change and AI research, we compare the general research fields and countries of publication for each research cluster set. Each research cluster is assigned a broad discipline,[34] which represents the majority of member papers in a given research cluster, and does not indicate that every member paper falls unambiguously under this area. Figure 3 displays the percentages of climate change related research clusters by their general discipline (displaying discipline areas that have at least 1%).

Figure 3. Comparison of Climate and Climate + AI Research Clusters by Discipline



Source: CSET Research Clusters

The climate change research cluster set is comprised of 50% earth science publications and 43% social science publications, and also includes materials science, engineering and biology publications. In contrast, the climate change and AI dataset is comprised of 54% earth science and 41% social science publications, along with some engineering, computer science and materials science publications. While there is not a huge difference in fields between climate change research and the climate change and AI research subset, biology drops off and is replaced by computer science in the second category as a related field.

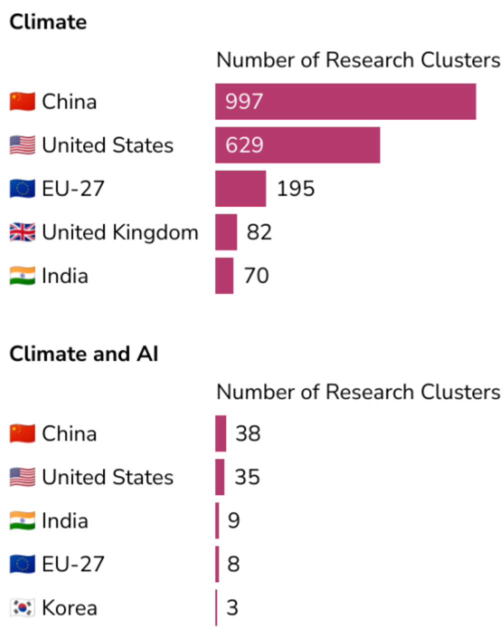
Articles at the intersection of climate change and AI research include multiple disciplines from both the natural and social sciences. While the earth sciences dominate the research clusters identified, this is very closely followed by the social sciences. It is somewhat surprising that engineering and computer science do not show up in greater percentages in this area, likely because most climate change related research is in fact not being done in these fields, but rather the models and techniques are being applied by climate researchers in their respective fields. A potential limitation of these categorizations, however, is that much of this work is interdisciplinary and may in fact span the natural and social sciences.

Each research publication is assigned to specific countries using the location of the organization that an author is affiliated with. This means that if there are multiple authors from different countries, a given publication will have multiple countries assigned. For all member publications in a given research cluster, a "top country" categorization is assigned based on the country being listed on the most publications in that research cluster. We treat all EU-27 countries as one entity due to their high rates of collaboration and research funding allocation. Figure 4 displays the top five leading countries by research cluster count.

We find that China produced more research in our climate research clusters and climate and AI research clusters, with U.S. authors producing the second highest number of research in both sets. It is perhaps not surprising given China's role in climate change research, and its strong role in AI research.[35] Yet China has a more sizable publication output lead in climate change research generally than in climate and AI research.

The other countries that produce significant climate and AI research outputs differ from those that produce more climate research generally. On general climate change research, the EU-27, UK, and India follow China and the United States. Whereas, the order shifts somewhat on research at intersection of climate change and AI with India, the EU-27, and South Korea following China and the United States.

Figure 4. Comparison of Climate and Climate and AI Research Clusters by Top Country



Source: CSET Research Clusters

Due to the publication output lead that China and the U.S. hold, we further refine our set of 111 climate change and AI research clusters to the 67 clusters that have either China or the U.S. listed as the top country and have on average more than 2 citations per paper to filter for clusters with community engagement.

AI Tasks and Methods Used in Climate Change Research

In order to better understand how specific AI tasks and methods are being applied within specific climate change-related research, we examine the leading AI and climate change tasks and methods by cluster at the individual publication level. To identify the AI-related tasks and methods we use the assignments made by a named entity recognition model trained on AI and machine learning (AI/ML) tasks and methods identified and listed in Table 1.[36] We then assign each cluster the top five most frequently appearing AI/ML tasks and methods across its member publications, similar to the general discipline assignment.

To identify the climate change-related tasks and methods, we analyze the most frequently appearing keywords and phrases, most cited papers, and review papers for each cluster. We manually assign it a climate change subfield of research derived from the top extracted keyword or phrase. In this way, each research cluster is assigned the most frequent AI tasks and methods and a top climate change subfield. We construct Table 1 by denoting the AI and climate change tasks, methods, and subfields that co-occur across the 67 research clusters of interest (see Appendix for more details). Table 1 only displays co-occurrence and not frequency.

Table 1. Mapping AI Tasks and Methods within Climate Change Research Subfields

	Causal Interference	Computer Vision	Graphs	Methodology	Natural Language Processing	Neural Networks	Reinforcement Learning	Robots	Time Series
Climate Impacts	✓	✓			✓	✓		✓	✓
Climate Modeling		✓	✓			✓		✓	✓
Emissions Trends						✓		✓	✓
Energy Efficiency		✓				✓		✓	
Energy Technologies		✓		✓	✓		✓		
Energy Trends				✓					
Land Use Change		✓				✓	✓		
Public Perception					✓				
Transportation				✓		✓			

Source: CSET Research Clusters

In Table 1 we see a wide range of AI tasks and methods being applied to the 9 climate research areas that we extract from our climate and AI research cluster dataset. For example, we identify six AI tasks and methods being used in studies of climate impacts, including causal interference, computer vision, natural language processing, neural networks, robots and time series. Studies involving climate modeling are using at least five AI tasks and methods including computer vision, graphs, neural networks, robots and time series.

This analysis also reveals some areas of climate research that are using fewer AI tasks and methods. While energy technologies research is using multiple methods, including computer vision, AI methodology, natural language processing, and reinforcement learning, we see other areas of energy research such as energy trends studies and public perception studies using fewer methods. As a result, there appear to be gaps in certain climate research areas where AI tasks and methods are not being used as widely and where there may be useful applications. Exploring these gaps identified in Table 1 is an area for future research.

Leading Institutions and Funders

In order to identify research institutes with the highest global publication output at the intersection of climate change and AI, we examine the research institutes that the study authors are associated with. Here, we shift our analysis to the member publications of the research clusters, thus Tables 2-4 are counts of publications as opposed to research clusters. The top 10 institutes are listed in Table 2.

Table 2. Top 10 Publishers of Research on Climate and AI

	Organzation	Country	Number of Publications
1	Chinese Academy of Sciences	China	1,359
2	Beijing Normal University	China	228
3	University of Maryland, College Park	USA	191
4	Wuhan University	China	186
5	Wageningen University & Research	Netherlands	174
6	United States Geological Survey	USA	171
7	Tsinghua University	China	152
8	University of Wisconsin–Madison	USA	139
9	United States Forest Service	USA	138
10	University of New South Wales	Australia	135

Source: CSET Merged Corpus

Leading CAS-Components by Publications

As China is the leading country by author affiliation, we see that many research institutes publishing at the intersection of climate and AI research are based in China. The Chinese Academy of Sciences, the largest research institute in China, is by far the dominant research institute where research at the intersection of climate and AI is being conducted. Within the Chinese Academy of Sciences (CAS), the leading research institute associated with climate change and AI publications in our database is University of the Chinese Academy of Sciences (438 publications), followed by the Institute of Geographic Sciences and Natural Resources (277 publications), and the Institute of Remote Sensing and Digital Earth (246 publications). Other leading Chinese research institutes include Beijing Normal University, Wuhan University, and Tsinghua University.

The Chinese Academy of Sciences (CAS) is listed in Table 1 as being associated with the largest number of publications at the intersection of climate and AI by far. However, CAS is a large organization comprised of multiple research institutes distributed throughout the country. As a result, we took a closer look at the specific research institutes within CAS to better understand their contributions to research in this area. We found that the University of Chinese Academy of Sciences is the source of the highest number of publications, followed by the Institute of Geographic Sciences and Natural Resources Research, and the Institute of Remote Sensing and Digital Earth as listed in Table 3.

Table 3. Top Producers within the CAS of Climate/AI Publications

Name of CAS Research Institute	Publications	Website
University of the Chinese Academy of Sciences	438	https://english.ucas.ac.cn
Institute of Geographic Sciences and Natural Resources Research	277	http://english.igsnrr.cas.cn
Institute of Remote Sensing and Digital Earth	246	http://english.radi.cas.cn
Aerospace Information Research Institute	53	http://english.aircas.ac.cn
Northeast Institute of Geography and Agroecology	34	http://english.neigaehrb.cas.cn
Northwest Institute of Eco-Environment and Resources	28	http://english.nieer.cas.cn
Institute of Soil Science	25	http://english.issas.cas.cn
Institute of Tibetan Plateau Research	18	http://english.itpcas.cas.cn
Nanjing Institute of Geography and Limnology	13	http://english.niglas.cas.cn
Institute of Atmospheric Physics	11	http://english.iap.cas.cn

Source: CSET Merged Corpus

The names of the CAS institutes give some indication of the type of research where AI is being applied to climate research, including in the areas of geographic sciences and remote sensing.

Leading non-Chinese Institutions by Publications

Within the United States, the University of Maryland, College Park has the largest number of publications in our climate and AI dataset, followed by the United States Geological Survey, University of Wisconsin-Madison, and the United States Forest Service. The two other countries with research institutes that show up in the top ten are the Netherlands and Australia.

Leading Funding Organizations by Publications

We examine the observable funding organizations associated with climate and AI publications and also find that China-based funding organizations have supported research that contributed to the largest number of publications, including the National Natural Science Foundation of China (4,391 publications) and China's Ministry of Science and Technology (1,938 publications) in the first and second position. In third place is the United States National Science Foundation (1,527 publications), followed by the European Commission (998 publications) and the Chinese Academy of Sciences (710) which not only conducts but also funds research. The top ten funders are listed in Table 4.

While no private companies appear as leading research institutes or funders, we took a closer look to determine which companies are the most active producers of climate and AI publications in our database. The top five companies that appear in our database in either a funding capacity or researcher affiliation are Google, based in the United States, (62 publications), Science Systems and Applications, based in the United States, (30 publications), State Grid Corporation, based in China, (30 publications),[37] IBM, based in the United States, (22 publications), and Volkswagen Group, based in Germany, (15 publications).

Table 4. Top 10 Funders Associated with Climate and AI Publications

	Organization	Country	Number of publications
1	National Natural Science Foundation of China	China	4,391
2	Ministry of Science and Technology of the People's Republic of China	China	1,938
3	National Science Foundation (US)	USA	1,527
4	European Commission	EU	998
5	Chinese Academy of Sciences	China	710
6	National Aeronautics & Space Administration (NASA)	USA	676
7	Ministry of Education of the People's Republic of China	China	367
8	Brazilian Federal Agency for Support and Evaluation of Graduate Education	Brazil	319
9	United States Geological Survey	USA	307
10	United States Department of Energy	USA	248

Source: CSET Merged Corpus

What Does Research at the Intersection of Climate and AI Look Like?

To get a better sense of how AI is being employed within specific research fields we look more closely at some of the research clusters that emerge from the above analysis in Box 1.

Box 1. Selected Climate Change and AI Research Cluster Summaries

- **Cluster 6201: Remote Sensing for Land Cover**

Cluster 6201 includes mostly papers on remote sensing, using the methods of Double Q Learning, Auto Classifier, and 3dis in tackling how to classify land cover types and mapping land covers. The majority of papers in this cluster are written by authors affiliated with the Chinese Academy of Sciences. The majority of the papers in this cluster are funded by the Chinese government through its National Natural Science Foundation Ministry of Science and Technology, as well as its National Key Research and Development Program.

AI Tasks and Methods: Reinforcement Learning

- **Cluster 97340: City & Urban Climate Modeling**

Cluster 97340 includes many papers on contemporary climate analogs with a focus on urban areas using the methods of Inception V3, Auxiliary Classifier, and Generative Models in tackling Automated Writing Evaluation and Domain Adaptation. This cluster represents a diverse range of global researchers, including the University of Geneva, Stanford University, Arizona State University, University of Tokyo.

AI Tasks and Methods: Natural Language Processing

- **Cluster 7470: Bike-Sharing Systems**

Cluster 7470 includes mostly papers on bike sharing systems and relevant subjects such as routing, fleet management, network analysis, etc. using the methods of Double Q-Learning, MAD-Learning, and Recurrent Neural Networks in tackling System Identification, Classification, and Traffic Prediction. Papers written by authors from China dominate this cluster. More than half of the 2,043 papers in the cluster are written by authors from China.

AI Tasks and Methods: Neural Networks

- **Cluster 2327: Wildfire Modeling and Management**

Cluster 2327 includes mostly papers on wildfire modeling and management, using the methods of MAD-Learning, Recurrent Neural Networks, and VQA Models in detecting fire, tackling classification, and mapping landslide susceptibility. The majority of papers in this cluster are written by authors in the United States, and the majority of funders are also from the U.S.

AI Tasks and Methods: Neural Networks

- **Cluster 92063: Predictions for Global Grid Interconnection, Decarbonization, & Renewable Policies**

Cluster 92063 includes papers on the outlook for global energy transformation and are published mostly by Chinese authors in Chinese journals. Many of the authors are affiliated with the State Grid Corporation and its affiliated organizations.

AI Tasks and Methods: Natural Language Processing

- **Cluster 70395: Climate Modeling & Climate Econometrics**

Cluster 70395 includes mostly papers on climate modeling and climate econometrics, using the methods of Backbone Architectures, AutoML, and VQA Models in tackling classification, fault detection, and data classification. Most authors contributing to this cluster are in the United States and some EU countries.

AI Tasks and Methods: Computer Vision

- **Cluster 74178: Agriculture, Meteorology, & Sustainability**

Cluster 74178 includes papers on various topics in agriculture, such as irrigation, meteorology, and sustainability. These papers use methods of Recurrent Neural Networks, VQA Models, and SPP Net in tackling system identification, time series analysis, and feature selection. The majority of papers are written by authors in China; authors in India, Iran, and Brazil also contributed to many of the papers in this cluster.

AI Tasks and Methods: Time Series, Neural Networks

- **Cluster 90328: Social Media Content Analysis for Climate-and-Energy-Related Topics**

Cluster 90328 includes papers mostly on social media content analysis as relevant to climate and energy related topics, using the methods of Natural Language Processing, Double Q Learning, and Mad Learning in tackling Sentiment Detection, Topic Detection, and Change Detection. Looking at papers in this cluster, most papers are written by authors in the United States.

AI Tasks and Methods: Natural Language Processing, Neural Networks

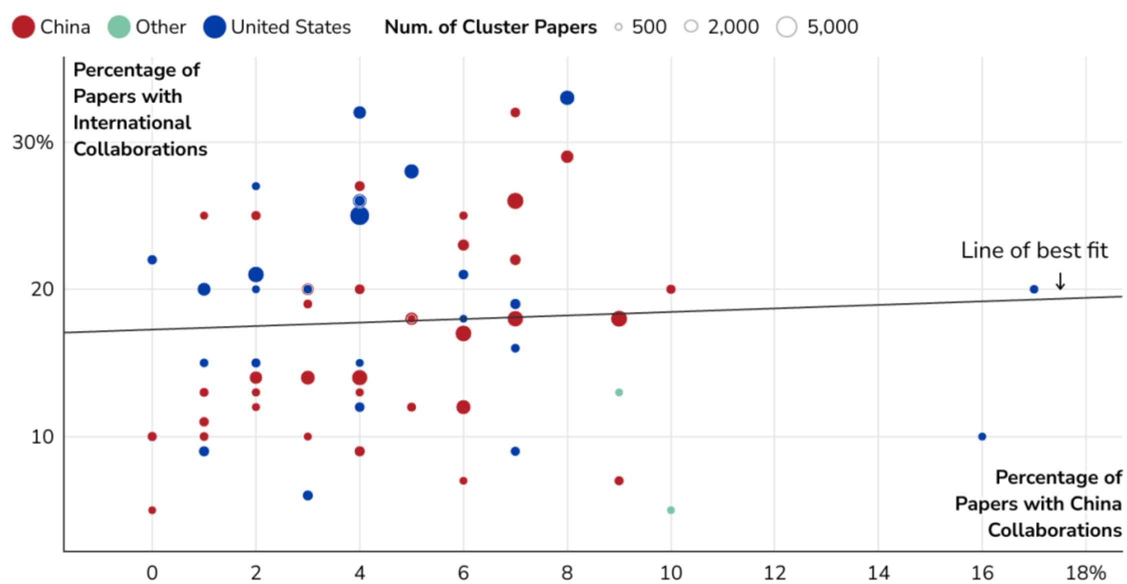
The list above consists of 8 clusters selected from the set of 67 identified to represent a diverse range of applications of AI to climate research. The cluster numbers are hyperlinked to a more detailed description of the cluster in CSET's Map of Science.

The Role of International Collaboration

We analyzed the role of international collaboration in the 67 research clusters of interest (clusters led by China or U.S. publication output) by computing the percentage of international collaborations for each cluster. Here, we consider a paper to have an international collaboration if more than one country is listed on the publication. We also compute the percentage of papers that have China listed on them and at least one other country, as well as the percentage of papers that have the United States listed on them and at least one other country. This allows us to compare rates of international collaboration overall between China and the U.S. among clusters where they represent leading research producers.

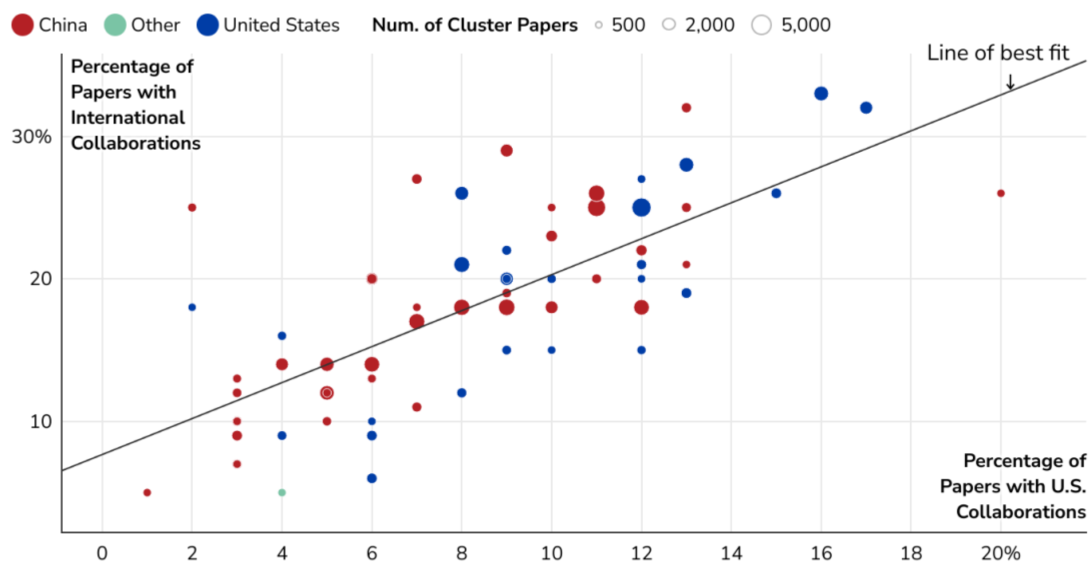
In Figures 5 and 6 we display the international China-specific and U.S.-specific collaboration rates for member papers in the 67 research clusters of interest. On each figure, the dots represent one research cluster, colored by the leading publishing country (China, U.S., or Other), and sized by the number of member publications.

Figure 5. China-specific International Collaboration Rates versus Overall International Collaboration Rates by Research Cluster



Source: CSET Merged Corpus

Figure 6. U.S.-specific International Collaboration Rates versus Overall International Collaboration Rates by Research Cluster



Source: CSET Merged Corpus

We find that the percentage of papers with U.S.-specific international collaborations has a stronger linear relationship to the general rate of international collaboration, whereas China-specific international collaborations do not. This highlights that the U.S. is more involved in global collaboration efforts among the research clusters in the climate and AI research domain than China. Specifically, even in research clusters where China has the most publications, the U.S. has more collaborative publications.

Conclusion

Given the vast potential of AI methods to revolutionize all aspects of research and analysis, it is not surprising that they are being applied to one of today's most pressing global challenges, addressing climate change. Our study contributes to the understanding of how AI is being used in climate related research by examining the way in which specific AI is being applied to climate change research, as well as specific national contributions.

We find that Chinese research institutions lead the world in publishing and funding research at the intersection of climate and AI, followed by the United States. Specifically, the Chinese Academy of Sciences, the largest research institute in China, produced the greatest number of publications we identified at the intersection of climate and AI. We also find that the leading funders associated with climate and AI publications are also based in China. China's dominance in AI applications has been well documented, and we show that China also leads the world in climate-related research, as well as at the climate-AI interface.

By mapping the specific AI tasks or methods being applied to specific climate research fields, we identify potential opportunities to expand the use of AI in climate research. Climate change research areas such as climate modeling, climate impact, and energy technologies make use of a wide range of AI techniques, whereas other areas such as transportation and energy trends have fewer AI implementations. There appear to be gaps in certain climate research areas where AI tasks and methods are not being used as widely and where there may be useful applications. Exploring these gaps as well as understanding the major research centers and collaborations in adjacent intersections identified is proposed as an area for future research.

While we believe this is the first systematic study of its kind, we acknowledge some deficiencies in our methods, namely that we manually identified subfields in climate research using keyword analysis as well as subjective judgement, and that our pairing of AI-related tasks and methods to climate-related research areas represents the occurrence, but not the frequency, of these pairings. However, our findings raise multiple questions that present opportunities for future research and inquiry, including why certain tasks and methods are being used in specific fields, and what other fields might learn from applications to date.

Given the limited time remaining to avoid increasingly severe global climate change impacts, the expanded use of AI tasks and methods presents the opportunity to transform our ability to understand and address climate change. This paper helps to identify opportunities to expand the use of AI tasks and methods in climate related research, and the predominance of China and the United States in this area raises important questions about national leadership and competitiveness.

Authors

Joanna Lewis is Provost's Distinguished Associate Professor of Energy and Environment and Director of the Science, Technology and International Affairs Program (STIA) at Georgetown's School of Foreign Service, Autumn Toney is a data research analyst at CSET, and Xinglan Shi was a research assistant at CSET until May 2023.

Acknowledgments

For feedback and assistance, we would like to thank Igor Mikolic-Torreira, Dewey Murdick, Melissa Flagg, Ben Murphy, and Catherine Aiken. For research assistance we would like to thank Laura Edwards.

CSET Product ID: 20210017
Document Identifier: doi: 10.51593/20210017
Document Last Modified: 14 November 2023

Appendix A. Methodology

Keyword Search

We identify relevant climate change publications using a keyword search in English and Chinese; the terms along with their regular expression search are listed in Table A.1.

Table A.1. Top 10 Funders Associated with Climate and AI Publications

English	Chinese	SQL
climate change," "climate changes," "climatic change," and "climatic changes."	气候变化， 气候变迁	REGEXP_CONTAINS(str, r"(?i)((\bclimat.* change.*\b)|(气候变化)|(气候变迁))"))
global warming	全球暖化， 全球升温， 全球气候变暖	REGEXP_CONTAINS(str, r"(?i)((\bglobal warming\b)|(全球暖化)|(全球升温)|(全球气候变暖)")
carbon emissions	碳排放	REGEXP_CONTAINS(str, r"(?i)((\bcarbon emission.*\b)|(碳排放))")
low carbon	低碳	REGEXP_CONTAINS(str, r"(?i)((\blow carbon\b)|(低碳))")

We ran a search through the CSET merged corpus of scholarly literature using the terms generated above and publications were selected as being related to climate change research if their title or abstract contained at least one keyword. We based these keywords on other studies that have conducted bibliometric analysis. This search resulted in 947,616 climate change-related publications. We select research clusters that contain at least one of these climate change publications, which results in 46,703 research clusters.

Research Cluster (Down) Selection

Next, we narrowed down the resulting research clusters to a set that are in the 95th percentile of containing climate change focused literature which results in 2,351 research clusters that have 5% or more climate change-related publications.

The Map of Science contains data on AI relevance predictions which we use to filter for research clusters with AI-related publications. Publications in English from 2010 to present day are passed through a SciBERT model trained on arXiv publications that predicts if a research publication is AI-related or not AI-related. Publications in Chinese from 2010 to present are labeled as AI-related or not AI-related using a regular expression query. Each research cluster has a percentage of papers that are AI-related out of all papers in the cluster using these two AI relevance labels. Thus, similarly to how we filter for climate change-related research clusters, we can filter for AI-related research clusters.

This allowed us to sort our dataset both by climate and AI relevance. We did this by looking at the clusters in both the 95th percentile of climate research and the 95th percentile of AI research. This substantially cuts down the dataset to a total of 111 clusters.

To come up with a more targeted list of clusters relevant to this research, we take this list of 111 RCs with at least 5% climate change publications and 5% AI-related publications and we apply an additional filter for RCs with an average publication citation of two or more and the top country being either US or China. This results in a total of 67 clusters.

Table A.2. Summarizing Data Analysis Methods

Sequence	Sort criteria	Dataset	Number of climate change-related publications	Number of research clusters	Number of RC publications
1	Keyword search	CSET merged corpus	947,616	N/A	N/A
2a	Identify RCs of interest	Climate change publications	717,105	46,703	65,710,833
2b	95th percentile of climate focused literature (>5%)	Research clusters linked from climate publications from step 2	413,303	2,351	2,820,097
3	95th percentile of climate focused and AI relevance (>5%)	Climate change research clusters from step 3	8,431	111	87,633
4	95th percentile of climate focused and AI relevance >5%; citations >2, top country (author affiliation is US or China)	Climate change and AI research clusters from step 4	6,906	67	67,669

AI Tasks and Methods Analysis

In order to construct Table 1, we used AI-related tasks and methods and manually labeled climate-related categories for our finalized set of 67 research clusters. AI-related tasks and methods are automatically assigned to individual research publications using a named entity recognition model trained on tasks and methods as developed in Dunham, et al (2020). Each task and method label falls under several broad areas, such as Natural Language Processing or Causal Inference. For our analysis, we aggregated the tasks and methods that appeared in member publications of our 67 research clusters of interest. For each RC, we looked at the top five most frequent tasks and methods from the research clusters' member publications and represented them in nine distinct categorizations from the Papers with Code taxonomy: causal inference, computer vision, graphs, methodology, natural language processing, neural networks, reinforcement learning, robots, and time series.[38]

Next, we manually verified nine climate-related categorization labels based on the occurrence of keywords in the research cluster metadata: climate impacts, climate modeling, emission trends, energy efficiency, energy technology, energy trends, land use change, public perception, and transportation. We then identified all distinct pairings between the nine AI-related tasks and methods and the nine climate-related categories. For example, if a research cluster had both climate modeling and neural networks labels, that would be represented in Table 1 by a checkmark. In this way, Table 1 denotes the AI-related tasks and methods that have been applied to climate-related areas, but does not represent the frequency of these pairings.

Endnotes

[1] World Economic Forum, "Harnessing Artificial Intelligence for the Earth," Fourth Industrial Revolution for the Earth Series, January 2018, http://www3.weforum.org/docs/Harnessing_Artificial_Intelligence_for_the_Earth_report_2018.pdf; Chris Huntingford et al., "Machine Learning and Artificial Intelligence to Aid Climate Change Research and Preparedness," *Environmental Research Letters* 14, no. 12 (November 2019): 124007, https://doi.org/10.1088/1748-9326/ab4e55.

[2] Gemma J. Anderson and Donald D. Lucas, "Machine Learning Predictions of a Multiresolution Climate Model Ensemble," *Geophysical Research Letters* 45, no. 9 (2018): 4273–80, https://doi.org/10.1029/2018GL077049.

[3] Christopher Kadow, David Matthew Hall, and Uwe Ulbrich, "Artificial Intelligence Reconstructs Missing Climate Information," *Nature Geoscience* 13, no. 6 (2020): 408–13, https://doi.org/10.1038/s41561-020-0582-5.

[4] You Han et al., "Estimation of Corporate Greenhouse Gas Emissions via Machine Learning," *ArXiv:2109.04318 [Cs, Stat]*, September 9, 2021, http://arxiv.org/abs/2109.04318.

[5] J. Jake Nichol et al., "Machine Learning Feature Analysis Illuminates Disparity between E3SM Climate Models and Observed Climate Change," *Journal of Computational and Applied Mathematics* 395 (2021): 113451-, https://doi.org/10.1016/j.cam.2021.113451.

[6] Andrew Crane-Droesch, "Machine Learning Methods for Crop Yield Prediction and Climate Change Impact Assessment in Agriculture" 13, no. 11 (October 2018): 114003, https://doi.org/10.1088/1748-9326/aae159.

[7] Cheng Chen et al., "Artificial Intelligence on Economic Evaluation of Energy Efficiency and Renewable Energy Technologies," *Sustainable Energy Technologies and Assessments* 47 (October 1, 2021): 101358, https://doi.org/10.1016/j.seta.2021.101358.

[8] Robin Haunschild, Lutz Bornmann, and Werner Marx, "Climate Change Research in View of Bibliometrics," *PLOS ONE* 11, no. 7 (July 29, 2016): e0160393, https://doi.org/10.1371/journal.pone.0160393; Federica Zennaro et al., "Exploring Machine Learning Potential for Climate Change Risk Assessment," *Earth-Science Reviews* 220 (September 1, 2021): 103752, https://doi.org/10.1016/j.earscirev.2021.103752.

[9] David Rolnick et al., "Tackling Climate Change with Machine Learning," *ArXiv:1906.05433 [Cs, Stat]*, November 5, 2019, http://arxiv.org/abs/1906.05433; Ricardo Vinuesa et al., "The Role of Artificial Intelligence in Achieving the Sustainable Development Goals," *Nature Communications* 11, no. 1 (January 13, 2020): 233, https://doi.org/10.1038/s41467-019-14108-y.

[10] Craig Smith, "Climate Change, China and AI," Paperspace.com, February 2, 2020, https://blog.paperspace.com/climate-change-china-and-ai/; Hongfang Lu et al., "Carbon Trading Volume and Price Forecasting in China Using Multiple Machine Learning Models," *Journal of Cleaner Production* 249 (March 10, 2020): 119386, https://doi.org/10.1016/j.jclepro.2019.119386; Yu Feng et al., "Comparison of Artificial Intelligence and Empirical Models for Estimation of Daily Diffuse Solar Radiation in North China Plain," *International Journal of Hydrogen Energy* 42, no. 21 (May 25, 2017): 14418–28, https://doi.org/10.1016/j.ijhydene.2017.04.084; Yinger Zheng, Haixia Zheng, and Xinyue Ye, "Using Machine Learning in Environmental Tax Reform Assessment for Sustainable Development: A Case Study of Hubei Province, China," *Sustainability* 8, no. 11 (November 2016): 1124, https://doi.org/10.3390/su8111124.

[11] Xiangning Wu, "Technology, Power, and Uncontrolled Great Power Strategic Competition between China and the United States," *China International Strategy Review* 2, no. 1 (June 1, 2020): 99–119, https://doi.org/10.1007/s42533-020-00040-0; Michael C. Horowitz et al., "Strategic Competition in an Era of Artificial Intelligence" (Washington, DC: CNAS, July 2018).

[12] Oliver Watt-Meyer et al., "Correcting Weather and Climate Models by Machine Learning Nudged Historical Simulations," *Geophysical Research Letters* 48, no. 15 (2021): n/a, https://doi.org/10.1029/2021GL092555; D. Watson-Parris, "Machine Learning for Weather and Climate Are Worlds Apart," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 379, no. 2194 (April 5, 2021): 20200098, https://doi.org/10.1098/rsta.2020.0098; Thomas C. M. Martin, Humberto R. Rocha, and Gabriel M. P. Perez, "Fine Scale Surface Climate in Complex Terrain Using Machine Learning," *International Journal of Climatology* 41, no. 1 (2021): 233–50, https://doi.org/10.1002/joc.6617; K. Kashinath et al., "Physics-Informed Machine Learning: Case Studies for Weather and Climate Modelling," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 379, no. 2194 (April 5, 2021): 20200093, https://doi.org/10.1098/rsta.2020.0093.

[13] Carozza and Boudreault, "A Global Flood Risk Modeling Framework Built With Climate Models and Machine Learning"; Amir Mosavi, Pinar Ozturk, and Kwok-wing Chau, "Flood Prediction Using Machine Learning Models: Literature Review," *Water* 10, no. 11 (November 2018): 1536, https://doi.org/10.3390/w10111536; Sang-Jin Park and Dong-Kun Lee, "Prediction of Coastal Flooding Risk under Climate Change Impacts in South Korea Using Machine Learning Algorithms" 15, no. 9 (August 2020): 094052, https://doi.org/10.1088/1748-9326/aba5b3; Omid Zabihi et al., "A Smart Sustainable System for Flood Damage Management with the Application of Artificial Intelligence and Multi-Criteria Decision-Making Computations," *International Journal of Disaster Risk Reduction* 84 (January 1, 2023): 103470, https://doi.org/10.1016/j.ijdrr.2022.103470.

[14] G. Edwin Prem Kumar and M. Lydia, "Machine Learning Algorithms for Modelling Agro-Climatic Indices: A Review," in *Smart Computing Techniques and Applications*, ed. Suresh Chandra Satapathy et al., Smart Innovation, Systems and Technologies (Singapore: Springer, 2021), 15–23, https://doi.org/10.1007/978-981-16-1502-3_3; Haijiao Yu et al., "Uncertainty Analysis of Artificial Intelligence Modeling Daily Reference Evapotranspiration in the Northwest End of China," *Computers and Electronics in Agriculture* 176 (September 1, 2020): 105653, https://doi.org/10.1016/j.compag.2020.105653; Ju-Young Shin, Kyu Rang Kim, and Jong-Chul Ha,

"Seasonal Forecasting of Daily Mean Air Temperatures Using a Coupled Global Climate Model and Machine Learning Algorithm for Field-Scale Agricultural Management," *Agricultural and Forest Meteorology* 281 (2020): 107858-, https://doi.org/10.1016/j.agrformet.2019.107858.

[15] Stevert Lobo et al., "Analyzing the Impact of Deforestation and Population on Carbon Footprint in Indian Cities Using Statistical and Deep Learning Techniques," in *Soft Computing and Signal Processing*, ed. V. Sivakumar Reddy et al., Advances in Intelligent Systems and Computing (Singapore: Springer, 2021), 89–99, https://doi.org/10.1007/978-981-33-6912-2_9.

[16] Geun Ho Gu et al., "Machine Learning for Renewable Energy Materials," *Journal of Materials Chemistry A* 7, no. 29 (July 23, 2019): 17096–117, https://doi.org/10.1039/C9TA02356A.

[17] P. S. M. Thilakarathna et al., "Embodied Carbon Analysis and Benchmarking Emissions of High and Ultra-High Strength Concrete Using Machine Learning Algorithms," *Journal of Cleaner Production* 262 (July 20, 2020): 121281, https://doi.org/10.1016/j.jclepro.2020.121281; Hua Meng and Weixin Wang, "Definition Method for Carbon Footprint of Iron and Steel Energy Supply Chain Based on Relational Dispersed Degree," *Journal of Intelligent & Fuzzy Systems* 38, no. 6 (2020): 7407–16, https://doi.org/10.3233/JIFS-179814; Nikhil John et al., "How Key-Enabling Technologies' Regimes Influence Sociotechnical Transitions: The Impact of Artificial Intelligence on Decarbonization in the Steel Industry," *Journal of Cleaner Production* 370 (October 10, 2022): 133624, https://doi.org/10.1016/j.jclepro.2022.133624.

[18] Klemens Katterbauer et al., "An Innovative Artificial Intelligence Framework for Reducing Carbon Footprint in Reservoir Management" (SPE Annual Technical Conference and Exhibition, OnePetro, 2021), https://doi.org/10.2118/205856-MS; Soheil Fathi and Ravi Srinivasan, "Climate Change Impacts on Campus Buildings Energy Use: An AI-Based Scenario Analysis," in *Proceedings of the 1st ACM International Workshop on Urban Building Energy Sensing, Controls, Big Data Analysis, and Visualization*, UrbSys'19 (New York, NY, USA: Association for Computing Machinery, 2019), 112–19, https://doi.org/10.1145/3363459.3363540; Mateusz Ploszaj-Mazurek, Elzbieta Rynska, and Magdalena Grochulska-Salak, "Methods to Optimize Carbon Footprint of Buildings in Regenerative Architectural Design with the Use of Machine Learning, Convolutional Neural Network, and Parametric Design," *Energies (Basel)* 13, no. 20 (2020): 5289-, https://doi.org/10.3390/en13205289; Chen et al., "Artificial Intelligence on Economic Evaluation of Energy Efficiency and Renewable Energy Technologies."

[19] Sunil Kr. Jha et al., "Renewable Energy: Present Research and Future Scope of Artificial Intelligence," *Renewable and Sustainable Energy Reviews* 77 (September 1, 2017): 297–317, https://doi.org/10.1016/j.rser.2017.04.018; Tanveer Ahmad et al., "Artificial Intelligence in Sustainable Energy Industry: Status Quo, Challenges and Opportunities," *Journal of Cleaner Production* 289 (March 20, 2021): 125834, https://doi.org/10.1016/j.jclepro.2021.125834; Domenico Mazzeo et al., "Artificial Intelligence Application for the Performance Prediction of a Clean Energy Community," *Energy* 232 (October 1, 2021): 120999, https://doi.org/10.1016/j.energy.2021.120999; Amani Al-Othman et al., "Artificial Intelligence and Numerical Models in Hybrid Renewable Energy Systems with Fuel Cells: Advances and Prospects," *Energy Conversion and Management* 253 (February 1, 2022): 115154, https://doi.org/10.1016/j.enconman.2021.115154.

[20] Saeid Mehdizadeh, Javad Behmanesh, and Keivan Khalili, "Comparison of Artificial Intelligence Methods and Empirical Equations to Estimate Daily Solar Radiation," *Journal of Atmospheric and Solar-Terrestrial Physics* 146 (August 1, 2016): 215–27, https://doi.org/10.1016/j.jastp.2016.06.006; Feng et al., "Comparison of Artificial Intelligence and Empirical Models for Estimation of Daily Diffuse Solar Radiation in North China Plain"; Ping-Huan Kuo and Chiou-Jye Huang, "A Green Energy Application in Energy Management Systems by an Artificial Intelligence-Based Solar Radiation Forecasting Model," *Energies* 11, no. 4 (April 2018): 819, https://doi.org/10.3390/en11040819; A. Khosravi et al., "Comparison of Artificial Intelligence Methods in Estimation of Daily Global Solar Radiation," *Journal of Cleaner Production* 194 (September 1, 2018): 342–58, https://doi.org/10.1016/j.jclepro.2018.05.147.

[21] René Jursa and Kurt Rohrig, "Short-Term Wind Power Forecasting Using Evolutionary Algorithms for the Automated Specification of Artificial Intelligence Models," *International Journal of Forecasting*, Energy Forecasting, 24, no. 4 (October 1, 2008): 694–709, https://doi.org/10.1016/j.ijforecast.2008.08.007; Tonglin Fu and Chen Wang, "A Hybrid Wind Speed Forecasting Method and Wind Energy Resource Analysis Based on a Swarm Intelligence Optimization Algorithm and an Artificial Intelligence Model," *Sustainability* 10, no. 11 (November 2018): 3913, https://doi.org/10.3390/su10113913; Xuejing Zhao et al., "Research and Application Based on the Swarm Intelligence Algorithm and Artificial Intelligence for Wind Farm Decision System," *Renewable Energy* 134 (April 1, 2019): 681–97, https://doi.org/10.1016/j.renene.2018.11.061.

[22] Miftah Al Karim, Jonathan Currie, and Tek-Tjing Lie, "A Distributed Machine Learning Approach for the Secondary Voltage Control of an Islanded Micro-Grid," in *2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, 2016, 611–16, https://doi.org/10.1109/ISGT-Asia.2016.7796454; Weiguo Yao, "Analysis on the Application of the Artificial Intelligence Neural Network on the New Energy Micro Grid," in *Proceedings of the 2017 4th International Conference on Machinery, Materials and Computer (MACMC 2017)* (2017 4th International Conference on Machinery, Materials and Computer (MACMC 2017), Xi'an, China: Atlantis Press, 2018), https://doi.org/10.2991/macmc-17.2018.144; Manohar Mishra, Rasmi Ranjan Panigrahi, and Pravat Kumar Rout, "A Combined Mathematical Morphology and Extreme Learning Machine Techniques Based Approach to Micro-Grid Protection," *Ain Shams Engineering Journal* 10, no. 2 (June 2019): 307–18, https://doi.org/10.1016/j.asej.2019.03.011.

[23] Olufemi Aiyegbusi, Rossitsa Yalamova, and John Usher, "Carbon Pricing in Dynamic Regulation and Changing Economic Environment - Agent Based Model," *Regional and Business Studies* 3, no. 1 Suppl. (February 15, 2011): 497–509.

[24] Sun Wei, Zhang Chongchong, and Sun Cuiping, "Carbon Pricing Prediction Based on Wavelet Transform and K-ELM Optimized by Bat Optimization Algorithm in China ETS: The Case of Shanghai and Hubei Carbon Markets," *Carbon Management* 9, no. 6 (November 2, 2018): 605–17, https://doi.org/10.1080/17583004.2018.1522095.

[25] Hongfang Lu et al., "Carbon Trading Volume and Price Forecasting in China Using Multiple Machine Learning Models," *Journal of Cleaner Production* 249 (March 10, 2020): 119386, https://doi.org/10.1016/j.jclepro.2019.119386.

[26] Marianne Ojo, “The Future of UK Carbon Pricing: Artificial Intelligence and the Emissions Trading System,” MPRA Paper (University Library of Munich, Germany, July 2019), https://econpapers.repec.org/paper/pramprapa/94887.htm.

[27] China Meteorological Administration and Chinese Academy of Sciences, “China Meterological Science and Technology Development Plan (2021-2035) 中国气象科技发展规划（2021—2035年),” March 3, 2022, https://www.gov.cn/xinwen/2022-03/03/content_5676714.htm.

[28] China National Knowledge Infrastructure is furnished for use in the United States by East View Information Services, Minneapolis, MN, USA. Dimensions is provided by Digital Science, Web of Science is provided by Clarivate Analytics, and China National Knowledge Infrastructure is furnished for use in the United States by East View Information Services, Minneapolis, MN, USA.

[29] The data for this study was extracted on April 21, 2022. The latest version of the database is available at https://sciencemap.eto.tech/?mode=map.

[30] We determined the 5% threshold by computing the 95th percentile of climate change concentration percentages in all research clusters containing at least one climate change publication.

[31] Autumn Toney, "Locating AI Research in the Map of Science" (Center for Security and Emerging Technology, July 2021).

[32] James Dunham, Jennifer Melot, and Dewey Murdick, “Identifying the Development and Application of Artificial Intelligence in Scientific Text” (arXiv, May 28, 2020), https://doi.org/10.48550/arXiv.2002.07143.

[33] Daniel Chou, "Counting AI Research: Exploring AI Research Output in English- and Chinese-Language Sources" (Center for Security and Emerging Technology, July 2022). https://doi.org/10.51593/20220010

[34] Cluster disciplines are assigned from the following list: Biology, Chemistry, Computer Science, Earth Science, Engineering, Humanities, Materials Science, Mathematics, Medicine, Physics, and Social Science.

[35] Chao Min et al., “Has China Caught up to the US in AI Research? An Exploration of Mimetic Isomorphism as a Model for Late Industrializers” (arXiv, July 11, 2023), https://doi.org/10.48550/arXiv.2307.10198.

[36] Yousuf et al., “Lessons from Deep Learning Applied to Scholarly Information Extraction.”

[37] The State Grid Corporation of China is technically a state-owned as opposed to a purely privately held company.

[38] Papers with Code, “Papers with Code - The Methods Corpus,” 2023, https://paperswithcode.com/methods.