Landscape Assessment of AI for Climate and Nature

May 2024

Columbia University

Commissioned by and in collaboration with

Bezos Earth Fund

In partnership with

University at Albany
State University of New York

esri

Foreword

We are in a decisive decade. Urgent and ambitious actions are needed to combat climate change and protect nature while working towards a just and prosperous future for all of humanity.

Recent innovations in artificial intelligence (AI) hold the potential to profoundly transform and accelerate climate and nature stewardship for a positive global impact. We need efforts at collaboration and cross-pollination, such as those facilitated here by the Bezos Earth Fund, to help us realize these opportunities.

AI is everywhere, from the headlines to the apps on our phones, but it is not a panacea or silver bullet. Collectively, we need to approach this new technology with cautious optimism and encourage critical and honest thinking about the ways AI can—or cannot—help solve our climate and nature crises. This report synthesizes current advances and applications of AI across a range of thematic areas that can aid in the transition to a low-carbon economy, enhance climate resilience, or improve the protection, restoration, and management of nature. Initiatives and institutes working at the intersection of AI, climate, and nature are also highlighted to showcase current strategies and solutions. The Landscape Assessment examines key issues concerning AI ethics, equity, safety, and sustainability and explores existing barriers to impact at scale, highlighting the importance of data, trust, governance, deployment, and workforce development.

Each sector has a unique responsibility in the AI for climate and nature solution space. The private sector provides the critical engine of growth to accelerate scalable solutions. Philanthropy can unleash the potential of promising ideas. Policymakers and nonprofits play fundamental roles in upholding the preservation of safety, privacy, and accessibility. Academia can nurture and leverage intellectual leadership, creativity—and critique—to incubate the ideas and people that will change the world. All these sectors need to safeguard equity and justice. The report highlights opportunities to buttress AI foundations, explore untapped thematic areas, and identify where investment in the enabling environment can unlock further impact.

Columbia University's Climate School and Engineering School have collaborated in partnership with the University at Albany, State University of New York, and Esri, to produce this report. The study was made possible through the valuable contributions of many domain experts from academia, the nonprofit sector, and private industry, who provided their expertise and time to this report.

The Landscape Assessment was commissioned by and in collaboration with the Bezos Earth Fund; we thank the Earth Fund for spearheading this initiative and convening global experts and industry leaders around this important topic. We sincerely appreciate Dr. Pierre Gentine's leadership in producing the Landscape Assessment.

Columbia University is committed to developing and inspiring science, education, and innovation to address the inherently complex and interdisciplinary challenges facing the world. We know that these goals cannot be met alone. Thank you to our partners and to the many collaborators that contributed to this report.

Together, we can meet the opportunity of AI for climate and nature. •

Jeffrey Shaman
Interim Dean, Columbia Climate School

Shih-Fu Chang
Dean, Fu Foundation School of Engineering and Applied Science

Our planet is in crisis. We are experiencing biodiversity loss to such an extent that researchers suggest we are in the midst of a mass extinction event.[1] The rampant increase in greenhouse gas emissions is leading to catastrophic climate extremes, and "hottest year ever" records are being broken nearly annually.[2] Of the nine planetary boundaries that have been identified to keep Earth livable, we have already breached six of them.[3]

Transformative system-oriented changes are urgently needed to address these challenges, yet progress toward policy ambitions to achieve these changes, such as the Paris Agreement and the Sustainable Development Goals, are off-track.[4,5]

Artificial intelligence offers us a way to better understand these vital and complex problems and—if applied strategically—to dramatically accelerate the pace of solutions. This report explores both the current uses of AI in climate and nature as well as emerging opportunities at the nexus of those fields; we are particularly focused on the development of applications that will hasten the implementation of impactful and scalable solutions while ensuring they remain trustworthy, ethical, and equitable.

The State of AI

Key Concepts in AI

Artificial Intelligence. AI models are computer programs that perform tasks considered sufficiently complicated to require some level of higher reasoning or intelligence.

Artificial Neural Network. A popular type of machine learning model that was inspired by the organization, structure, and function of neurons within biological brains. It incorporates large numbers of nonlinear components arranged like neurons, with connections sharing information among them.

Bioacoustic Systems. Bioacoustic systems use sound information as their primary input. Similar to computer vision data, the analysis of bioacoustic data is dependent upon the task, which can include detecting, identifying, or counting items or people in images, and predicting the trajectories or positions of objects.

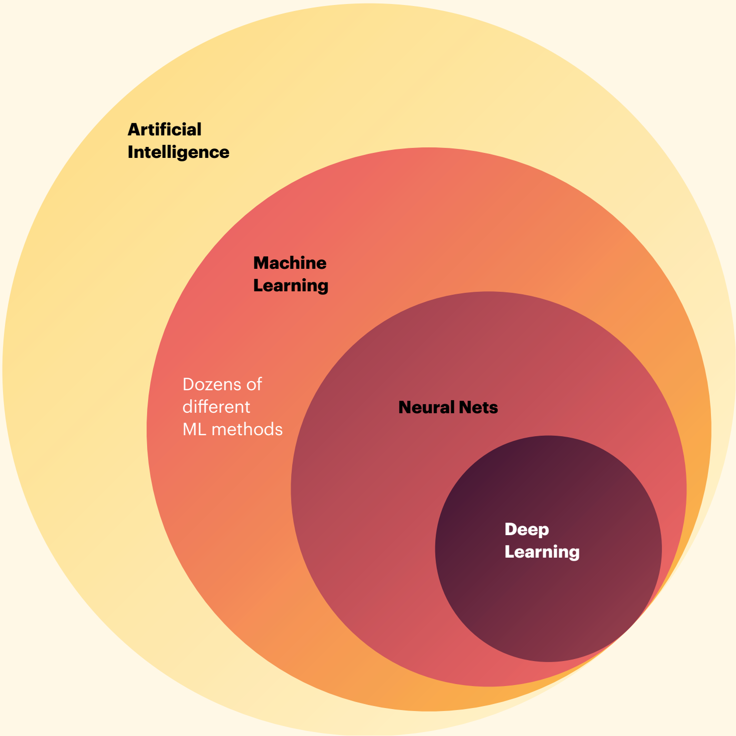
Computer Vision Systems. Computer vision systems derive information and meaning from visual data (e.g., images and video). Computer vision data can be analyzed in various ways depending upon the task. This can include detecting, identifying, classifying and segmenting images, or predicting the trajectories or positions of objects.

Convolutional Neural Network. Convolutional Neural Network is a class of deep neural networks, most commonly applied to analyzing visual images. They are used to recognize patterns and structures within images or sequences, and are a cornerstone of computer vision applications.

Deep Learning. Deep learning is a more recent type of machine learning that uses deep neural networks, i.e., with many hidden layers, to mimic the complexity and level of abstractions of the human brain, and is capable of more advanced visual and language learning.

Digital Twins. Digital Twins are sophisticated computer simulations of a process, assembly, or phenomenon aimed at mimicking a complex system with a high level of realism. They are meant to be digital counterparts (twins) of real-world systems or processes that can be used to accurately, quickly, and inexpensively simulate their real-world counterparts, such as for design or evaluation of their response to specific actions.

Edge AI (tiny ML). These are AI and machine learning systems deployed in the field at low cost via power-efficient devices. Using the increasing power of small computing low-power systems, they do analyses that previously could only be accomplished at centralized server centers. Edge AI systems can instead make near real-time predictions or perform local actions, thus decreasing response time and promoting security and privacy by transmitting less data.



Currently, AI allows us to:

- **Process and digest vast quantities of data.** AI can go beyond human capacity to identify and interpret complex relationships among seemingly disparate and extremely large datasets.
- **Automate monitoring.** AI can be used to monitor environmental changes and their impact in near real-time.
- **Optimize solutions.** AI can quickly sift through large volumes of data, constraints, and alternatives to find optimal (or close to optimal) solutions.
- **Build predictive models and forecasts.** When trained on abundant data, AI can efficiently and accurately predict future outcomes, bolstering a wide range of predictions.
- **Develop realistic simulations of the real world.** AI-accelerated "digital twins" can allow scientists and stakeholders to experiment without risk as they explore the impact of certain actions on specific environments.
- **Accelerate new discoveries.** AI can lead to faster and new discoveries across a range of applications.

To harness AI fully, we will need to:

- **Ensure data accessibility.** Datasets should be made as broadly and publicly accessible as possible to engage the AI community and drive algorithmic and application developments.
- **Improve cross-disciplinary collaboration.** Framing important domain questions and problems with the AI community is critical to fostering collaboration and accelerating progress.
- **Develop clear and quantifiable benchmarks.** In conjunction with public datasets, benchmarking is critical to AI development and acceleration.
- **Increase availability of domain specific data.** AI models are typically trained on diverse datasets, but they may lack domain-specific knowledge required for certain applications.

Federated Learning. Federated learning is a specialization of machine learning applied to preserve data privacy in situations where the data in question comes from separate sources (e.g., medical data). It frequently uses edge AI techniques to take advantage of decentralized learning and other processing.

Foundation Models. A foundation model is a machine-learning model that has been trained on a broad and diverse set of data to enable its application across a wide range of tasks in a self-supervised manner. For example, a model might initially be trained on general text data from the internet, but can then be used or subsequently refined for a more specific task, such as grammar or editing. These models learn rich representations that can then be adapted to various downstream tasks through techniques like fine-tuning on task-specific data.

Generative AI. Generative AI systems can generate text, images, or other data (often in response to user prompts) by learning the patterns and structure of training data and then generating new data with similar characteristics. This is in contrast with discriminative AI systems, which can only choose among alternatives or produce a single numerical value.

Graph Neural Networks (GNNs). GNNs are a type of neural network architecture designed to operate on graph-structured data (unlike convolutions working on 2 or 3D structures). Graphs are composed of nodes (vertices) and edges that connect these nodes, allowing for the representation of complex relationships and interactions between different nodes.

Internet of Things (IoT). The Internet of Things describes devices with sensors, processing ability, software, and other technologies that connect and exchange data with other devices and systems over the internet or other communications networks. IoT devices are frequently deployed in the field for various monitoring tasks.

Labeled data. Labeled data refers to datasets that have been tagged with one or more labels identifying certain properties or classifications of the data points.

Large Language Models (LLMs). LLMs are foundation models specifically trained on language tasks; for example, these models can be trained on large amounts of text and then use that input to do question-answering, summarization, translation, etc.

Machine Learning. Machine learning is a subset of AI where an algorithm learns what a system needs to know or do, by training (learning) on data rather than specifying the rules of the model or program.

Multimodal AI. Multimodal AI uses multiple types of data inputs (e.g., text, image, acoustic) for AI tasks. Multimodal AI is able to integrate and process data from different modalities simultaneously, allowing it to perform tasks that require a more comprehensive understanding of the world or system than unimodal AI systems, which are limited to a single type of data.

Natural Language Processing (NLP). NLP is a subfield of computer science and linguistics primarily concerned with giving computers the ability to interpret, support, and manipulate human language.

Reinforcement Learning. Reinforcement Learning is a branch of machine learning that aims to emulate how an agent would optimally interact with an environment; this is often characterized as a sequence of multiple steps or actions that maximize the reward received over the course of or at the end of the task.

Self-Supervised Learning. Self-supervised learning is a machine learning paradigm that falls between supervised learning and unsupervised learning. In self-supervised learning, the data itself provides the supervision, without requiring manually labeled data. The key idea is to create auxiliary prediction tasks from the unlabeled input data itself, where the model learns to predict part of the input from other parts. By solving these pretext tasks, the model builds useful representations that capture meaningful information and patterns in the data.

Supervised Learning. Supervised learning is a type of machine learning technique where the model is trained on a labeled dataset. In supervised learning, the training data consists of inputs paired with the corresponding correct outputs, and the goal is to learn a function that maps the inputs to the outputs.

Unsupervised Learning. Unsupervised learning is a type of machine learning technique where the models are trained on unlabeled data, without any associated target outputs or rewards. The goal of unsupervised learning is to discover inherent patterns, structures, or relationships within the input data itself (e.g., data clustering or dimensional reduction).

Additional acronyms to note

- **AV** Autonomous Vehicle
- **CCS** Carbon Capture and Storage
- **CO_2** Carbon Dioxide
- **EV** Electric Vehicle
- **GHG** Greenhouse Gas
- **GPS** Global Positioning System
- **GPT** Generative Pretrained Transformers
- **GPU** Graphics Processing Units
- **HVAC** Heating, Ventilation, and Air Conditioning
- **LiDAR** Light Detection and Ranging
- **LULCC** Land-use and Land-cover Change
- **MOF** Metal-organic frameworks
- **NASA** National Aeronautics and Space Administration
- **NCS** Natural Carbon Solutions
- **UAV** Unmanned Aerial Vehicle

In the past decade, AI models that include sequential or spatial data, combined with deep architectures capable of developing higher levels of abstraction, have started to demonstrate superhuman performance on image recognition and text translation.[6,7]

These advancements have been facilitated by tremendous developments in hardware: accelerated parallelized computing power (especially graphics processing units, or GPUs);[8] the creation of benchmark datasets to evaluate the performance of new algorithms (such as ImageNet for training image recognition models); and the development of modern AI libraries in high-level languages (such as Tensorflow and Pytorch), enabling the use of efficient optimization algorithms for model training.

In parallel, we have seen the active development of generative models, a type of AI algorithm designed to create new data samples that resemble the training data, such as generative adversarial networks,[9] variational autoencoder,[10] diffusion models,[11] and transformer-based models like generative pretrained transformers (GPT).[12] These models learn the underlying distribution of a dataset in order to produce new, plausible outputs (images, sounds, text) similar to the original dataset.

We are now at the dawn of a new era. The AI market is estimated to grow at more than 37% annually from 2023–2030.[13] Stocks of companies developing GPUs have skyrocketed: as of 2024, Nvidia's valuation has exceeded $2 trillion, more than Google or Amazon.

The recent emergence of large language models (LLMs) and chatbots (such as ChatGPT,[14] Llama2,[15] and Gemini[16]), with their ability to handle multiple tasks, has driven rapid and profound changes and innovations, with applications ranging from personal assistants to financial information and drug discovery. Within a mere two months of its November 2022 debut, ChatGPT surpassed 100 million users.[17]

While LLMs have captured the popular imagination, recent developments in multimodal and generative models have further extended their capabilities—those models are now being used for text-to-image generation (e.g., Dall-E or Craiyon), text-to-video generation (e.g., SORA), analysis of images (e.g., OpenAI's GPT-4V(ision)[18]), and analysis of image, audio, and video (e.g., Google Gemini). These advances in software and hardware are driving innovations and value creation across sectors and industries, and hold tremendous potential for the application and use of AI to accelerate climate and nature solutions.

Key AI Capabilities

While AI certainly opens new avenues for innovation in the context of climate and nature, it is important to emphasize that these are multifaceted problems; success will require a combination of capabilities, as well as diverse expertise and domain knowledge. It is unlikely that transformative change will come from one solution, model, tool, or technique, but rather through a combination. There is vast potential in combining AI's capabilities with expertise and knowledge from diverse domains to create new high-impact opportunities for solutions—the most promising of these capabilities include:

» **High-Volume Data Analysis.** AI's capacity to process and interpret vast quantities and varieties of data is unprecedented. Data can be integrated from high-volume datasets and various sources (known as multimodal data fusion), including images from cameras, drones, unmanned aerial vehicles, and remote sensing satellite imagery; sensor data and Internet of Things (IoT) network connectivity; bioacoustic data; and more. It can also be used to identify and interpret complex relationships in large datasets and more efficiently compress and share large amounts of data.

» **Monitoring.** Previously time- and labor-intensive monitoring processes, such as analysis of massive datasets coming from satellites or real-time energy consumption, can now be streamlined and automated. AI can classify, segment, or analyze this data—from images to time

ABOUT THIS REPORT

This report is the product of a collaboration among Columbia University's Climate School and Engineering School; the University at Albany, State University of New York; and Esri, commissioned by and in collaboration with the Bezos Earth Fund.

Four primary data collection strategies informed this assessment:

- **Literature review** of peer-reviewed journal articles on the use of AI in climate and nature from 2015 to the present
- **Internet searches** (both manually and with the assistance of fine-tuned large language models) to locate key initiatives in the space of AI for climate and nature
- **Qualitative surveys** (n=14) and semi-structured interviews (n=31) with key representatives from academia, industry, government, and non-profit organizations
- **Feedback from experts** in relevant domains on draft versions of this report

Other relevant pieces of work on this topic include Climate Change AI's foundational report *Tackling Climate Change with Machine Learning* released in 2019 and the 2023 *Artificial Intelligence for Climate Change Mitigation Roadmap*, which explores high-potential opportunities for using AI to fight climate change and provides extensive policy analysis and recommendations.[40,41]

Additional details on the methodology and related sources are provided in the appendix.

To cite this report: Gentine, Pierre, Geneva List, Kyoko Thompson, Theresa Pardo, Xin Li, George Berg, Lauren Bennett, et al., Landscape Assessment of AI for Climate and Nature. (May 2024). Available at bezosearthfund.org/ai-climate-nature.

series information—much more quickly and accurately, allowing faster, better-informed decision-making. For example, it can monitor and detect changes in land cover and land use, species populations, and vegetation health to support more successful conservation efforts.

» **Optimization.** Given its speed, accuracy, and low computing requirements compared to other computational techniques (once trained), AI is already invaluable to climate solutions. Applications using vehicle routing optimization, efficient transportation, and optimal power network design (generation, transmission, and distribution component specifications and siting) can contribute to a reduction in emissions and other environmental benefits.

» **Predictive Modeling and Forecasting.** Trained on massive amounts of data using past and current conditions as inputs, AI can more accurately and more efficiently predict future behavior or conditions. Applying this capability to assess and optimize crop yields, energy demand, transportation mobility, carbon sinks, and weather or climate projections (among other examples) can lead to both cost savings and emissions reduction.

» **Digital Twins.** Digital twins are sophisticated and accurate computer simulations of an object, process, or system. They can be transformative in climate and nature applications where simulations are computationally expensive, require large amounts of data that are either unavailable or expensive to gather, or where ethical considerations limit real-time evaluations. Creating digital counterparts of terrestrial, aquatic, industrial, or urban environments, for example, enables experimentation or counterfactuals without risk of harm to that environment—while still accelerating solution-oriented designs, informing implementation strategies, and supporting efficient decision-making for climate mitigation, adaptation, and nature-based solutions.

» **Acceleration of Discovery.** AI can play a pivotal role in uncovering novel solutions, leveraging its unique capability to process vast amounts of data across various disciplines as well as its ability to learn nonlinear and intricate relationships within data. Critically dependent on open data and data availability, this can

INITIATIVE HIGHLIGHTS

Institute for Trustworthy AI in Law & Society (TRAILS)

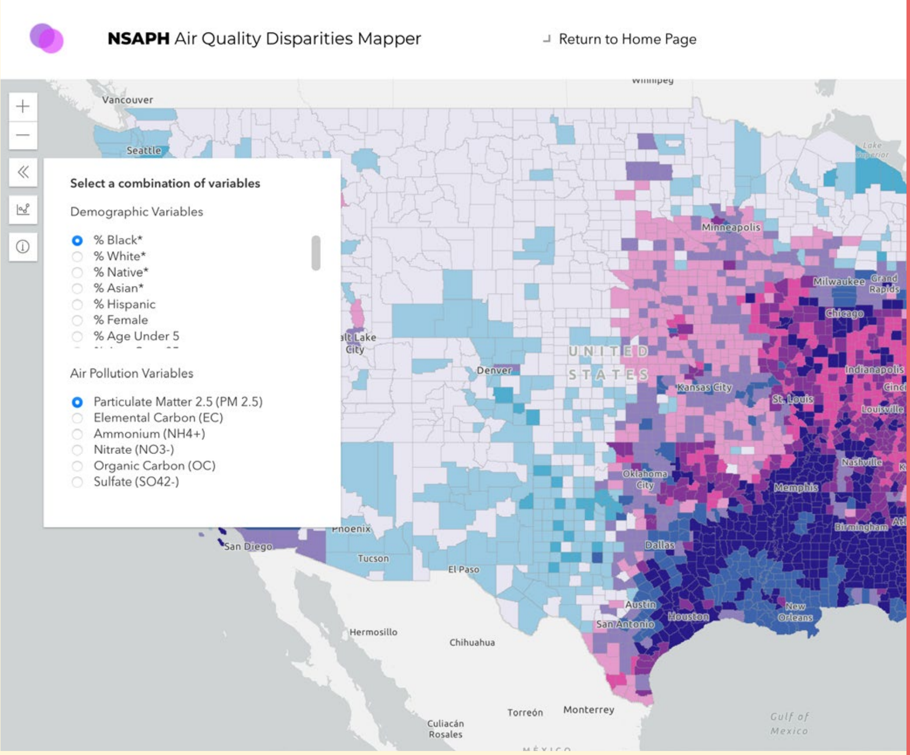
Led by the University of Maryland, TRAILS aims to bring attention to ethics, human rights, and support for marginalized communities to the forefront of mainstream AI development. TRAILS is the first institute of its kind to integrate participatory design, technology, and governance of AI systems and technologies; its focus is on investigating what trust in AI looks like, whether current technical solutions for AI can be trusted, and which policy models can effectively sustain AI trustworthiness. TRAILS is funded by a partnership between the National Science Foundation and National Institute of Standards and Technology.

Harvard T.H. Chan School of Public Health: Research Driving Equitable Policy

Dr. Francesca Dominici and her team at the Harvard T.H. Chan School of Public Health explore the impacts of air pollution, noise pollution, and climate change on health, with a particular emphasis on identifying systemic inequities. Their work brings together large, heterogeneous datasets to identify and understand the health impacts of environmental threats and inform policy. By including the advancement of equity and environmental justice as a central tenet of their research, they provide a model for rigorous scientific research that can also drive meaningful policy change.

Examples:

- Air pollution and mortality at the intersection of race and social class
- Air pollution exposure disparities across US population and income groups
- Air quality disparities mapper: An open-source web application for environmental justice (below)



accelerate progress in a variety of areas, including the development of new and more efficient materials for carbon capture, sequestration, and storage.

The Need for Open Data and Collaboration

Many climate and nature applications are inherently tied to a particular location and must be evaluated and approached within that context in order to ensure that environmental and societal impacts are considered when solutions are proposed. To that end, there is a long history of using computer vision algorithms in the collection and analysis of remote sensing data, leveraging observations from cameras, drones, aircraft, and satellites to describe the Earth and its processes. AI algorithms can process these data for various monitoring applications, including land-cover and land-use change (such as land degradation or deforestation), agricultural crop productivity, inundation, polar ice changes, carbon stocks and their evolution, and more. New satellites continue to be launched with finer spatial, temporal, and spectral resolution or in increased numbers through constellations to increase both spatial and temporal coverage, paving the way for deeper understanding of our planet.

Thanks to open data policies promoted and implemented by government and intergovernmental satellite agencies such as the National Aeronautics and Space Administration (NASA), the European Space Agency, and the Japan Aerospace Exploration Agency, as well as innovations initially driven by efforts such as Google Earth Engine, remote sensing is now more widely available and analysis-ready through better structured web services with public Application Programming Interfaces. Collections and catalogs like Google Earth Engine, Microsoft Planetary Computer, Esri's ArcGIS Atlas of the World, and the Food and Agriculture Organization System for Earth Observation Data Access, Processing and Analysis for Land Monitoring were developed to simplify the process of finding and using that data. However, this is only a small percentage of the petabytes of data collected every year by more than a thousand satellites imaging the Earth. Indeed, many satellites are commercial operations or are operated by governments that do not provide free, open access and therefore cannot be leveraged by most AI models.

The success of AI in developing meaningful and impactful interventions to address climate and nature challenges requires openness and collaboration across disciplines, each with its own specialized knowledge and terminology.

How Recent AI Can Be Used for Climate and Nature

Many current and emerging AI models and applications have the potential to create high-impact opportunities in the context of climate and nature, even if they were not originally developed for that purpose. For example, advances in unstructured data analysis and prediction, edge computing, and multimodal AI could all lead to the acceleration of solutions. Beyond the key AI capabilities (high-volume data analysis, monitoring, optimization, digital twins, predictive modeling, and the acceleration of discoveries), we have seen important recent developments in AI that could present important tools for climate and nature applications.

» **Graph-Structured Data Analysis and Prediction.** Many datasets are not organized as sequences or over spatially regular grids. Graph Neural Networks (GNNs) are powerful tools that can model the intricate relationships of graph-like structured data. GNNs are well suited for many climate and nature applications because of their capacity to handle complex structured data such as those present in hydrological networks; sparse weather or pollution station data; and the multi-scale nature of turbulent fluids found in the atmosphere. By incorporating information from neighboring nodes and edges within the graph structure, GNNs can produce a generic model to improve the prediction of complex spatio-temporal behaviors across scales.

» **Edge Computing.** The edge computing ecosystem allows computations to be performed in close proximity to the data collection points (i.e., at the edge such as near an observing camera), limiting the needs for substantial internet bandwidth.[19] This approach leverages IoT to address issues of data collection, communication at scale, and real-time decision-making. Edge computing technologies help expedite the development of data infrastructure by enabling the wider distribution of edge devices. In-house monitoring, smart grids, and real-time analysis of energy consumption are all current edge computing applications.

Edge computing has significant transformative potential in real-time monitoring, which is critical to evaluating developments in climate and nature. In the field of bioacoustics, for example, audio data collected from ocean- and species-monitoring sensors can be processed in remote and challenging environments. Edge

RELATED EFFORTS

The Bezos Earth Fund commissioned and collaborated on this Landscape Assessment, along with two additional reports:

AI for Climate and Nature Workshop: Summary Report. The Bezos Earth Fund's AI for Climate and Nature Workshop, held in San Francisco in October 2023 in partnership with Foresight Institute, invited practitioners, researchers, and entrepreneurs across AI, climate, and nature. Designed to provide critical insights to inform next steps, the workshop illuminated AI "superpowers", priority climate and nature challenge areas, and 59 opportunity spaces most suited to bringing together this "supply and demand."

Grand Challenge Initiatives in AI for Climate & Nature. Climate Change AI's report conducts a comprehensive assessment and evaluation of 200+ past and present Grand Challenges and open-innovation initiatives at the intersection of AI, Climate, and Nature. Augmented by 60+ stakeholder interviews, it provides strategic insights and actionable recommendations for designing and operationalizing impactful Grand Challenges that drive systemic change.

All three reports can be found at bezosearthfund.org/ai-climate-nature.

In addition, the Bezos Earth Fund and Columbia Climate School hosted a convening on AI for Climate and Nature in New York City on April 10–11, 2024 This event aimed to identify how AI can contribute to solving pressing issues related to climate and nature, and explore the most promising opportunities to leverage impact.

computing enables efficient and scalable solutions that are instrumental in advancing bioacoustics monitoring efforts. The accumulated biodiversity data can then be used to establish foundational models in climate and environmental studies.

» **Multimodal AI.** Multimodal AI is designed to analyze and amalgamate data from multiple sources, with varying levels of coverage, resolution, and quality. These techniques enable in-depth analysis of intricate relationships and foster a comprehensive understanding of system dynamics and shifts. In the climate and nature domain, multimodal requirements are the norm; environmental data are acquired by various sensors with varying coverage, resolution, and quality. Multimodal AI can optimally integrate these diverse data streams and synthesize climate and nature data from multiple sources—such as in-situ observations, drones, and various remote sensing platforms—thereby facilitating monitoring of land cover, land use, vegetation health, and environmental changes across temporal and spatial scales. Data from sources like acoustic sensors, camera traps, and GPS tracking devices can also be optimally leveraged through multimodal AI and used to analyze species distributions, monitor wildlife populations, and assess biodiversity metrics.

Considerations for AI Development

The innovation and economic growth that have delivered remarkable gains in human wellbeing and wealth since the Industrial Revolution have also had negative consequences, including widespread destruction of the natural world and deepening inequality. The very engines of growth (e.g., the energy sector, industry, agriculture, forestry) are the primary drivers of climate change. In turn, the compounding impacts of climate change and its drivers—including land and sea use change and exploitation of natural resources, along with pollution and invasive species—are leading to the widespread degradation of nature.[20] And with the rapid advances in both development and deployment of AI, its potential for negative social and environmental consequences—often in ways not yet understood—is raising concerns for funders, developers, policymakers, and practitioners alike.

Given the strong connection between ethics, equity, and climate and nature impact, AI applications for climate and nature must foreground ethics and equity, governance structures, safety and security, and sustainability.

» **Ethics.** Many discussions about the responsible use of AI to address societal problems focus on issues of ethics, including privacy, intellectual property rights, algorithmic transparency, accountability, and trust. For nature and climate, they are complemented by ethical considerations on environmental impact and regulation of human intervention (e.g., geoengineering). How do we evaluate the ethical implications of AI when defining our values and creating ethical frameworks are not neutral undertakings? There is no single definitive set of social values; instead, social values need to be agreed upon and can reproduce bias or alignment with a particular worldview, such as WEIRD (Western, Educated, Industrialized, Rich, and Democratic) values.[21] How can AI solutions promote and leverage the vast traditional ecological knowledge and values of Indigenous Peoples in relation to nature? Moreover, who is included when ethical implications are considered? Will AI solutions focusing on traditional ecological knowledge adhere to the principles of free, prior, and informed consent, ensuring that indigenous communities consent to the integration of their knowledge into AI applications for climate and nature? In addition, non-human species are often left out of the conversation when AI technologies are used in areas such as farming and species tracking; who will speak to the impacts on them?[22] These are questions that must be answered in order to ensure that AI solutions are operating ethically.

» **Equity and Inclusion.** Environmental racism and injustice as well as social inequality are the result of systemic discrimination stemming from long-standing prejudices and biases perpetuated against individual communities, countries or regions. The use of AI technologies to find and scale up solutions to the climate and nature crises must consistently consider issues of equity and inclusion in order to avoid unintentionally exacerbating existing inequalities. Safeguarding equity and inclusion in AI solutions can take many forms:
- Evaluating model inputs to ensure that they are representative and free of bias. Indeed, most datasets are acquired in specific and privileged regions of the world (North America or Europe) that can bias the results when applied in other regions of the globe. For example, in the past, many AI models were shown to have biased predictions when applied to racial minorities, which can have hurtful and even serious consequences.[23,24]

- Evaluating outputs to ensure that they do not maintain or exacerbate existing inequities and biases.
- Involving and empowering community members from diverse and historically marginalized communities, including Indigenous Peoples, at the outset to ensure all perspectives are considered, both when asking questions and when designing AI solutions.

» **Governance.** To ensure that AI is used ethically, it needs to exist in an ecosystem of technology governance. While the innovative and disruptive nature of technology start-ups and tech culture can often outpace regulation, regulatory frameworks for AI are beginning to emerge. For example, in 2024 the European Commission endorsed the AI Act, which aims to ensure that AI is safe, transparent, non-discriminatory, and environmentally friendly, with different rules applicable to different levels of risk.[25] As part of this agreement, biometric identification and cognitive manipulation among others have been deemed to have unacceptable risk and are therefore banned from AI algorithm training; endeavors deemed as high risk, such as the management of critical infrastructure, require prior and ongoing assessment; while areas of limited risk, including generative AI applications, require the transparent disclosure of AI use. Additional governance frameworks include:
- The G7 International Guiding Principles for Advanced AI Systems and code of conduct (Hiroshima AI process)[26]
- The Biden Administration Executive Order on AI[27]
- The United Nations Interim Report on Governing AI for Humanity[28] and the United Nations General Assembly resolution on the promotion of "safe, secure, and trustworthy" AI[29]

Developing processes that ensure proper ethical design and governance of AI requires new kinds and levels of investment. For example, the newly created Institute for AI and Ethics at Oxford University is exploring rules, norms, and ethical frameworks for an age with AI.[30] Other organizations dedicated to this mission include the AI Now Institute, which studies the social implications of AI; the AI4People nonprofit research and advocacy group, which promotes ethics, privacy, governance, and responsible use of AI for social good; and the U.S. Artificial Intelligence Safety Institute, a new research consortium established by the US Department of Commerce's National Institute of Standards and Technology to support and demonstrate pathways to developing safe and trustworthy artificial intelligence.[31,32,33]

Given the clear connection between climate and nature applications and ethical and societal considerations, good governance is essential to the use and leveraging of AI for climate and nature solutions. In a recent report, Climate Change AI and the Centre for AI and Climate propose that governments could take leadership in AI governance to address climate change by: fostering the responsible development of, and access to, data and digital infrastructure; supporting deployment and systems integration of AI-for-climate applications via targeted policy design and evaluation; embedding responsible AI principles into the design of AI initiatives; fostering climate-cognizant impact assessment of AI via AI emission data collection, measurement, and reporting frameworks; and building capacity for implementation, evaluation, and governance.[34]

> "Infrastructure is climate justice.
>
> **DR. UYI STEWART**[42]
> **Data.org**

» **Equality of Opportunity.** Many important AI tasks require significant financial resources. The training and operationalization of massive AI models requires engineers and computer scientists, access to large quantities of GPUs, and data center infrastructure. Building and maintaining these types of AI models is exorbitantly expensive. For instance, training a LLM typically costs several to tens of millions of dollars, mainly in hardware and computational costs. As a result, large AI models are increasingly likely to be designed, trained, and maintained by a small number of large corporate actors.

This concentration of powerful AI capabilities in just a few highly resourced players (typically companies) raises equity concerns, particularly when one evaluates the allocation of resources for AI within the Global South. For example, in the roadmap for research on responsible artificial intelligence for development in African countries, the authors note the importance of monitoring monopolies over data and maintaining awareness of the potential widening of the gap between rich countries (who possess the monopolies) and the poor countries (who do not own their own data technology).[35] New innovative partnerships such as the one recently announced by the University at Albany, SUNY and IBM bring together industry and academic partners are needed to ensure that researchers and their community partners have access to the most cutting edge AI technologies. With this partnership, UAlbany researchers are the first in the world to receive a prototype computing cluster specifically optimized for AI inferencing.

» **Safety and Security.** AI has enormous potential to accelerate nature and climate solutions, yet can create safety and security risks. The safety and security of using AI must be evaluated in advance of its use in specific circumstances. Safety risks from using AI occur when AI fails to operate as intended or has unintended consequences. Many applications of AI discussed in this Landscape Assessment have potential safety risks. For example:
  - AI systems that help integrate renewable power into the electric grid in real-time could create risks of blackouts and threats to human safety.
  - Manufacturing facilities operating with AI-driven recommendations without adequate testing could create risks of catastrophic failures and unstable operating conditions and worker injuries.
  - AI applications in agriculture with poor or inapplicable data could lead to over-use of arable land and crop failures.

  Security risks from using AI occur when an actor with malicious intent exploits vulnerabilities in an AI system. In general, AI can expand the attack surface beyond that found in conventional software programs. These security risks can be especially serious when AI is used in real-time workflows. AI can also empower bad actors, such as poachers who may use AI-generated insights to improve targeting of threatened or endangered species.

  Attention to safety and security risks should be central to any program for using AI to accelerate climate and nature solutions.

» **Sustainability.** It is impossible to address the potential of AI without also scrutinizing its energy consumption. The computing power required to process and analyze massive amounts of data necessitates significant energy consumption and water resources for cooling of hardware.

  This tension has prompted proposed legislation in the United States entitled the *Artificial Intelligence Environmental Impacts Act of 2024* that seeks to produce a comprehensive study on the positive and negative environmental impacts of AI, including energy consumption, pollution and e-waste; convene a consortium to develop standards to measure and report on AI's environmental impacts; and to create a voluntary reporting system on these impacts for AI developers.[36]

  In order for AI to gain credibility as a tool for climate change mitigation and the protection of nature, efforts are needed to improve the sustainability and lower the carbon footprint of AI models during training and inference. Emerging work using specialized hardware and software designed for AI (different from conventional computers) is showing promise in speeding up the training and operation of large-scale AI systems, which in turn has the potential to lower the carbon footprint of these models and make them more sustainable.[37,38]

  Another option is investing in low-cost, lower-complexity models. LLMs/foundation models and other widely used methods are part of a trend to create larger models that push the envelope of data, processing, and computing power needs, but in many applications, this is overkill. Complex algorithms, with their accompanying hardware and energy consumption needs, are unnecessary for many smaller AI tasks that could be accomplished with simpler algorithms that have more modest and sustainable computing needs. Edge AI and TinyML approaches, in particular, use inexpensive, power-efficient hardware to do AI in the field; for example, they can enable on-device processing of satellite imagery or other locally gathered sensor data to monitor changes in land use and land cover, which is particularly useful for assessing deforestation, urbanization, and other environmental changes.

  Looking further into the future, quantum computing holds the intriguing, yet unsure, prospect of radically changing the computing landscape, by greatly speeding up large-scale computing, improving energy efficiency, and lowering the carbon footprint of those models.[39] As of now, however, it is unclear if and when those benefits might be realized.

ENDNOTES: THE STATE OF AI

1 “What Is the Sixth Mass Extinction and What Can We Do about It,” WWF, https://www.worldwildlife.org/stories/what-is-the-sixth-mass-extinction-and-what-can-we-do-about-it#:~:text=Unlike%20previous%20extinction%20events%20caused,been%20converted%20for%20food%20production.

2 “2023 Was the World’s Warmest Year on Record, by Far,” National Oceanic and Atmospheric Administration, January 12, 2024, https://www.noaa.gov/news/2023-was-worlds-warmest-year-on-record-by-far#:~:text=Earth%27s%20average%20land%20and%20ocean,0.15%20of%20a%20degree%20C).

3 Katherine Richardson et al., “Earth Beyond Six of Nine Planetary Boundaries,” *Science Advances*, no. 37 (2023).

4 “New Analysis of National Climate Plans: Insufficient Progress Made, COP28 Must Set Stage for Immediate Action,” United Nations Climate Change, November 14, 2023, https://unfccc.int/news/new-analysis-of-national-climate-plans-insufficient-progress-made-cop28-must-set-stage-for-immediate#:~:text=UN%20Climate%20Change%20News%2C%2014,goals%20of%20the%20Paris%20Agreement

5 “Halfway to 2030, World ‘Nowhere Near’ Reaching Global Goals UN Warns,” United Nations News, July 17, 2023, https://news.un.org/en/story/2023/07/1138777.

6 Jianqiu Chen, “Image Recognition Technology Based on Neural Network,” *IEEE Access* 8 (2020): 157161-157167.

7 Felix Stahlberg, “Neural Machine Translation: A Review,” *Journal of Artificial Intelligence Research* 69 (2020): 343-418.

8 Manar Abu Talib et al., “A Systematic Literature Review on Hardware Implementation of Artificial Intelligence Algorithms,” *The Journal of Supercomputing* 77, no. 2 (2021): 1897-1938.

9 Ian Good et al., “Generative Adversarial Networks,” *Communications of the ACM* 63, no. 11 (2020): 139-144.

10 Aman Singh and Tokunbo Ogunfunmi, “An Overview of Variational Autoencoders for Source Separation, Finance, and Bio-Signal Applications,” *Entropy* 24, no. 1 (2021): 55.

11 Jascha Sohl-Dickstein et al. “Deep unsupervised learning using nonequilibrium thermodynamics.” In International conference on machine learning, pp. 2256-2265. PMLR, 2015. https://dl.acm.org/doi/10.5555/3045118.3045358

12 Gokul Yenduri et al., “Generative Pre-Trained Transformer: A Comprehensive Review on Enabling Technologies, Potential Applications, Emerging Challenges, and Future Directions,” *arXiv preprint arXiv:2305.10435* (2023).

13 Grand View Research, *Artificial Intelligence Market Size, Share & Trends Analysis by Solution (Hardware, Software, Services), by Technology (Deep Learning, Machine Learning, NLP), by Function, by End-Use, by Region, and Segment Forecasts, 2023-2030* (Grand View Research 2023), 125, https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market.

14 “Introducing ChatGPT,” OpenAI, November 30, 2022, https://openai.com/blog/chatgpt.

15 Hugo Touvron et al., “Llama: Open and Efficient Foundation Language Models.” *arXiv preprint arXiv:2302.13971* (2023).

16 Gemini Teamt et al., “Gemini: A Family of Highly Capable Multimodal Models,” *arXiv preprint arXiv:2312.11805* (2023).

17 Krystal Hu. “ChatGPT sets record for fastest-growing user base - analyst note”. Reuters. February 2, 2023. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

18 OpenAI, *GPT-4V(ision) System Card* (OpenAI, 2023), 18,: https://cdn.openai.com/papers/GPTV_System_Card.pdf.

19 “What is Edge Computing,” Azure, accessed December 10, 2023, https://azure.microsoft.com/en-us/resources/cloud-computing-dictionary/what-is-edge-computing.

20 “Media Release: Nature’s Dangerous Decline ‘ Unprecedented’: Species Extinction Rates ‘Accelerating’,” Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services, May 5, 2019, https://www.ipbes.net/news/Media-Release-Global-Assessment.

21 Jason D’Cruz, Notes on statements from AI Convening Meeting, Albany, New York, November 30, 2023.

22 Peter Singer and Yip Fai Tse, “AI Ethics: The Case for Including Animals,” *AI and Ethics* 3, no. 2 (2023): 539-551.

23 Olga Akselrod, “How Artificial Intelligence Can Deepen Racial and Economic Inequities,” ACLU, July 13, 2021, https://www.aclu.org/news/privacy-technology/how-artificial-intelligence-can-deepen-racial-and-economic-inequities.

24 Nico Grant and Kashmir Hill, “Google’s Photo App Still Can’t Find Gorillas and Neither Can Apple’s,” *The New York Times*, May 22, 2023, https://www.nytimes.com/2023/05/22/technology/ai-photo-labels-google-apple.html.

25 “High-Level Summary of the AI Act,” EU Artificial Intelligence Act, accessed May 6, 2024, https://artificialintelligenceact.eu/high-level-summary/.

26 Coran Darling et al., “G7 Publishes Guiding Principles and Code of Conduct for Artificial Intelligence,” November 6, 2023, https://www.dlapiper.com/en/insights/publications/ai-outlook/2023/g7-publishes-guiding-principles-and-code-of-conduct-for-artificial-intelligence.

27 Bridget Neill et al., “Key Takeaways From the Biden Administration Executive Order on AI,” October 31, 2023, https://www.ey.com/en_us/public-policy/key-takeaways-from-the-biden-administration-executive-order-on-ai.

28 United Nations, AI Advisory Body, *Interim Report: Governing AI for Humanity*, December 31, 2023, https://www.un.org/sites/un2.un.org/files/ai_advisory_body_interim_report.pdf.

29 “General Assembly Adopts Landmark Resolution on Artificial Intelligence | UN News,” United Nations, accessed May 6, 2024, https://news.un.org/en/story/2024/03/1147831.

30 “Institute for Ethics in AI,” University of Oxford, accessed December 28, 2023, https://www.oxford-aiethics.ox.ac.uk/.

31 “Computational Power and AI,” AI Now, accessed January 2, 2024, https://ainowinstitute.org/.

32 “AI4People Institute,” Atomium European Institute for Science Media and Democracy, accessed January 2, 2024, https://eismd.eu/ai4people/.

33 Mike Nolan, “UAlbany Partners on New U.S. Artificial Intelligence Safety Insitute Consortium,” University at Albany, February 8, 2024, https://www.albany.edu/news-center/news/2024-ualbany-partners-new-us-artificial-intelligence-safety-institute-consortium.

34 Centre for AI and Climate and Climate Change AI, *Climate Change and AI: Recommendations for Government Action*, (Global Partnership on Artificial Intelligence, 2021), https://gpai.ai/projects/responsible-ai/environment/climate-change-and-ai.pdf.

35 Arthur Gwagwa et al., “Road Map for Research on Responsible Artificial Intelligence for Development (AI4D) in African Countries: The Case Study of Agriculture,” *Patterns* 2, no. 12 (2021).

36 U.S. Senate, *Artificial Intelligence Environmental Impacts Act of 2024*, BAG24029 7NT,118th Congress 2D Session, Introduced February 1, 2024, https://www.markey.senate.gov/imo/media/doc/artificial_intelligence_environmental_impacts_act_of_2024_-_020124pdf.pdf

37 Ali Momeni et al., “Backpropagation-Free Training of Deep Physical Neural Networks,” *Science* 382, no. 6676 (2023): 1297-1303.

38 Logan G. Wright et al., “Deep Physical Neural Networks Trained With Backpropagation,” *Nature* 601, no. 7894 (2022): 549-555.

39 M. Halem and J. LeMoigne, “A Quantum Annealing Computer Team Addresses Climate Change Predictability,” (presentation, ESTF Forum 2016, Annapolis, MD, June 14, 2016).

40 David Rolnick et al., “Tackling Climate Change With Machine Learning,” *ACM Computing Surveys* (CSUR) 55, no. 2 (2022): 1-96.

41 David B. Sandalow et al., *Artificial Intelligence for Climate Change Mitigation Roadmap* (Innovation for Cool Earth Forum, 2023) https://doi.org/10.7916/cfn0-xj39.

42 Bezos Earth Fund, *AI for Climate & Nature Workshop: Summary Report* (Bezos Earth Fund 2023).

Current Applications of AI

- **Nature**
- **Food + Agriculture**
- **Power**
- **Cities + Built Environment**
- **Greenhouse Gas Emissions**
- **Climate Impacts**

Systems Change Lab is an initiative dedicated to providing valuable insights and catalyzing action to confront the world's most critical challenges. The lab monitors and analyzes more than 70 shifts across 15 global systems that require transformative changes in order to limit global warming, halt biodiversity loss, and secure a more just and equitable society.

This report focuses on AI applications across 10 of the 15 named systems—in addition, it examines greenhouse gas emissions (including technological carbon removal) and climate impacts.

GLOBAL SYSTEMS EXAMINED IN THIS REPORT

Nature

- Forest and Land Management
- Ocean Management
- Freshwater Management

Food + Agriculture

Industry

Cities + Built Environment

Transport

Greenhouse Gas Emissions

Climate Impacts

AI CAPABILITIES SEEN IN EACH GLOBAL SYSTEM

	Data Processing	Monitoring	Optimization	Prediction	Digital Twins	Accelerating Discovery
Nature (Forest and Land Management, Ocean Management, Freshwater Management)	●	●	●	●	●	
Food + Agriculture	●	●	●	●	●	●
Power	●	●	●	●	●	●
Industry	●	●	●	●	●	●
Cities + Built Environment	●	●	●	●	●	
Transport	●	●	●	●	●	●
Greenhouse Gas Emissions (Technological Carbon Removal)	●	●		●	●	●
Climate Impacts	●	●		●	●	

CURRENT APPLICATIONS IN AI

Nature

The most recent flagship Living Planet Report from the World Wildlife Federation found that wildlife populations have declined by 69% since 1970.[43] Researchers believe we are in the midst of the planet's sixth mass extinction event—one caused entirely by human activity.[44] Currently, species extinction rates are between 1,000 and 10,000 times greater than natural extinction rates.[45]

Land-use change—from deforestation, agriculture, and urban expansion—has been the dominant driver of this loss, in addition to pollution, unsustainable harvests, and the introduction of invasive species. Together, these drivers are reducing natural habitats and contributing to ecosystem degradation across terrestrial, marine, and freshwater systems. In the coming years, however, climate change is expected to become the leading cause of biodiversity loss. By 2050, it's estimated that 70–90% of coral reefs will be rendered functionally degraded if warming is not limited to 1.5 degrees C.[46]

Clearly, actions are urgently required to change the trend of our negative impact on the environment. AI can accelerate monitoring and prediction, and offer strategies to improve our understanding of terrestrial, marine, and freshwater systems, supporting solutions for protection, restoration, and sustainable management of species and ecosystems.

INITIATIVE HIGHLIGHTS: CONSERVATION AND BIODIVERSITY

- **Conservation X Labs' Sentinel AI** uses wildlife monitoring tools (like trail cameras and acoustic recorders) alongside AI to process environmental data in real-time as it is collected. Satellite and cellular networks give conservationists the ability to respond rapidly to wildlife-related problems such as monitoring invasive species, poaching and wildlife trafficking, zoonotic diseases, and changing animal behavior.
- **Wildlife Insights** combines field expertise, sensors, and advanced analytics to generate valuable wildlife data. Users all over the world can upload images of wildlife—which Wildlife Insight's algorithm automatically identifies. It dramatically increases the speed of processing and analyzing images and camera trap data to get information to decision makers in near- real-time.[136]
- **Conservation AI** uses advanced machine learning techniques to identify a wide range of animal species in different habitats from images. They can also identify humans and man-made objects, which can support conservation efforts (such as identifying vehicles, which are often used in poaching activities).
- **Rainforest Connection's Arbimon** is an open-source ecoacoustic analysis platform empowering scientists and conservationists with an efficient way to upload, store, and analyze mass amounts of acoustic data, enabling the ability to derive insights about the ecosystem at scale.
- **Earth Species Project** uses AI to decode and deepen the understanding of non-human communication. The publicly available machine learning models support ongoing research into the behavior of other species to help enable species protection and conservation efforts.

Forest and Land Management

Monitoring, Protecting, and Managing Species on Land

Using both visual and audio data, AI can perform real-time monitoring of wildlife populations to inform wildlife conservation strategies.[47] This is accomplished through computer vision and bioacoustics analysis made possible by a range of sensors (e.g., camera traps, cell phone microphones, drones, remote sensing), as well as by integrating citizen science via crowdsourced data.[48,49,50] Taxonomy data and images are used in combination with AI to enable species recognition.[51] AI also classifies rare species such as birds or bats from audio recordings, even with limited training data.[52,53,54]

AI is beginning to play a pivotal role in tracking animals, offering insights into animal behavior, population dynamics, and the impact of environmental changes.[55,56] For instance, AI analyzes information from GPS tracking of individual animals to assess population movement, routes, and migrations. Camera traps and automatic AI-based detection are also used to identify species, count individuals, and analyze behaviors from the collected footage. Drones equipped with cameras can monitor larger animal movements in regions that are difficult to access.

AI-based image recognition is increasingly being used to identify and monitor insect species, including pollinators.[57,58] Cameras and sensors capture images of insects visiting flowers, and AI models are used to identify the species. These algorithms can track pollinator populations, diversity, and behavior over time, providing key information for conservation and management strategies. AI combined with remote sensing can map habitats critical for pollinators; by identifying areas rich in biodiversity and understanding landscape connectivity, conservationists can target efforts to protect and restore habitats that best support pollinators.

Through large-scale and rapid analysis of cameras and acoustic sensors, AI can also assist in wildlife restoration.[59,60] This information in turn can be used to optimally restore ecosystems or reintroduce species to their natural habitats. Research has shown that bioacoustic analysis can be used to monitor post-agriculture tropical forest recovery, based on the community composition of vocalizing vertebrates.[61] Another important area, which has been a long-standing challenge, is habitat connectivity. AI analysis of remote sensing–based landscape connectivity can provide new insights on wildlife movement and its barriers, [62] promoting new wildlife corridors and restoring habitats, allowing species to migrate, breed, and thrive.

Through modeling—improved by data augmentation techniques that use synthetic data to artificially inflate a dataset, alongside iterative expert (and labor-intensive) labeling and model retraining—AI can provide new insights into species activity and abundance (e.g., automated plant image identification to bridge the botanical taxonomic gap).[63,64] AI is also able to forecast and model future scenarios of species distributions. Process-based models informed by AI have been used to predict the potential global distribution of invasive species under current and future climate scenarios.[65,66] Researchers have also developed a framework using reinforcement learning to assess cost and benefit tradeoffs, which can optimize biodiversity protection strategies for conservation planning and policy.[67]

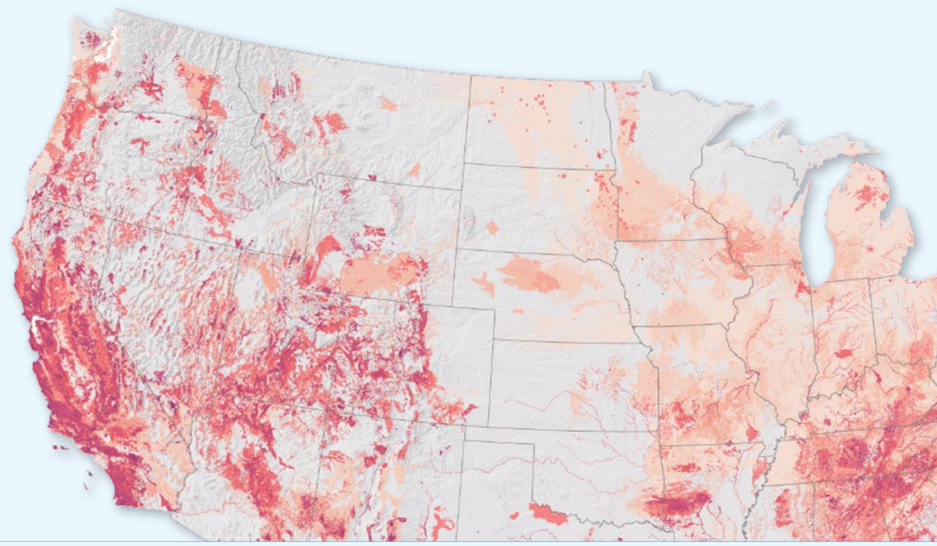
Plant and tree biodiversity monitoring using remote sensing has been a rapidly growing field for AI applications and proves a scalable solution when integrated with multiple technologies.[68,69] Hyperspectral or LiDAR data combined with AI can cluster and identify individual plant species or map species density and distribution.[70] Phenology (the study of cyclic and seasonal natural phenomena in nature) is monitored using remote sensing, especially vegetation indices.[71] This includes tracking changes in vegetation greenness over years, which is indicative of plant health, biodiversity, and the impact of climate change. Remote sensing can also help in the detection of illegal activities that threaten biodiversity, such as illegal deforestation associated with drug trafficking.[72]

AI algorithms can also efficiently process and analyze the massive datasets generated by genomic sequencing. This is crucial to identifying genetic variations and patterns within and across species, and thus understanding evolutionary history and adaptive strategies. AI models can be used to evaluate how

INITIATIVE HIGHLIGHTS

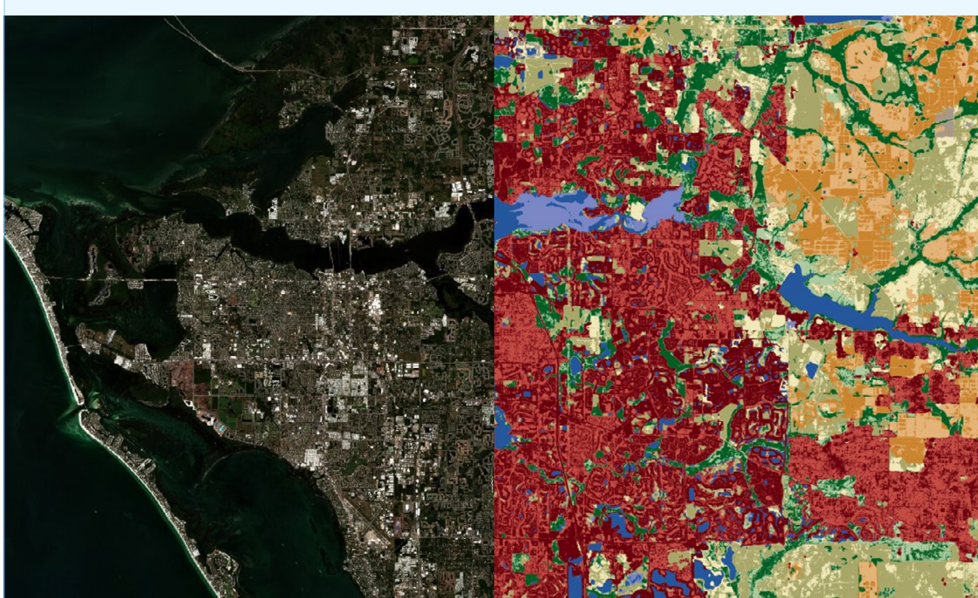
NatureServe: The Map of Biodiversity Importance

In collaboration with The Nature Conservancy, Esri, and Microsoft, NatureServe uses machine learning and cloud computing to create The Map of Biodiversity Importance, high-resolution individual species habitat maps for thousands of at-risk species in the conterminous US. These maps include detailed habitats of vertebrates, plants, aquatic invertebrates, and insects, providing a new synoptic view of biodiversity importance for imperiled species. When these maps are combined and overlaid with protected areas, it is easy to identify the most critical places in the country for conserving at-risk species.



Impact Observatory's IO Monitors

Impact Observatory, in collaboration with Microsoft and Esri, uses deep learning to transform satellite imagery into land cover maps used to monitor change and understand risks. Using billions of human-labeled pixels to train their models, they are able to provide consistent mapping of land cover across the globe. The data is used for understanding and tracking deforestation, land degradation, wetland restoration, urban growth, natural disasters, and ecosystem health, among many other applications.



Impact Observatory map of land use land cover change in Bradenton, FL.
Source 2023-11-04-00_00_2023-11-04-23_59_Sentinel-2_L2A_True_color from Sentinel Hub; 10m Land Cover © 2024 Impact Observatory.

genetic diversity within species contributes to ecosystem services and resilience by mapping and analyzing essential biodiversity variables.[73]

Monitoring, Protecting, and Managing Ecosystems on Land

AI is used to measure carbon and biomass, monitor land cover change and map deforestation, monitor ecosystem health, and even evaluate restoration and conservation initiatives.[74, 75] Deep learning has been used to accurately estimate and monitor tree resources and forest characteristics—estimating tree location and height, crown area, and canopy height—to lay the foundation for digitalized national databases where trees and forests are spatially traceable and manageable.[76] Precisely measuring canopy height is "essential to estimate important biophysical parameters, including above-ground biomass, carbon stock density, and habitat quality," which can in turn inform conservation action and policy.[77]

Deep learning models applied on high-resolution (meter-scale) satellite images have led to improved estimates of carbon stocks and sequestration in trees.[78] A recent study mapped 9.9 billion trees in Africa and found AI-informed, above-ground biomass estimates to be inconsistent with previous ecosystem models of the same area (which estimated higher levels of carbon storage), uncovering the need for potentially significant changes in conservation efforts and in the understanding of carbon sequestration in the region.

The challenge of monitoring land cover changes and detecting crucial environmental indicators is being addressed through the advanced capabilities of deep learning. The availability of hyperspectral and multispectral imagery, coupled with increased computational resources, has propelled deep learning to the forefront of remote sensing analysis. This technology underpins the creation of high-temporal-frequency land use land cover maps, such as the Dynamic World project, which play a critical role in understanding the impacts of human activity on natural ecosystems. Similarly, change-detection techniques using machine learning are crucial for identifying significant changes like deforestation, thereby informing conservation efforts.

Interactive tools are bolstered with AI to assist in the use and interpretation of land-cover models for researchers and practitioners.[79] For example, forestry agencies can use AI-augmented mapping tools to support conservation and restoration governance.[80] Already, large-scale data efforts in ecosystem management are increasingly studied with AI. This includes the United States Forest Service Forest Inventory and Analysis,[81] which collects annualized forest resources and health data, and the Forest Global Earth Observatory, a global network of scientists and forest research sites dedicated to advancing long-term study of the world's forests. Simple AI tools are increasingly being used to analyze those datasets and understand environmental drivers of the observed changes; however, more advanced techniques are needed and will likely be used in the near future.[82]

Restoring Terrestrial Ecosystems

AI offers innovative solutions to monitor, analyze, and restore ecosystems that have been degraded, damaged, or destroyed. AI-driven classification of land use and land cover based on satellite images is used to monitor progress in reforestation across scales and potential illegal logging, such as the open Global Forest Watch project.[83, 84] Tree planting is facilitiated, automated, and optimized with AI-operated drones, which send biodegradable pods containing pre-germinated seeds and essential nutrients into the soil, significantly accelerating the pace of reforestation efforts.[85]

AI can also optimally analyze data from drones or satellites to assess soil health and guide restoration of degraded agricultural soil. It is able to predict soil properties and conditions such as soil sand and clay fraction, soil moisture content, pH levels, organic carbon content, and nutrient levels by analyzing data from remote sensing, ground sensors, and historical soil databases.[86] With improved monitoring of soil moisture, AI provides key insights on droughts and dryness trends.[87] By integrating data from diverse sources, including microbial DNA sequencing, it can also be used to assess soil biodiversity and health. [88] Through the analysis of remote sensing imagery and their changes over time, AI is able to identify areas at risk of soil degradation and erosion. Together, these applications can be critical for early detection of land degradation and early restoration interventions to prevent further damage.

INITIATIVE HIGHLIGHTS: RESTORATION

- **Dendra Systems** uses AI to generate ecosystem insights and assist with managing land and environments to support the rehabilitation of ecosystems and restoration of natural landscapes. Applications include aerial seeding service powered by drone technology.
- **MORFO**, a Brazilian firm, uses forest engineering, computer vision, and drones for large-scale ecological restoration of forest ecosystems. They focus primarily in tropical and subtropical regions that have been deforested, becoming unproductive.

Ocean Management

AI's ability to extract patterns and build models from large datasets is proving particularly effective in monitoring ocean biodiversity and deep-sea resources.[89] It can analyze data from underwater sensors, satellite imagery, and autonomous underwater vehicles to identify and track marine species.[90,91,92] Acoustic data can be used to identify specific sounds made by marine organisms, from the songs of whales to the clicks of dolphins.[93,94] This can in turn be used to understand species distribution, abundance, and behavioral patterns.

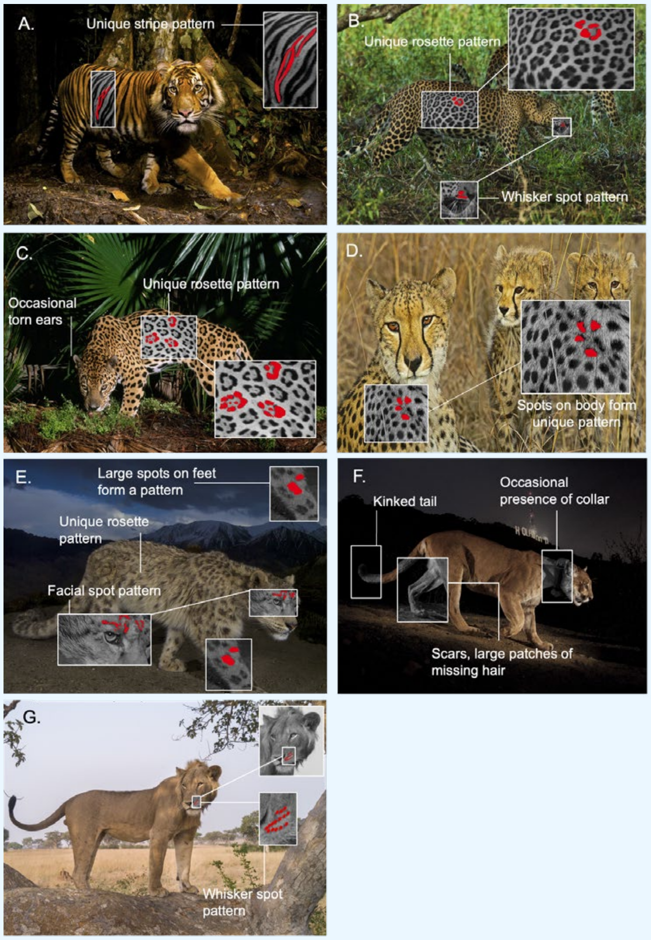
Sensors and cameras—in combination with machine learning—can monitor health and diseases in ocean organisms through changes in species' populations, distribution, and behavior.[95] Similarly, sensors and visual data are used to monitor commercial fisheries, detecting potential overfishing by observing vessel location and aquatic populations.[96] By analyzing catch data, satellite imagery, and oceanographic data, AI can help more accurately and more rapidly predict fish stocks and their distribution.

AI is also revolutionizing ocean exploration and research with initiatives like FathomNet and Ocean Vision AI, which leverage machine learning to process vast amounts of underwater imagery and data. FathomNet, an open-source database, aggregates underwater images to train AI algorithms for faster and more sophisticated ocean data analysis. Ocean Vision AI aims to accelerate the processing of ocean images, facilitate large-scale biological observations, and promote sustainable marine stewardship.

Coral reefs have attracted significant interest given their critical importance as natural habitats, pivotal role in coastal resilience, and rapid decline due to various climatic, environmental, and human threats. Through digital twins and improved monitoring, AI can help drive informed decisions on conservation, protection, and intervention.[97] It can also identify coral bleaching, map coral habitats, monitor invasive species, and assess coral cover through pattern detection across pixels (a technique also applied to recognize beach debris and shoreline erosion).[98] The results of AI analysis of coral reef mapping and health, and the impacts of stressors like bleaching, can help direct restoration efforts where they are needed most.[99] AI-driven robots or autonomous underwater vehicles such as CUREE (Curious Underwater Robot for Ecosystem Exploration) have also been developed to study the human impact on coral reefs and their ecosystems.[100]

By analyzing high-resolution images and sonar data, AI can also generate detailed maps of the ocean floor and identify deep-sea vent communities. AI data analysis from deep-sea

Using AI to identify species



An example of how AI models are trained on morphology to identify and differentiate species of big cats. Source: https://www.frontiersin.org/articles/10.3389/fevo.2022.866403/full

The need for open data in nature and conservation

Wildlife Insights, iNaturalist, iWildCam, Wild Me's Codex and Wildbook, and FathomnNet/Ocean Vision AI are all initiatives in conservation and biodiversity that leverage citizen science and crowdsourced data from sensors and camera traps–using AI for automatic detection–in order to provide valuable information to decision makers and scientists.

Open data is crucial for enhancing AI applications by increasing model accuracy and reliability, improving collaboration for research efficiency, and promoting public engagement and awareness.

- Open and standardized data is important to set up benchmarks for general/global models for comparative studies. Benchmarks help transfer existing knowledge and models to leverage wider application.
- Encouraging open data sharing also fosters collaboration between researchers and accelerates the scaling of AI applications to different initiatives, which can help to overcome redundant efforts that "reinvent the wheel."
- Ultimately, open data helps to improve public participation and engagement in nature and conservation efforts and can help to increase the acceptance of AI applications for environmental conservation.

expeditions can identify areas rich in natural resources and provide a deeper understanding of the environmental impact of resource extraction in these areas. Taken together, the suite of AI-powered technologies are transforming the exploration and conservation of the deep oceans.

In addition, the development of digital twins that pair large marine data with AI-based oceanographic modeling is also allowing for a broader, crucial understanding of marine environments and the impact of climate change on marine life.[101] Researchers have explored the promise of image recognition and adaptive management models to help identify and manage marine protected areas.[102] For example, autonomous and semi-autonomous monitoring of ocean ecosystems from LiDAR systems can provide granular geospatial information and ecologically relevant data to aid in marine conservation management decisions.[103]

AI also supports the reduction of marine pollution through marine monitoring devices—equipped with sensors connected to IoT networks—that identify areas with high concentrations of marine pollution and alert relevant authorities to the target locations for pollution reduction efforts.[104,105,106]

Coastal ecosystems, such as estuaries and deltas, are critically important for biodiversity, coastal protection, and human livelihoods.[107,108] AI can monitor their health and changes through satellite imagery, detecting changes over time to sediment deposition, erosion, and water quality.[109,110]

AI can also be used to predict the impacts of climate change such as sea-level rise and increased storm intensity on estuaries and deltas for better flood forecasting or to predict salinity intrusion.[111] Lastly, AI can optimize restoration efforts in deltas by analyzing data from past restoration projects and ongoing monitoring efforts to identify the most effective strategies for habitat restoration, species conservation, and water quality improvement.[112]

Freshwater Management

In freshwater environments, AI is used to monitor fish and aquatic plants, water, and the health of ecosystems. With computer vision and digital imagery, AI can track native freshwater species, assess fish population connectivity, and inform predictions of future species distribution.[113,114,115,116] With remote sensing data, AI is also used to monitor water quality metrics like pH levels, dissolved oxygen, and the presence of pollutants or algal blooms.[117,118]

AI-based ecosystem models are being developed to simulate the complex

INITIATIVE HIGHLIGHTS: OCEAN MANAGEMENT

Digital Twin Ocean

A high-resolution, multi-dimensional representation of the earth's oceans with nearly real-time accuracy by integrating a wide array of data sources, including sensors and satellites. The initiative's goal is to provide an interactive digital twin (i.e., an ansatz of the real world) of the ocean to strengthen ocean governance, restore marine habitats and biodiversity, and improve disaster-risk management.

Allen Coral Atlas

Managed by Arizona State University and developed with a host of partners from academia to nonprofits, the Allen Coral Atlas uses satellite imagery and machine learning to automate coral reef monitoring, generating near-real-time maps. The data garnered is used by policymakers and marine conservationists to help make informed decisions on ocean conservation, protection, and intervention. It is one of the United Nations' Decade of Ocean Science for Sustainable Development officially endorsed projects.

World Wildlife Fund ManglarIA

The World Wildlife Fund's ManglarIA ("AI for Mangroves" in Spanish) will deploy various sensors—such as weather stations, camera traps, and drones—in Mexico's Yucatan Peninsula and Pacific Coast. These sensors and other technologies will provide data on mangrove health including air and sea surface temperatures, seawater salinity, freshwater flows, and the presence of animals. This information will be used to adapt mangrove conservation strategies to help ensure the long-term viability of mangroves as a nature-based solution to climate change.

The Ocean Cleanup

The Ocean Cleanup, a nonprofit that develops technology to extract plastic pollution from the oceans, uses Microsoft Azure Machine Learning to support their efforts cleaning up plastic and debris from the ocean. Their goal is to remove 90% of plastic from the ocean by 2040.

INITIATIVE HIGHLIGHTS: FRESHWATER MANAGEMENT

Global Wetland Watch

Global Wetland Watch, an alliance between DHI A/S and the United Nations, will use AI to automate the analysis and interpretation of satellite images to detect and delineate wetlands on a global level in order to provide accurate, reliable and accessible data depicting the speed and scale of wetland changes. The project will generate readily available high-resolution maps (at national and ecosystem scales down to a 10-meter resolution) and statistics that detail near real-time changes to different wetland ecosystems across the globe. The project is supported by google.org.

HydroGen

Researchers from Princeton University and the University of Arizona were awarded $5 million by the National Science Foundation to develop the HydroGEN (Hydrologic Scenario Generation) project, which uses AI to develop simulated models of the U.S. watershed systems. The project aims to integrate various data sources and modeling techniques to improve the prediction and management of water systems. This initiative addresses critical challenges such as water scarcity, flooding, and infrastructure needs, and is part of a broader effort to enhance the resilience and sustainability of U.S. water resources in the face of changing climate conditions and increasing demand.

NASA's TERRAHydro

The Terrestrial Environmental Rapid-Replication and Assimilation Hydrometeorological (TERRAHydro) software aims to revolutionize the creation of composite hydrological models using AI. This open-source tool, developed by NASA, uses tensor-based modeling to help researchers more effectively integrate existing datasets and AI components into new models that describe dynamic aspects of the water cycle. TERRAHydro is poised to become a foundational software for Earth System Digital Twins, enhancing real-time model updates, predictions, and 'what-if' analyses using data from diverse airborne, spaceborne, and in-situ sensors.

interactions between different components of freshwater ecosystems—such as hydrology, nutrient cycles, and food webs.[119,120] These models are then being used to understand the impacts of environmental changes, invasive species, or management strategies. AI's capacity to evaluate various and complex factors (such as environmental needs, demand, and climate projections) quickly and efficiently can lead to better informed decisions to improve and preserve these critical ecosystems.

AI can also help to predict the impact of various restoration actions on wetlands, allowing conservationists to prioritize efforts that yield the highest benefits, such as water quality or carbon uptake.[121] These models analyze data from remote sensing, historical restoration outcomes, and real-time monitoring to inform the impact of different restoration strategies.

Water management—such as dam operations, irrigation scheduling, and water allocation—also benefits from AI.[122,123] AI can be used to forecast demand and consumption, for both irrigation and residential uses, and optimize water distribution, reducing costs and improving delivery.[124,125] AI technologies are already being used to improve the prediction and monitoring of reservoirs and streamflow, aiding real-time operation and maintenance of reservoirs.[126,127,128,129] Lastly, AI is capable of predicting groundwater quality[130] and quantity,[131,132] mapping groundwater vulnerability and forecasting groundwater table depth,[133] and modeling saltwater intrusion into freshwater bodies.[134]

More broadly, AI is being applied to water infrastructure maintenance and hydrological disaster monitoring.[135] By analyzing real-time data from various sources (e.g., remote sensing and crowdsourcing), AI helps develop early warning systems for extreme events like floods or harmful algal blooms, thereby providing timely alerts to authorities and stakeholders.

ENDNOTES: NATURE

43 World Wildlife Fund, *Living Planet Report 2022*,115, https://wwflpr.awsassets.panda.org/downloads/lpr_2022_full_report.pdf.

44 Gerardo Ceballos et al., "Accelerated Modern Human-Induced Species Losses: Entering the Sixth Mass Extinction," *Science Advances* 1, no. 5 (2015).

45 "What Is the Sixth Mass Extinction and What Can We Do about It," WWF, accessed September 10, 2023, https://www.worldwildlife.org/stories/what-is-the-sixth-mass-extinction-and-what-can-we-do-about-it#:~:text=Unlike%20previous%20extinction%20events%20caused,been%20converted%20for%20food%20production.

46 Responsible Seafood Advocate, "Experts: World's Coral Reefs Could Vanish by 2050 Without Climate Action," April 20, 2022, https://www.globalseafood.org/advocate/experts-worlds-coral-reefs-could-vanish-by-2050-without-climate-action/.

47 Mohammad Sadegh Norouzzadeh et al., "Automatically Identifying, Counting, and Describing Wild Animals in Camera-Trap Images With Deep Learning," *Proceedings of the National Academy of Sciences* 115, no. 25 (2018).

48 Devis Tuia et al., "Perspectives in Machine Learning for Wildlife Conservation," *Nature Communications* 13, no. 1 (2022): 792.

49 Dan Stowell, "Computational Bioacoustics with Deep Learning: A Review and Roadmap," *PeerJ* 10 (2022).

50 Marco Willi et al., "Identifying Animal Species in Camera Trap Images Using Deep Learning and Citizen Science," *Methods in Ecology and Evolution* 10, no. 1 (2019): 80-91.

51 "Alliance for Tropical Forest Science: Accelerating Research and Capacity Building to Improve Understanding of Tropical Forests," Alliance for Tropical Forest Science, accessed March 28, 2024, https://www.alliancetropicalforestscience.net/.

52 Ming Zhong et al., "Acoustic Detection of Regionally Rare Bird Species Through Deep Convolutional Neural Networks," *Ecological Informatics* 64 (2021): 101333.

53 John Atanbori et al., "Automatic Classification of Flying Bird Species Using Computer Vision Techniques," *Pattern Recognition Letters* 81 (2016): 53-62.

54 G. Botto Nuñezet al., "The First Artificial Intelligence Algorithm for Identification of Bat Species in Uruguay." *Ecological Informatics* 46 (2018): 97-102.

55 Ran Nathan et al., "Big-Data Approaches Lead to an Increased Understanding of the Ecology of Animal Movement," *Science* 375, no. 6582 (2022): eabg1780.

56 Simone Olivetti et al., "Merging Computational Fluid Dynamics and Machine Learning to Reveal Animal Migration Strategies," *Methods in Ecology and Evolution* 12, no. 7 (2021): 1186-1200.

57 Spiesman, Brian J., Claudio Gratton, Richard G. Hatfield, William H. Hsu, Sarina Jepsen, Brian McCornack, Krushi Patel, and Guanghui Wang. "Assessing the Potential for Deep Learning and Computer Vision to Identify Bumble Bee Species from Images." Scientific Reports 11, no. 1 (April 7, 2021): 7580. https://doi.org/10.1038/s41598-021-87210-1.

58 Ferreira, Alef Iury Siqueira, Nádia Felix Felipe Da Silva, Fernanda Neiva Mesquita, Thierson Couto Rosa, Victor Hugo Monzón, and José Neiva Mesquita-Neto. "Automatic Acoustic Recognition of Pollinating Bee Species Can Be Highly Improved by Deep Learning Models Accompanied by Pre-Training and Strong Data Augmentation." Frontiers in Plant Science 14 (April 14, 2023): 1081050. https://doi.org/10.3389/fpls.2023.1081050.

59 Hung Nguyen et al., "Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring," In 2017 *IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, pp. 40-49, IEEE, 2017.

60 C. Chalmers et al., "Modelling Animal Biodiversity Using Acoustic Monitoring and Deep Learning," In *2021 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–7, IEEE, 2021.

61 Müller, J., Mitesser, O., Schaefer, H.M. et al., "Soundscapes and deep learning enable tracking biodiversity recovery in tropical forests," *Nat Commun* 14, (2023): 6191.

62 Evlyn Pless et al., "A Machine-Learning Approach to Map Landscape Connectivity in Aedes Aegypti with Genetic and Environmental Data," *Proceedings of the National Academy of Sciences* 118, no. 9 (March 2, 2021): e2003201118.

63 Yu Sun et al., "Deep Learning for Plant Identification in Natural Environment," *Computational Intelligence and Neuroscience* 2017 (2017).

64 Jana Waldchen et al., "Automated Plant Species Identification: Trends and Future Directions," *PLoS Computational Biology* 14, no. 4 (2018).

65 Wang-Hee Lee et al., "Spatial Evaluation of Machine Learning Based Species Distribution Models for Prediction of Invasive Ant Species Distribution," *Applied Sciences* 12, no. 20 (2022): 10260.

66 K. Ullas Karanth and James D. Nichols, "Estimation of Tiger Densities in India Using Photographic Captures and Recaptures," *Ecology* 79, no. 8 (1998): 2852-2862.

67 Daniele Silvestro et al., "Improving Biodiversity Protection Through Artificial Intelligence," *Nature Sustainability* 5 (2022): 415-424.

68 Jeannine Cavender-Bares, John A. Gamon, and Philip A. Townsend, *Remote Sensing of Plant Biodiversity*, Springer Nature, 2020.

69 Frederick C. Draper et al., "Quantifying Tropical Plant Diversity Requires an Integrated Technological Approach," *Trends in Ecology & Evolution* 35, no. 12 (2020): 1100-1109.

70 Rout George Kerry et al., "An Overview of Remote Monitoring Methods in Biodiversity Conservation," *Environmental Science and Pollution Research* 29, no. 53 (2022): 80179-80221.

71 Bartosz Czernecki, Jakub Nowosad, and Katarzyna Jabłońska, "Machine Learning Modeling of Plant Phenology Based on Coupling Satellite and Gridded Meteorological Dataset," *International Journal of Biometeorology* 62 (2018): 1297-1309.

72 David Wrathall et al., "The Impacts of Cocaine-Trafficking on Conservation Governance in Central America," *Global Environmental Change* 63 (2020): 102098.

73 Walter Jetz et al., "Essential Biodiversity Variables for Mapping and Monitoring Species Populations," Nature Ecology & Evolution 3, no. 4 (March 11, 2019): 539–51, https://doi.org/10.1038/s41559-019-0826-1.

74 Kadukothanahally Nagaraju Shivaprakash et al., "Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India," *Sustainability* 14, no. 12 (2022): 7154.

75 Kadukothanahally Nagaraju Shivaprakash et al., "Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India," *Sustainability* 14, no. 12 (2022): 7154.

76 Sizhuo Li et al.,"Deep learning enables image-based tree counting, crown segmentation, and height prediction at national scale," PNAS nexus 2, no. 4 (2023): pgad076.

77 Ibrahim Fayad et al., "Hy-TeC: A Hybrid Vision Transformer Model for High-Resolution and Large-Scale Mapping of Canopy Height," Remote Sensing of Environment 302 (2024): 113945.

78 Compton Tucker et al., "Sub-Continental-Scale Carbon Stocks of Individual Trees in African Drylands," *Nature* 615, no. 7950 (2023): 80-86.

79 Haifei Chen, Liping Yang, and Qiusheng Wu, "Enhancing Land Cover Mapping and Monitoring: An Interactive and Explainable Machine Learning Approach Using Google Earth Engine," *Remote Sensing* 15, no. 18 (2023): 4585.

80 Dhanuj Mount Gandikota et al., "AI Augmentation to Remote Sensing Imagery in Forestry Conservation & Restoration for Increased Responsive Capabilities," *2022 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, pp. 1-16. IEEE, 2022.

81 "Forest Inventory and Analysis," USDA, accessed April 12, 2024, https://www.fs.usda.gov/research/programs/fia.

82 Georgios Giannarakis et al., "Towards Assessing Agricultural Land Suitability with Causal Machine Learning," In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1442-1452, 2022.

83 Global Forest Watch, "Investigate Forest Change With Recent Satellite Imagery," March 15h 2022, https://www.globalforestwatch.org/help/map/guides/investigate-forest-change-satellite-imagery/.

84 Gyri Reiersen et al., "ReforesTree: A Dataset for Estimating Tropical Forest Carbon Stock with Deep Learning and Aerial Imagery," *Proceedings of the AAAI Conference on Artificial Intelligence* 36, no. 11 (June 28, 2022): 12119–25.

85 "Dendra's Integrated Aerial Seeding," Dendra Systems, accessed 12, 2024, https://dendra.io/solutions/aerial-seeding/.

86 Yangyang Li et al., "Soil Database Development with the Application of Machine Learning Methods in Soil Properties Prediction," *Engineering Geology* 306 (September 2022): 106769.

87 Olya Skulovich and Pierre Gentine, "A Long-Term Consistent Artificial Intelligence and Remote Sensing-Based Soil Moisture Dataset," *Scientific Data* 10, no. 1 (2023): 154.

88 Wilhelm, Roland C., Harold M. Van Es, and Daniel H. Buckley. "Predicting Measures of Soil Health Using the Microbiome and Supervised Machine Learning." Soil Biology and Biochemistry 164 (January 2022): 108472. https://doi.org/10.1016/j.soilbio.2021.108472.

89 Ranran Lou et al., "Application of Machine Learning in Ocean Data" *Multimedia Systems* (2021): 1-10.

90 Lv Zhihan et al., "Artificial Intelligence in Underwater Digital Twins Sensor Networks," *ACM Transactions on Sensors Networks* 18, no. 3 (2022): 1-27.

91 Guirado, Emilio, Siham Tabik, Marga L. Rivas, Domingo Alcaraz-Segura, and Francisco Herrera. "Whale Counting in Satellite and Aerial Images with Deep Learning." Scientific Reports 9, no. 1 (October 3, 2019): 14259. https://doi.org/10.1038/s41598-019-50795-9.

92 Katija, Kakani, Paul L D Roberts, Joost Daniels, Alexandra Lapides, Kevin Barnard, Mike Risi, Ben Y Ranaan, Benjamin G Woodward, and Jonathan Takahashi. "Visual Tracking of Deepwater Animals Using Machine Learning-Controlled Robotic Underwater Vehicles." In *2021 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 859–68. Waikoloa, HI, USA: IEEE, 2021. https://doi.org/10.1109/WACV48630.2021.00090.

93 Shashidhar Siddagangaiah et al., "Automatic Detection of Dolphin Whistles and Clicks Based on Entropy Approach Approach," *Ecological Indicators* 117 (2020): 106559.

94 Katie Kowarski and Hilary Moors-Murphy, "A Review of Big Data Analysis Methods for Baleen Whale Passive Acoustic Monitoring," *Marine Mammal Science* 37, no. 2 (2021): 652-673.

95 Arghya Mandal and Apurba Ratan Ghosh, "AI-Driven Surveillance of the Health and Disease Status of Ocean Organisms: A Review," *Aquaculture International* (2023): 1-12.

96 M. Rizwan Khokher et al., "Early Lessons in Deploying Cameras and Artificial Intelligence Technology for Fisheries Catch Monitoring: Where Machine Learning Meets Commercial Fishing," *Canadian Journal of Fisheries and Aquatic Sciences* 79, no. 2 (2022): 257-266.

97 Manuel Gonzalez-Rivero et al., "Monitoring of Coral Reefs Using Artificial Intelligence: A Feasible and Cost-Effective Approach," *Remote Sensing* 12, no. 3 (2020): 489.

98 Sarah M. Hamylton, Zhexuan Zhou, and Lei Wang, "What Can Artificial Intelligence Offer Coral Reef Managers?," *Frontiers in Marine Science* (2020): 1049.

99 Chiara Moore, "Reinvigorating Our Pulse on the Reef: Advancements in Coral Bleaching Monitoring," Allen Coral Atlas, April 20, 2023, https://allencoralatlas.org/blog/advancements-in-coral-bleaching-monitoring/.

100 Yogesh Girdhar et al, "CUREE: A Curious Underwater Robot for Ecosystem Exploration," *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 11411-11417. IEEE, 2023.

101 Ge Chen et al.,"Toward Digital twin of the Ocean: From Digitalization to Cloning," *Intelligent Marine Technology and Systems* 1, no. 1 (2023): 3.

102 Şeyma Merve Kaymaz Mühling, "Utilizing Artificial Intelligence (AI) for the Identification and Management of Marine Protected Areas (MPAs): A Review," *Journal of Geoscience and Environment Protection* 11, no. 9 (2023): 118-132.

103 Ellen M. Ditria et al., "Artificial Intelligence and Automated Monitoring for Assisting Conservation of Marine Ecosystems: A Perspective," *Frontiers in Marine Science* 9 (2022): 918104.

104 Qingliang Guo, Fangyu Wu, and Chao Zhang, "Marine Environment Monitoring Device Based on Artificial Intelligence," *International Journal of Frontiers in Engineering Technology* 5, Issue 10: 34-37, DOI: 10.25236/IJFET.2023.051006

105 Odei Garcia-Garin et al., "Automatic Detection and Quantification of Floating Marine Macro-Litter in Aerial Images: Introducing a Novel Deep Learning Approach Connected to a Web Application in R," *Environmental Pollution* 273 (2021):116490.

106 Mattis Wolf et al., "Machine Learning for Aquatic Plastic Litter Detection, Classification and Quantification (APLASTIC-Q)," *Environmental Research Letters* 15, no. 11 (2020): 114042..

107 Joko Sampurno et al., "Integrated Hydrodynamic and Machine Learning Models for Compound Flooding Prediction in a Data-Scarce Estuarine Delta," *Nonlinear Processes in Geophysics* 29, no. 3 (2022): 301-315.

108 William Weber de Melo, José LS Pinho, and Isabel Iglesias, "Emulating the Estuarine Morphology Evolution Using a Deep Convolutional Neural Network Emulator Based on Hydrodynamic Results of a Numerical Model," *Journal of Hydroinformatics* 24, no. 6 (2022): 1254-1268.

109 Yaying Lou et al., "Image-Based Machine Learning for Monitoring the Dynamics of the Largest Salt Marsh in the Yangtze River Delta," *Journal of Hydrology* 608 (May 2022): 127681.

110 Benoit Laignel et al., "Observation of the Coastal Areas, Estuaries and Deltas from Space," *Surveys in Geophysics* 44, no. 5 (October 2023): 1309–56.

111 Yuri Costa et al, "Trends of Sea-Level Rise Effects on Estuaries and Estimates of Future Saline Intrusion," *Ocean & Coastal Management* 236 (April 2023): 106490. https://doi.org/10.1016/j.ocecoaman.2023.106490.

112 Jiangjie Yang et al., "Image-Based Machine Learning for Monitoring the Dynamics of Deltaic Islands in the Atchafalaya River Delta Complex between 1991 and 2019," *Journal of Hydrology* 623 (August 2023): 129814.

113 Russell G. Death et al., *Does Artificial Intelligence Modelling Have Anything to Offer Traditional Management of Freshwater Food Resources*, Environmental Research Institute, University of Waikato, 2017.

114 Goodwin, Morten, Kim Tallaksen Halvorsen, Lei Jiao, Kristian Muri Knausgård, Angela Helen Martin, Marta Moyano, Rebekah A. Oomen, Jeppe Have Rasmussen, Tonje Knutsen Sørdalen, and Susanna Huneide Thorbjørnsen. "Unlocking the Potential of Deep Learning for Marine Ecology: Overview, Applications, and Outlook," 2021. https://doi.org/10.48550/ARXIV.2109.14737.

115 Sebastian Lopez-Marcano et al., "The Slow Rise of Technology: Computer Vision Techniques in Fish Population Connectivity," *Aquatic Conservation: Marine and Freshwater Ecosystems* 31, no. 1 (2021): 210-217.

116 Sajad Soleyman Hasani, Alireza Mojtahedi, and Mir Amir Mohammad Reshadi, "Development of a Novel Fuzzy Logic-Based Wetland Health Assessment Approach for the Management of Freshwater Wetland Ecosystems," *Wetlands* 41 (2021): 1-25.

117 Sikandar Ali Abdulla et al., "Computer Vision Based Deep Learning Approach for the Detection and Classification of Algae Species Using Microscopic Images," *Water* 14, no. 14 (2022): 2219.

118 Silvia Beatriz Alves Rolim et al., "Remote Sensing for Mapping Algal Blooms in Freshwater Lakes: A Review," *Environmental Science and Pollution Research* 30, no. 8 (2023): 19602-19616.

119 Kaire Toming et al., "Estimation of the Biogeochemical and Physical Properties of Lakes Based on Remote Sensing and Artificial Intelligence Applications," *Remote Sensing* 16, no. 3 (2024): 464.

120 Caili Du et al., "Prediction of Aquatic Vegetation Growth Under Ecological Recharge Based on Machine Learning and Remote Sensing," *Journal of Cleaner Production* (2024): 142054.

121 Swades Pal and Pankaj Singha, "Image-Driven Hydrological Parameter Coupled Identification of Flood Plain Wetland Conservation and Restoration Sites," *Journal of Environmental Management* 318 (September 2022): 115602.

122 Patricia Schmidt, Andreas Probst, and Maximilian Lackner, "Surface Monitoring at Dams Using Drones and AI-Based Analysis for Advanced Anomaly Assessment," (paper presented at the International Conference on Interactive Collaborative Learning, Madrid, Spain, September 26, 2023), https://link.springer.com/chapter/10.1007/978-3-031-53382-2_36.

123 Andres-F. Jimenez et al., "A Survey on Intelligent Agents and Multi-Agents for Irrigation Scheduling," *Computers and Electronics in Agriculture* 176 (2020): 105474.

124 Hubert Jenny et al., "Using Artificial Intelligence for Smart Water Management Systems," (2020).

125 M. Kavya "Short Term Water Demand Forecast Modelling Using Artificial Intelligence for Smart Water Management," *Sustainable Cities and Society* 95 (2023): 104610.

126 Keivan Karimizadeh and Jaeeung Yi, "Modeling Hydrological Responses of Watershed Under Climate Change Scenarios Using Machine Learning Techniques," (2023).

127 Fabio Di Nunno, Giovanni de Marinis, and Francesco Granata, "Short-Term Forecasts of Streamflow in the UK Based on a Novel Hybrid Artificial Intelligence Algorithm," *Scientific Reports* 13, no. 1 (2023): 7036.

128 Guanjun Liu et al., "Assessing Spatial Connectivity Effects on Daily Streamflow Forecasting Using Bayesian-Based Graph Neural Network," *Science of the Total Environment* 855 (2023): 158968

129 Tao Yang et al., "Evaluation and Machine Learning Improvement of Global Hydrological Model-Based Flood Simulations," *Environmental Research Letters* 14, no. 11 (2019): 114027.

130 Marwah Sattar Hanoon et al., "Application of Artificial Intelligence Models for Modeling Water Quality in Groundwater: Comprehensive Review, Evaluation and Future Trends," *Water, Air, & Soil Pollution* 232 (2021): 1-41.

131 Hoang Tran et al., "Development of a Deep Learning Emulator for a Distributed Groundwater–Surface Water Model: ParFlow-ML," *Water* 13, no. 23 (2021): 3393.

132 Jiabo Yin et al., "GTWS-MLrec: Global Terrestrial Water Storage Reconstruction by Machine Learning from 1940 to Present," *Earth System Science Data Discussions* 2023 (2023): 1-29.

133 Benjamin D. Bowes et al., "Forecasting Groundwater Table in a Flood Prone Coastal City With Long Short-Term Memory and Recurrent Neural Networks," *Water* 11, no. 5 (2019): 1098.

134 Marjan Moazamnia et al.,"Vulnerability Indexing to Saltwater Intrusion from Models at Two Levels Using Artificial Intelligence Multiple Model (AIMM)," *Journal of environmental management* 255 (2020): 109871.

135 Hamid Mehmood, Danielle Liao, and Kimberly Mahadeo, "A Review of Artificial Intelligence Applications to Achieve Water-Related Sustainable Development Goals," *2020 IEEE/ITU International Conference on Artificial Intelligence for Good (AI4G)*, pp. 135-141. IEEE, 2020.

136 "Wildlife Insights," Wildlife Insights, accessed December 28, 2023, wildlifeinsights.org.

CURRENT APPLICATIONS IN AI

Food and Agriculture

Agriculture and livestock are a significant source of greenhouse gas (GHG) emissions. According to the United Nations Food and Agriculture Organization, agriculture is responsible for about 12% of all human-caused GHG emissions (including methane and nitrous oxide), 70% of global freshwater use, and 90% of all deforestation.[137,138] Forty percent of all land surfaces have been converted for food production, driving both climate change and biodiversity loss.[139,140]

When considering the food system as a whole, the contribution to total GHG emissions ranges from 21–37%.[141] This includes land-use and land-cover change, farming activities, and emissions associated with the value chain (i.e., storage, transport, packaging, processing, retail, and consumption). This estimate also includes emissions from food loss and waste.

In the coming decades, global food demand is expected to increase dramatically: the United Nations believes that the world population will reach 8.5 billion within the next six years and 9.7 billion by 2050; more than half of newborns are expected to be born in Africa alone.[142] While we need to produce enough food to nourish the global population, we simultaneously need to reduce its impact—reducing GHG emissions, avoiding expansion to natural areas, reducing food loss and waste, and minimizing harmful impacts on soil, water, and ecosystem health. Food and agricultural systems also need to build in greater resilience to environmental and climatic shocks, in order to safeguard food security and nutrition, especially for vulnerable populations in low- and middle-income countries.

AI can provide advanced analytics to improve the sustainability of crop and livestock production, better manage and model food demand and value chains, and facilitate the transition to more sustainable diets.

Crop Production

AI has helped optimize the timing of irrigation, sowing and harvesting, as well as fertilizer and pesticide application.[143,144,145] AI supports crop monitoring with rapid data-collection infrastructures through IoT sensors, unmanned aerial vehicles (UAVs), remote sensing images from satellites (analyzed with computer vision), and smartphones. The use of AI and IoT (along with many on-the-ground sensors) can enable highly accurate precision farming while retaining a competitive execution time.[146] Specific crop monitoring applications include:

» **Smart farming and soil monitoring.** IoT sensors can collect data on and monitor soil pH, fertilizer concentrations, moisture, and salinity, which can then be used by

INITIATIVE HIGHLIGHTS

Amini

Amini is a Nairobi-based startup that aims to solve environmental data scarcity in Africa. Leveraging AI and space technologies, Amini aims to promote economic inclusivity and drive systemic change for farmers and supply chain resilience in Africa. Their programming initiatives aim to enhance data accessibility and utilize data-driven insights to improve sustainable agricultural practices, improve crop yields, and empower farmers.

International Rice Research Institute

The Fit-for-Future Genetic Resources unit has received a Google.org grant to integrate AI and high-throughput phenotyping methodologies into the largest rice gene bank in the world, consisting of over 132,000 varieties from 132 countries. AI will be used to assess existing rice genotypes for resistance to environmental stressors associated with climate change such as flooding, drought, and salinity.

NASA Harvest

NASA Harvest is a global consortium of multidisciplinary experts, led by the University of Maryland, aimed at broadening the use of Earth observations to deliver critical food security and agricultural assessments. The program leverages NASA's Earth observations from space to provide data, products, tools, and predictions relevant to agricultural producers, traders, agencies, and others. Many of their projects use AI to enhance its agricultural monitoring and food security applications, such as for crop mapping, yield prediction, drought monitoring or food insecurity mapping.[181]

Climax Foods

Climax Foods is a biotechnology company that utilizes machine learning to develop plant-based alternatives to animal-derived foods, focusing primarily on dairy products. The company is dedicated to creating alternatives that closely mimic the taste, texture, nutrition, and cost of traditional dairy, aiming to make plant-based options more accessible and appealing to a wider audience.

AI-based optimization and recommendation engines to optimize irrigation and fertilizer application.[147] This precision agriculture can significantly reduce water and fertilizer needs and thus make farming more sustainable.

» **Pest and disease detection.** Image processing and analysis can allow more precise and automated application of fungicides, herbicides, and insecticides. For example, efforts to merge AI with robotics to increase the timely application of pesticides could potentially lead both to the reduction of disease risk and increased efficacy.[148]

» **Yield prediction and integration with big data.** Machine learning can predict crop yield based on location and meteorological conditions—and with supplementary information like crop prices, these methodologies can help farmers make informed decisions about optimal farming strategies.[149,150] It can also be used to assess crop suitability to a specific region.[151]

» **Genomics.** By combining multiple data sources, AI can help build new genomics models, which might improve flavor, nutrition, or crop resilience.[152]

The integration of AI into the agricultural sector, particularly in the context of energy demand, showcases its potential to optimize resource allocation and enhance productivity. In rural settings, where energy can be a significant constraint on development, AI's ability to identify where investments would have the most substantial impact could prove transformative. Using AI facilitates a more precise management of resources by generating detailed land-use maps and monitoring agricultural variables such as crop types, planted areas, yields, and irrigation needs. This AI-based precision can enable a more accurate characterization of agricultural landscapes.

In the realm of crop yield prediction, AI can discern patterns within datasets, thereby estimating yields with increasing accuracy. This not only aids in forecasting yields but also plays a vital role in assessing crop growth, irrigation needs, and potential losses, directly contributing to food security. For smallholder farms, AI techniques that utilize MODIS and Sentinel-2 satellite data to reconstruct vegetation phenologies offer new avenues for detecting irrigation and assessing crop health, even in fields smaller than 30m.[153] This application of AI in agriculture underscores its potential to significantly improve the efficiency and sustainability of food production systems.

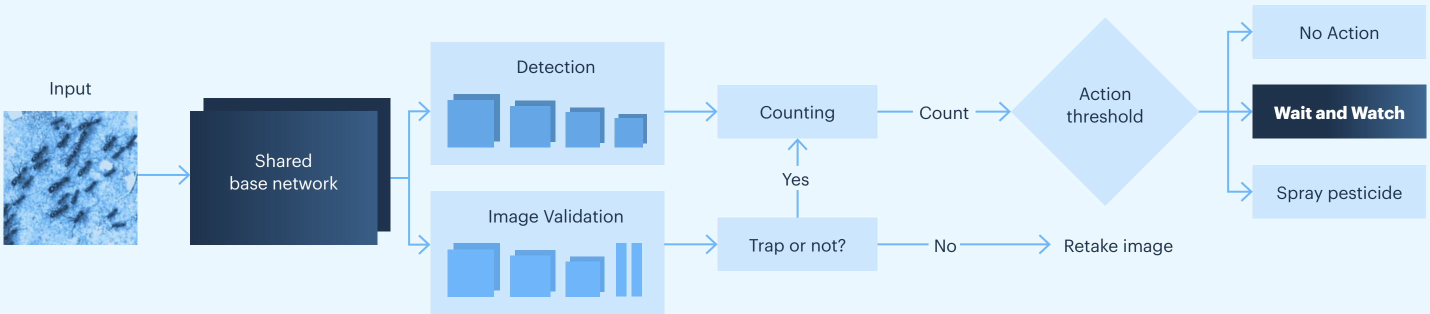
Livestock

There are 70 billion farm animals globally, which are increasingly managed in large-scale farms.[154] Wearable sensors and IoT devices can track location, health, and the well-being of livestock.[155] AI technology is being used for traceability purposes, giving farmers and producers the ability to automate herd monitoring—even enabling animal recognition at an individual level.[156] By combining

INITIATIVE HIGHLIGHT

Wadhwani AI's CottonAce

CottonAce is an AI-powered early warning system that helps farmers determine optimal pesticide spray times and schedules for their crops, protecting them from pests to increase crop outputs.[182] While cotton is a non-food crop, this approach and machine learning model can also be applied to food crops.



As shown in the diagram above, AI is used in CottonAce to detect and count pests on pheromone traps installed in cotton farms. If the number of pests exceeds the economic threshold limit, pesticide spraying is recommended. Model inference and recommendations are carried out on smartphones. Source: https://www.wadhwaniai.org/programs/pest-management/pest-management-ai-solution/

myriad biometric sensor data (visual, thermal, auditory, physiological, and biochemical), AI is helping to detect disease and offer recommendations for food optimization and animal well-being. By analyzing data on animal nutrition and its effects on both health and environmental impact, AI can also support optimized feeding strategies.[157] As a result, it can help reduce feed waste and methane emissions produced by ruminants like cows. AI could also be used to reduce antibiotic use in livestock, inspired by work using AI to control antimicrobial resistance[158] and for drug discovery to reduce livestock deaths.[159] This can enable early detection of illnesses or stressors, which can then be addressed swiftly to prevent disease outbreaks or to reduce the need for antibiotics. Through genetic analysis and predictive modeling, AI can also enhance selective breeding more resistant to disease or environmental stressors and identify traits that increase productivity while reducing environmental impact.

AI can also improve pastoral resource management, such as through water and energy use optimization. Smart farming solutions can regulate barn conditions, ensuring animals are kept in environments that minimize stress and resource wastage, further contributing to sustainability goals. AI can also evaluate and optimize the environmental impacts of livestock farming, including land use, water consumption, and GHG emissions. This information can guide policy and operational decisions to minimize the ecological footprint of livestock operations.

Aquaculture

Fish is an important protein source for much of the world and sustainable aquaculture can provide a solution to meet growing food demand without further depleting wild stocks. There are several opportunities for AI, utilizing sensors, drones, cameras, and machine learning, to improve the productivity and sustainability of aquaculture. The applications include detection and prevention of disease and parasites, assessing fish health and growth, performing environmental and water quality management, as well as optimizing feeding and selective breeding.[160] Integration of AI into the aquaculture industry can lead to more effective maintenance, better resource utilization, and reduce the need for labor.[161]

Food Demand

AI can improve food demand forecasting and management, which is crucial to improve food security, reduce food loss and waste, and optimize the food supply chain.[162] By accurately predicting food demand, producers, retailers, and policymakers can make more informed decisions and ensure that food production aligns closely with consumption needs. This can be achieved by developing more advanced food demand forecasting models that analyze historical sales data, weather patterns, socio-economic indicators, and other relevant factors to predict future food demand more accurately.

Another advantage of AI-based algorithms is that they can process vast amounts of data in real-time and allow businesses to adjust their forecasts based on current trends, unexpected events, or changes in consumer behavior. For example, AI can adjust their algorithms prediction based on newly available data thereby improving their forecasts, which helps to plan production, distribution, and inventory management more effectively.[163] This agility can reduce overproduction or underproduction, leading to a more efficient supply chain.

Supply Chain Management

AI can help inform and even automate supply chain decision-making to reduce supply bottlenecks. It can monitor and identify issues with specific food products and can help supply chain management in the event of large, wide-spread food supply disruptions (such as those caused by COVID-19).[164] Livestock supply chains can also benefit from AI, which assists with production planning, quality control, and predicting plant maintenance needs before they arise.[165]

Because AI can be used to forecast demand more accurately, it helps adjust storage needs to prevent overstocking or shortages.[166] This can reduce waste and ensure that perishable goods are sold while they are still fresh. Within storage facilities, AI and sensors such as IoT can be combined to continuously monitor and adjust the conditions (such as temperature and humidity) and optimize the lifecycle of perishable goods, while simultaneously reducing waste and energy consumption.[167] AI can optimize the processing and packaging of food to meet customers' preference or to increase sustainability criteria, reducing its environmental footprint.[168] Finally, AI is used to optimize food routes and vehicle load, further enabling the reduction of carbon emissions from the food supply chain.[169]

Digital Twins

Sophisticated computational models can simulate key components of food systems, from agricultural production,[170] processing,[171] and transport and storage,[172] to marketing, consumption, and waste management.[173] Leveraging more AI, these models could be accelerated and incorporate cross-disciplinary data streams and algorithms to reflect the myriad social, economic, and environmental factors that influence both global[174] and local food systems.[175] For example, such an AI-powered model could ingest satellite imagery, climate data, crop or livestock/animal genetics and yield information, commodity pricing, consumer demand forecasts, supply chain infrastructure capacity, and trade policies across regions. It could then run scenario simulations to predict outcomes and identify interventions that optimize for key targets like sustainability, nutrition, greenhouse gas emissions, food security, and farmer livelihoods. Using online learning (the capacity to continuously learn from newly acquired data), the model could improve its predictive accuracy continually by comparing simulated outcomes to emerging real-world measurements.

Policymakers and businesses could use such food systems' models to test proposals for agricultural innovations, infrastructure investments, subsidy adjustments, or nutrition programs. Models facilitate a holistic, evidence-based approach to assessing tradeoffs and synergies that is impossible through intuition alone.

Alternative Proteins

Protein is a crucial macronutrient for human nutrition. The production of animal-based proteins, in particular, is resource intensive and a major contributor to GHG emissions. Alternative proteins, including plant-based solutions and cultivated meats, can support healthier and more sustainable diets. By harvesting enormous amounts of data to gain deeper understanding of protein structures and formation, AI can provide innovative solutions to alternative protein.

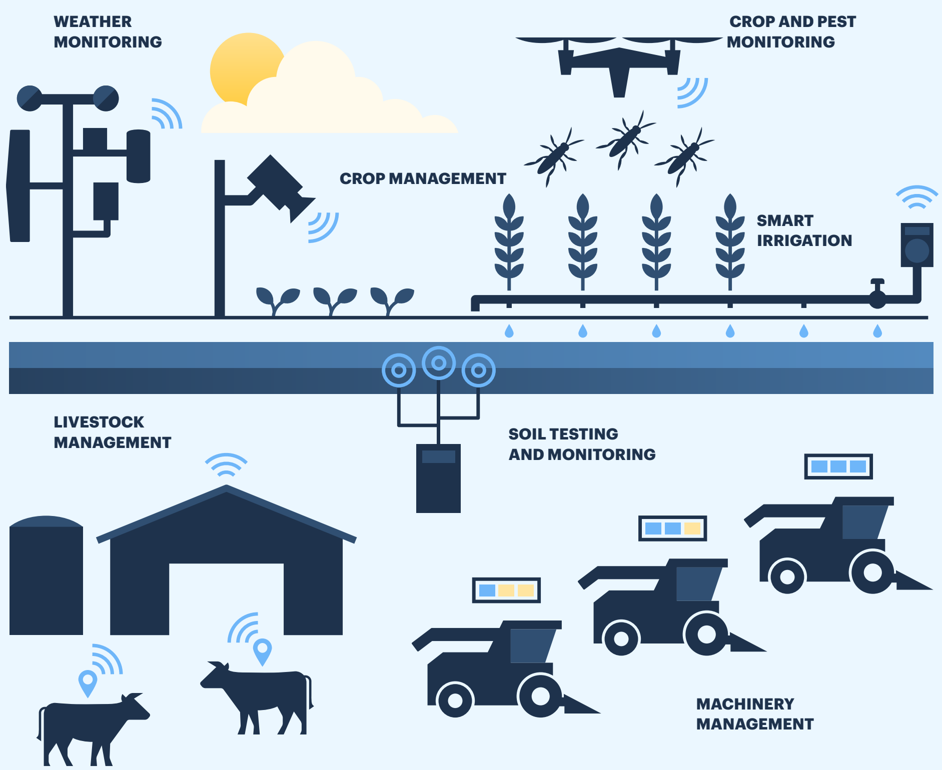
AI can be used to discover, design, and create new types of proteins. Recent progress shows that AI can predict the structure of individual protein chains and design new proteins faster and more efficiently.[176] Scientists suggest that such AI can be used to customize new proteins as alternative food sources.[177]

AI-driven computational methods can help understand and predict the structure and function of plant-based proteins and how they compare to their animal-based counterparts. This optimization can help identify plant proteins that can mimic the taste, texture, and nutritional value of animal proteins more closely, and increase the reach of plant-based alternatives.[178] AI can also be used to improve protein production from alternative sources. Novel food and protein production from sources such as algae, insects, and fungi is a complicated and uncertain industrial process, subject to stringent safety regulations. AI can help overcome important challenges in discovery and development, for example researchers suggest that AI can be used to support the production of microalgae as a viable alternative protein.[179] The combination of AI and 3D food printing as a future food production method could also improve the nutrition and cost of novel protein-based food.[180] Meanwhile, AI can also inform the personalization needs for health and nutrition from alternative food production.

AI algorithms can further analyze social media, online searches, and sales data to develop new insights into consumer preferences and emerging market trends. This information can in turn guide the development of more relevant alternative protein products that meet the evolving tastes and dietary choices of consumers. •

IoT in Agriculture

IoT and AI can enhance the monitoring and management of soils, crops, pests, and livestock. Nokia and the Vodafone Foundation's "Smart Agriculture as a Service" links field sensors and Nokia's IoT Network Grid through a mobile network to provide valuable and timely information to farmers via mobile and web-based applications. Source: https://www.nokia.com/about-us/newsroom/articles/iot-unlocking-the-potential-of-precision-farming/.



ENDNOTES: FOOD + AGRICULTURE

137 Ciniro Costa Jr et al., "Roadmap for Achieving Net-Zero Emissions in Global Food Systems by 2050," *Scientific Reports* 12, no. 1 (2022): 15064.

138 "What Is the Sixth Mass Extinction and What Can We Do about It," WWF, accessed September 10, 2023, https://www.worldwildlife.org/stories/what-is-the-sixth-mass-extinction-and-what-can-we-do-about-it#:~:text=Unlike%20previous%20extinction%20events%20caused,been%20converted%20for%20food%20production.

139 Xiaoming Xu "Global Greenhouse Gas Emissions From Animal-Based Foods are Twice Those of Plant-Based Foods," *Nature Food* 2, no. 9 (2021): 724-732.

140 Thomas Kastner et al., "Global Agricultural Trade and Land System Sustainability: Implications for eEcosystem Carbon Storage, Biodiversity, and Human Nutrition," *One Earth* 4, no. 10 (2021): 1425-1443.

141 Cynthia Rosenzweig et al., IPCC Special Report on Climate Change and Land Chapter 5 – Food Security --https://www.ipcc.ch/srccl/chapter/chapter-5/

142 "Population," Global Issues, Accessed January 2, 2024, https://www.un.org/en/global-issues/population.

143 C. L. De Abreu and J. P. van Deventer, "The Application of Artificial Intelligence (AI) and Internet of Things (IoT) in Agriculture: A Systematic Literature Review," *Southern African Conference for Artificial Intelligence Research*, pp. 23-46, Springer, Cham, 2022.

144 Showkat Ahmad Bhat and Nen-Fu Huang, "Big Data and AI REvolution in Precision Agriculture: Survey and Challenges," *IEEE Access* 9 (2021): 110209-110222.

145 Khongdet Phasinam, Thanwamas Kassanuk, and Mohammad Shabaz, "Applicability of Internet of Things in Smart Farming," *Journal of Food Quality* 2022 (2022): 1-7.

146 Amit Sharma et al., "Artificial Intelligence and Internet of Things Oriented Sustainable Precision Farming: Towards Modern Agriculture," *Open Life Sciences* 18, no. 1 (2023): 20220713.

147 Durai Raj Vincent et al., "Sensors Driven AI-Based Agriculture Recommendation Model for Assessing Land Suitability," *Sensors* 19, no. 17 (2019): 3667.

148 Vasiliki Balaska et al., "Sustainable Crop Protection Via Robotics and Artificial Intelligence Solutions," *Machines* 11, no. 8 (2023): 774.

149 Priyanga Muruganantham et al., "A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing," *Remote Sensing* 14, no. 9 (April 21, 2022): 1990.

150 Sandeep Gupta et al., "Machine Learning- and Feature Selection-Enabled Framework for Accurate Crop Yield Prediction," *Journal of Food Quality* 2022 (2022): 1-7.

151 Abigail Fitzgibbon, Dan Pisut, and David Fleisher, "Evaluation of Maximum Entropy (Maxent) Machine Learning Model to Assess Relationships Between Climate and Corn Suitability," *Land* 11, no. 9 (2022): 1382.

152 Luís Felipe V. Ferrão et al.,"Machine Learning Applications to Improve Flavor and Nutritional Content of Horticultural Crops Through Breeding and Genetics," *Current Opinion in Biotechnology* 83 (2023): 102968.

153 Terence Conlon, Christopher Small, and Vijay Modi, "A Multiscale Spatiotemporal Approach for Smallholder Irrigation Detection," *Frontiers in Remote Sensing* 3, (April 14, 2022), https://doi.org/10.3389/frsen.2022.871942.

154 Suresh Neethirajan, "Affective State Recognition in Livestock—Artificial Intelligence Approaches," *Animals* 12, no. 6 (2022): 759.

155 Paula De Freitas Curti et al., "Applications of Livestock Monitoring Devices and Machine Learning Algorithms in Animal Production and Reproduction: An Overview," *Animal Reproduction* 20, no. 2 (2023): e20230077.

156 Hai Ho Dac et al.,"Livestock Identification Using Deep Learning for Traceability," *Sensors* 22, no. 21 (2022): 8256.

157 Luis O. Tedeschi, "ASAS-NANP Symposium: Mathematical Modeling in Animal Nutrition: The Progression of Data Analytics and Artificial Intelligence in Support of Sustainable Development in Animal Science," *Journal of Animal Science* 100, no. 6 (2022): skac111.

158 Ali A. Rabaan et al., "Application of Artificial Intelligence in Combating High Antimicrobial Resistance Rates," *Antibiotics* 11, no. 6 (June 8, 2022): 784.

159 Parameswar Sahu and Dibyabhaba Pradhan, "AI-ML and System Biology for Drug Discovery in Livestock," In *Systems Biology, Bioinformatics and Livestock Science*, edited by Anupam Nath Jha, Sandeep Swargam, and Indu Kumari, 243–59. BENTHAM SCIENCE PUBLISHERS, 2023.

160 Mohd Ashraf Rather et al., "Exploring Opportunities of Artificial Intelligence in Aquaculture to Meet Increasing Food Demand," *Food Chemistry*: X 22 (June 2024): 101309, https://doi.org/10.1016/j.fochx.2024.101309.

161 Umar Farouk Mustapha et al., "Sustainable Aquaculture Development: A Review on the Roles of Cloud Computing, Internet of Things and Artificial Intelligence (CIA)," *Reviews in Aquaculture* 13, no. 4 (March 29, 2021): 2076–91, https://doi.org/10.1111/raq.12559.

162 Grigorios Tsoumakas, "A Survey of Machine Learning Techniques for Food Sales Prediction," Artificial Intelligence Review 52, no. 1 (June 2019): 441–47.

163 Reza Lotfi et al., "A Robust and Resilience Machine Learning for Forecasting Agri-Food Production," *Scientific Reports* 12, no. 1 (December 16, 2022): 21787.

164 Mehrdokht Pournader, "Artificial Intelligence Applications in Supply Chain Management," *International Journal of Production Economics* 241 (2021): 108250.

165 Petri Helo and Yuqiuge Hao, "Artificial Intelligence in Operations Management and Supply Chain Management: An Exploratory Case Study," *Production Planning & Control* 33, no. 16 (2022): 1573-1590.

166 Krzysztof Lutoslawski et al., "Food Demand Prediction Using the Nonlinear Autoregressive Exogenous Neural Network," *IEEE Access* 9 (2021): 146123–36.

167 Xinxin Wang et al., "Application of Machine Learning to the Monitoring and Prediction of Food Safety: A Review," *Comprehensive Reviews in Food Science and Food Safety* 21, no. 1 (January 2022): 416–34.

168 Md. Imran H. Khan et al., "Machine Learning based Modeling in Food Processing Applications: State of the Art," *Comprehensive Reviews in Food Science and Food Safety* 21, no. 2 (March 2022): 1409–38.

169 Chairote Yaiprasert and Achmad Nizar Hidayanto, "AI-Driven Ensemble Three Machine Learning to Enhance Digital Marketing Strategies in the Food Delivery Business," *Intelligent Systems with Applications* 18 (May 2023): 200235.

170 Cynthia Rosenzweig et al., "Assessing Agricultural Risks of Climate Change in the 21st Century in a Global Gridded Crop Model Intercomparison," *Proceedings of the National Academy of Sciences* 111.9 (2014): 3268-3273.

171 Firouzeh Taghikhah et al., "Integrated Modeling of Extended Agro-Food Supply Chains: A Systems Approach," *European Journal of Operational Research* 288.3 (2021): 852-868.

172 Anuj Mittal and Caroline C. Krejci, "A Hybrid Simulation Modeling Framework for Regional Food Hubs," *Journal of Simulation* 13.1 (2019): 28-43.

173 Matthew James Grainger et al., "The Use of Systems Models to Identify Food Waste Drivers," *Global Food Security* 16 (2018): 1-8.

174 Joha Rockström et al., "Planet-Proofing the Global Food System," *Nature Food* 1.1 (2020): 3-5.

175 Laura Enthoven and Goedele Van den Broeck, "Local Food Systems: Reviewing Two Decades of Research," *Agricultural Systems* 193 (2021): 103226.

176 Ewen Callaway, "Scientists Are Using AI to Dream up Revolutionary New Proteins," *Nature* 609, no. 7928 (September 22, 2022): 661–62.

177 Selena Ahmed, Maya Rajasekheren, and Tracy Shafizadeh, "Food: Use Artificial Intelligence to Create New Proteins," *Nature* 611, no. 7937 (November 24, 2022): 665–665.

178 Sezin Kircali Ata et al., "Predicting the Textural Properties of Plant-Based Meat Analogs with Machine Learning." *Foods* 12, no. 2 (January 11, 2023): 344.

179 Mohamed Helmy et al., "Perspective: Multiomics and Machine Learning Help Unleash the Alternative Food Potential of Microalgae," *Advances in Nutrition* 14, no. 1 (January 2023): 1–11.

180 Manuela Gallón Bedoya et al., "Promising Perspectives on Novel Protein Food Sources Combining Artificial Intelligence and 3D Food Printing for Food Industry," *Trends in Food Science & Technology* 128 (October 2022): 38–52.

181 Catherine Nakalembe and Hannah Kerner, "Considerations for AI-EO for Agriculture in Sub-Saharan Africa," *Environmental Research Letters* 18, no. 4 (2023): 041002.

182 "Pest Management for Cotton Farming," Wadhwani AI, accessed February 9, 2024, https://www.wadhwaniai.org/programs/pest-management/pest-management-ai-solution/.

CURRENT APPLICATIONS IN AI

Power

In order to meet the Paris Agreement's goal of limiting global average temperatures to 1.5°C above pre-industrial levels, deep cuts in global emissions of GHGs will be required in this decade and emissions must reach net-zero by around 2050. Data from the 2022 Intergovernmental Panel on Climate Change Report indicates that the power sector accounts for 34% of total net anthropogenic GHG emissions.[183] This field is witnessing rapid structural changes with the increased use of renewables, which has led to reduced carbon intensity yet has brought issues of intermittency and reduced predictability compared to fossil fuel or nuclear power generation. With the electrification needs of electric vehicles (EVs), space heating and cooling, industrial sectors, and green hydrogen,[184] the role of the power sector is growing in importance, as is the need and opportunity to decarbonize it.

AI can play a major role in accelerating the reduction of carbon emissions in the power sector and can be used across the power supply and demand pipelines. For instance, AI can dramatically improve the forecasting and optimization of complex and non-linear systems such as renewable energies. It can predict weather to inform future supply and demand estimates. In addition, it can harvest a multitude of sensors' input to help optimize the structure and localization of new sources of renewable energy, thereby accelerating the renewable energy transition. Notwithstanding the potential of AI for the energy sector, the adoption of these solutions has remained relatively slow due to stringent safety standards required of energy suppliers and complex regulatory and permitting restrictions. However, AI has the potential to enhance overall safety and reliability.

Renewable Energy Integration

As renewable energy becomes more ubiquitous, the power grid becomes more complex. Renewable energy sources can be unevenly distributed (geographically and temporally), and their outputs depend on variable environmental conditions (solar, wind or hydraulic), resulting in heterogeneous data that is normally difficult to process and optimize at speed. Given its ability to analyze large and disparate datasets, AI can enhance the coordination, storage, use, and distribution of renewable power more efficiently and effectively than a traditional system. AI can assist in forecasting renewable energy sources by "optimizing the matching of intermittent carbon-free and dispatchable resources on an hourly basis", while enabling load flexibility through incentives, curtailment, or onsite generation.[185]

AI can also be used to optimize renewables planning as it relates to layout, location, and power production.[186] Wind turbine construction and placement are mathematical and technical challenges that can be addressed with AI and machine learning tools.[187] Similarly, AI can optimize solar farm locations based on light, land slope, and temperature—as well as local supply—helping to minimize system cost.[188] It can also improve maintenance efficiency for renewables and generate a digital twin of the physical system to predict maintenance. As wind turbines are typically located in environments with high wind speeds and low population density, the maintenance costs during their lifetime are usually higher than their initial procurement cost.[189] By performing smart maintenance scheduling and detecting failure-risk early based on extensive data collected during turbine operation, AI can greatly reduce those maintenance costs.

Grid Efficiency and Reliability

Smart grids—networks that integrate energy distribution with digital communication, allowing for a bidirectional flow of both electricity and data—can reduce GHG emissions, as they facilitate optimization through intense data acquisition; AI in turn can leverage this flow of data to optimize grid operations even in complex settings that could not be supported by older-generation optimization algorithms.[190] Intelligent electricity grid management, which actively manages the grid to account for volatile power production and peak load, can improve reliability by reducing the stresses that overloading has typically imposed on grid infrastructure.[191] Using AI to reduce transmission and renewable production loss improves operational efficiency and resilience, and reduces emissions.

Smart grids can also support faster and more precise forecasting of load. The use of advanced smart metering infrastructure, together with AI-facilitated predictive analytics, allows utility companies to predict where and when fluctuations in energy demand or outages might occur. AI has already proven to be faster than prior forecasting techniques on smart grids, reducing analysis time by several orders of magnitude.[192] With this kind of speed and precision, utility companies are capable of making better and faster data-driven decisions, reducing the climate impact of power distribution and improving customers' quality of life. Weather forecasting can also be accelerated and improved in terms of accuracy with AI, providing key information for grid optimization as renewables are critically dependent on weather variability, such as wind and solar availability.[193] As such, AI can help maximize the output from solar panels and wind turbines, reducing reliance on fossil fuels.

AI can improve traditional grid planning and management as well. While the distribution grid has until now been too variable and complex to be managed accurately (i.e., the distribution grid is large and is reconfigured depending on operational needs), recent progress on distribution digitalization is allowing AI to perform real time grid mapping, power flow assessment, and fault localization.[194] For example, transmission grid efficiency and optimal planning has always been hampered by the highly computational and expensive-to-solve "optimal power flow problem," but AI has the capacity to provide cost-effective solutions to such problems, thereby enhancing grid resilience as well as the economics of the industry.[195] AI can also optimize grid dispatch to reduce the electricity loss in transmission lines, which in turn reduces carbon emission.[196]

Integration of New Technologies

AI can also enhance and accelerate integration with other new participants in the power sector, such as energy storage and electrification from EVs and green hydrogen. As renewables increasingly penetrate the power sector, energy storage must be integrated with the grid, and AI can play an important role by predicting storage planning needs[197] and optimizing the operation of such storage

INITIATIVE HIGHLIGHTS

Uplight + Autogrid

Uplight uses AI models to analyze vast amounts of energy consumption data and draw actionable insights for utility companies or their customers, allowing them to reduce energy consumption and costs. Autogrid, which was recently acquired by Uplight, offers AI-driven distributed energy resource management that helps forecast and optimize energy consumption for microgrids, EV grids, and virtual power plants. AutoGrid leverages AI to transform data into actionable intelligence for electricity providers, enabling them to automate grid operations, predict energy demand, and integrate renewable resources efficiently.

Stanford University DeepSolar Project

DeepSolar, led by Stanford University, uses a deep learning framework that analyzes satellite and aerial imagery to identify the GPS locations and size of solar photovoltaic panels across the world. The project analyzes spatiotemporal solar adoption patterns to inform policy and promote equitable deployment of solar energy. The algorithms and aggregate-level data are open to the public.

Wind Farm Energy Optimization

Google Deepmind applied machine learning algorithms to wind farms to assess weather and turbine data, predicting energy production up to 36 hours in advance. The AI model used that data to recommend energy delivery commitments a day in advance, raising the wind farms' energy value by approximately 20%.[214] The initiative aimed to strengthen the business case for wind power and increase the uptake of clean energy on power grids at scale.

Multi-Platform Inspection, Maintenance and Repair in Extreme Environments (MIMRee)

Funded by Innovate UK and led by ORE Catapult, the project brought together eight cross-sector collaborators in robotics, artificial intelligence, marine and aerial engineering, nanobiotechnology and space missions. MIMRee used AI and robotics to automate the repair of offshore wind turbines. Optimizing wind turbine maintenance enables increased performance and better energy outputs, making wind farms more viable. The MIMRee project paved the way for wind farms designed for robotic maintenance.

Husk Power Systems

Husk uses AI, IoT, and smart meters to upscale and remotely manage minigrid solar systems in Africa and Asia. Predictive AI is used to forecast supply and demand and then deploys AI-powered algorithms to deliver electricity to its customers at the lowest cost at any given time. The company provides renewable energy and power generation and transmission lines to offer affordable, maintainable energy solutions to historically energy-poor communities.

Open Climate Fix

Open Climate Fix uses AI to improve the efficiency and effectiveness of the energy sector. They focus on creating open-source models that predict solar photovoltaic electricity generation, enabling better integration of solar power into the grid. By forecasting solar energy output more accurately, utilities can reduce reliance on carbon-intensive power sources.

Nuclear Fusion

A moonshot, but with tremendous potential, Google DeepMind in collaboration with the Swiss Plasma Center created the world's first AI system to support nuclear fusion.[215] Traditionally nuclear fusion—the process that takes place within stars, where hydrogen collides and fuses with other hydrogen—is accomplished on Earth through the use of a doughnut-shaped vacuum called a tokamak. Magnetic coils surround the exterior of the tokamak, ensuring that the hydrogen plasma inside never touches the walls of its container while these reactions take place (as the alternative would damage the system). Google DeepMind's reinforcement learning system helps control those coils, adjusting voltage based on plasma properties, optimizing fusion reactions and reducing risk of heat loss and damage.[216]

to maximize its lifetime value.[198] The market for battery energy storage is growing significantly and is anticipated to reach between $120-$150 billion per year by 2030.[199] As this market expands, AI can help in solving the optimal sizing and investment time problem for grid energy storage deployment under various uncertainties such as battery capital expenditures.[200] Every additional percentage point of sizing optimization can translate to an additional $1 billion in revenue. Energy storage owners are already using AI to optimize their storage scheduling and offerings into electricity markets, and this process will likely expand with increased penetration of renewables.[201] Furthermore, AI can diagnose and predict lithium-ion battery degradation with the potential to optimize battery management and battery lifetimes.[202]

Energy demand from EVs is growing rapidly, demanding significant growth in charging infrastructure; AI can optimize that infrastructure planning as well as its operation with station placement, sizing, congestion reduction, and charge scheduling with minimum power price during the lower price of the day, typically when renewables are abundant or during the late night when load is low.[203] EV can also be considered distributed energy storage with vehicle-to-grid power flow. AI can leverage both system demand and EV user demand for optimal vehicle-to-grid control to maximize system resilience, reduce system cost, and improve EV owners' profit.[204] Green hydrogen, produced from renewable water electrolysis, is another way of indirect electrification for sectors requiring fuels to operate, such as heavy industry. While this is potentially very complex, in the future AI could aid in optimizing green hydrogen production and storage using previously discussed renewable prediction and grid optimization. It can also help plan hydrogen refueling stations, optimizing station-based production and storage.[205]

With the increased use and penetration of renewables, the power system is growing more unpredictable and complex, such that it is becoming more challenging to maintain current planning and operation methods based on existing planning and optimization algorithms. Conventional electric grids requiring additional components require significant energy storage and load optimization to enable the energy transition. AI has the unique power to harness the enormous amount of data to monitor and predict demand and load, as well as to provide integrated, better, and faster solutions to energy system decision-making as the system expands. AI can be used in the power sector to provide computation-efficient solutions as well as innovative solutions to still unsolved problems such as large-scale integrated system planning and operation; and weather, power, and demand control.

Battery optimization is another area where AI can excel. AI algorithms can optimize storage times and predict the best times to charge or discharge batteries based on various factors, including energy prices, demand forecasts, and grid conditions.[206,207] This optimization helps maximize economic returns and support prolonging battery life by limiting unnecessary cycles. AI is used to analyze vast amounts of data during the battery development process, including material properties, design parameters, and manufacturing techniques. This analysis has led to the discovery of new materials, improved battery designs, and more efficient manufacturing processes. This should ultimately result in batteries with higher capacities, longer lifespans, and lower costs.

Optimizing Power Generation in Underserved Communities

In remote or underserved regions, access to reliable and clean energy sources can be limited but would be transformative in supporting many services from home electricity to school energy supply. AI can optimize the deployment of low-cost renewable energy systems, such as solar mini-grids or small wind turbines, by analyzing local energy needs, weather conditions, and geographic features to maximize the systems' efficiency and sustainability. This can help tackle two problems at once: providing wider access to energy supply while reducing the carbon footprint.[208]

What's Next

In the power sector, adoption of those new technologies remains slower than in other sectors as the sector might not be amenable to emerging technological developments, and because of a complex regulatory environment.[209] For instance, questions remain as to how to leverage electric vehicle-to-grid technologies or autonomous vehicle deployment and engage with government and industry so that a positive and forward-looking outcome is obtained.[210,211] Electric vehicle-to-grid adoption faces regulatory hurdles, such as the need for clear guidelines on energy transactions between vehicle owners and utilities, standards for bidirectional charging infrastructure, and the resolution of potential impacts on electric vehicles battery lifespan. The integration of autonomous vehicles into the electricity grid provides innovative opportunities but also presents its own set of challenges and regulatory considerations. Regulatory issues for autonomous vehicle deployment include safety standards, liability in the event of accidents, and the development of infrastructure to support both the vehicles and the increased demand on the grid.

Further, there is a risk that large, AI—driven energy markets could operate outside the purview of governments and legal authorities, creating or exacerbating inequity as a result of income and educational gaps. AI can be used for enhancing power system stability and security,[212] but also facing multiple challenges about data and system security and customer education.[213] AI scientists and engineers who are interested in the power and energy sector should consider engaging with governments and utilities to help ensure that reasonable systems are defined to limit inequities.

ENDNOTES: POWER

183 Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change Summary for Policymakers*, (Geneva: Intergovernmental Panel on Climate Change, 2022).

184 International Energy Agency, *Net Zero by 2050: A Roadmap for the Global Energy Sector* (Paris: International Energy Agency, 2021).

185 Matt Wytock, "How AI-Powered Forecasting Can Advance the Energy Transition." Renewable Energy World, November 2, 2023, https://www.renewableenergyworld.com/opinion-and-commentary/how-ai-powered-forecasting-can-advance-the-energy-transition.

186 Tom Fleischman, "AI Enables Strategic Hydropower Planning Across Amazon Basin," Cornell Chronicle, February 17, 2022, https://news.cornell.edu/stories/2022/02/ai-enables-strategic-hydropower-planning-across-amazon-basin

187 Javier Serrano González, Manuel Burgos Payán, and Jesus Riquelme Santos, "A New and Efficient Method for Optimal Design of Large Offshore Wind Power Plants," *IEEE Transactions on Power Systems* 28, no. 3 (2013): 3075-3084.

188 Younes Noorollahi, Mohammadmahdi Rezaei, and Mohammadreza Mirzaei, "Energy Systems Modeling for Maximizing Renewable Energy Share in Fossil Fuel Dominated Mediterranean Climate," *Environmental Progress & Sustainable Energy* 42, no. 6 (2023): 1111-1126.

189 C. H. Yeh, et al., "Machine Learning for Long Cycle Maintenance Prediction of Wind Turbine," *Sensors*, 2019. 19(7).

190 SAP, "The Smart Grid: How AI Is Powering Today's Energy Technologies," SAP, accessed December 20, 2023,. https://www.sap.com/insights/smart-grid-ai-in-energy-technologies.html.

191 Baumgartner, Mario, and Andreas Ulbig. "Intelligent Electricity Grid Management." In Intelligent Decarbonisation, edited by Oliver Inderwildi and Markus Kraft, 86:107–15. Lecture Notes in Energy. Cham: Springer International Publishing, 2022. https://doi.org/10.1007/978-3-030-86215-2_12.

192 Alinson S. Xavier, Feng Qiu, and Shabbir Ahmed, "Learning to Solve Large-Scale Security-Constrained Unit Commitment Problems." *INFORMS Journal on Computing* 33, no. 2 (2021): 739-756.

193 R. Meenal et al., "Weather forecasting for renewable energy system: A review," *Archives of Computational Methods in Engineering* 29, no. 5 (2022): 2875-2891.

194 P. Stefanidou-Voziki et al., "A Review of Fault Location and Classification Methods in Distribution Grids," *Electric Power Systems Research*, 2022. 209.

195 Fouad Hasan, Amin Kargarian, and Ali Mohammadi, "A Survey on Applications of Machine Learning for Optimal Power Flow," *2020 IEEE Texas Power and Energy Conference (TPEC)*, pp. 1-6. IEEE, 2020.

196 Mario Baumgartner and Andreas Ulbig, "Intelligent Electricity Grid Management," In *Intelligent Decarbonisation: Can Artificial Intelligence and Cyber-Physical Systems Help Achieve Climate mitigation Targets?*, pp. 107-115. Cham: Springer International Publishing, 2022.

197 Panayiotis Moutis, Spyros Skarvelis-Kazakos, and Maria Brucoli, "Decision Tree Aided Planning and Energy Balancing of Planned Community Microgrids," *Applied Energy* 161 (2016): 197-205.

198 Kunshu Zhou, Kaile Zhou, and Shanlin Yang, "Reinforcement Learning-Based Scheduling Strategy for Energy Storage in Microgrid," *Journal of Energy Storage* 51 (2022): 104379.

199 "Enabling Renewable Energy With Battery Energy Storage Systems," McKinsey & Company, August 2nd, 2023, https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/enabling-renewable-energy-with-battery-energy-storage-systems.

200 Joseph J. Kelly and Paul G. Leahy, "Optimal Investment Timing and Sizing for Battery Energy Storage Systems," *Journal of Energy Storage* 28 (2020): 101272.

201 Fred Lambert, "Tesla Energy and its Autobidder Software Are Making Power Companies Nervous," Electrek, August 25, 2021, https://electrek.co/2021/08/25/tesla-energy-autobidder-software-making-power-companies-nervous/.

202 Alan G. Li, Alan C. West, and Matthias Preindl, "Towards Unified Machine Learning Characterization of Lithium-Ion Battery Degradation Across Multiple Levels: A Critical Review," *Journal of Applied Energy* 316 (2022): 119030.

203 Sanchari Deb, "Machine Learning for Solving Charging Infrastructure Planning Problems: A Comprehensive Review," *Energies* 14, no. 23 (2021): 7833.

204 Bartlomiej Mroczek and Amanda Kolodynska, "The V2G Process With the Predictive Model," *IEEE Access* 8 (2020): 86947-86956.

205 R. Venkatasatish and C. Dhanamjayulu, "Reinforcement Learning Based Energy Management Systems and Hydrogen Refuelling Stations for Fuel Cell Electric Vehicles: An Overview," *International Journal of Hydrogen Energy*, 2022. 47(64): p. 27646-27670.

206 Gonzague Henri and Ning Lu, "A Supervised Machine Learning Approach to Control Energy Storage Devices," *IEEE Transactions on Smart Grid* 10, no. 6 (November 2019): 5910–19.

207 Hyuna Kang et al., "A Bi-Level Reinforcement Learning Model for Optimal Scheduling and Planning of Battery Energy Storage Considering Uncertainty in the Energy-Sharing Community," *Sustainable Cities and Society* 94 (July 2023): 104538.

208 Ibrahim Abada, Mehdi Othmani, and Léa Tatry, "An Innovative Approach for the Optimal Sizing of Mini-Grids in Rural Areas Integrating the Demand, the Supply, and the Grid," *Renewable and Sustainable Energy Reviews* 146 (August 2021): 111117. https://doi.org/10.1016/j.rser.2021.111117.

209 Saima Akhtar et al., "Deep Learning Methods Utilization in Electric Power Systems," *Energy Reports* 10 (November 2023): 2138–51.

210 Chunhua Liu et al., "Opportunities and Challenges of Vehicle-to-Home, Vehicle-to-Vehicle, and Vehicle-to-Grid Technologies," *Proceedings of the IEEE* 101, no. 11 (November 2013): 2409–27.

211 Sonali Goel, Renu Sharma, and Akshay Kumar Rathore, "A Review on Barrier and Challenges of Electric Vehicle in India and Vehicle to Grid Optimisation," *Transportation Engineering* 4 (June 2021): 100057.

212 Oyeniyi Akeem Alimi, Khmaies Ouahada, and Adnan M. Abu-Mahfouz, "A Review of Machine Learning Approaches to Power System Security and Stability," *IEEE Access* 8 (2020): 113512–31.

213 Tanveer Ahmad et al., "Data-Driven Probabilistic Machine Learning in Sustainable Smart Energy/Smart Energy Systems: Key Developments, Challenges, and Future Research Opportunities in the Context of Smart Grid Paradigm," *Renewable and Sustainable Energy Reviews* 160 (May 2022): 112128.

214 Carl Elkin, "Machine Learning Can Boost the Value of Wind Energy," Google DeepMind, February 26, 2019, https://deepmind.google/discover/blog/machine-learning-can-boost-the-value-of-wind-energy/.

215 "Accelerating Fusion Science Through Learned Plasma Control," Google DeepMind, February 16, 2022, https://deepmind.google/discover/blog/accelerating-fusion-science-through-learned-plasma-control/.

216 Wolfgang Picot, "Magnetic Fusion Confinement with Tokamaks and Stellarators," International Atomic Energy Agency, accessed February 12, 2024, https://www.iaea.org/bulletin/magnetic-fusion-confinement-with-tokamaks-and-stellarators#:~:text=As%20stellarator%20configurations%20are%20challenging,reactor%20types%20have%20certain%20advantages.

CURRENT APPLICATIONS IN AI

Industry

Caused primarily by the burning of fossil fuels and chemical reactions required to create goods from raw materials, 24% of total net anthropogenic GHG emissions come from industry.[217] Furthermore, when emissions from the electricity and heat used by industry are factored in, the sector accounts for more than a third of total net anthropogenic GHG emissions.[218] Approximately 30 billion tons of concrete are produced globally each year; this is a massive increase since the end of the 20th century[219] and a process that is responsible for 9% of all CO2 emissions.[220] Furthermore, about 40% of GHG emissions in industry are generated by the combined production of cement and steel, two building materials for which demand is only expected to grow as more countries industrialize.[221]

There are two major impediments to any efforts to decarbonize industry:

» Immense energy and heat are required to produce building materials (including iron, chemicals, and plastics, and

» Emissions are an inevitable by-product of chemical reactions using conventional feedstocks (e.g., coal and iron ore, cement from clinker).

Synthetic or bio-materials could prove valuable in addressing these challenges, and AI is showing promise as a tool to identify and generate new materials that would reduce industry-related emissions over time.[222, 223]

Additionally, AI can streamline the production and manufacturing processes themselves by automating activities, monitoring equipment, reducing waste, lowering energy usage, and facilitating scheduling and transportation. These capabilities allow AI to effectively optimize a facility's operations, thereby reducing emissions in the industrial sector.[224]

Manufacturing

As of 2024, the use of AI in industry remains limited compared to other fields of applications, potentially due to "the enormous changes and expenditures needed to integrate AI applications into corporate structures and along entire value chains," but is quickly expanding.[225, 226, 227] Four main areas in which it does exist, however, are:

» **Process optimization.** Reducing material usage, minimizing manufacturing waste, lowering energy consumption, and predicting energy demand.

» **Quality control.** Automated defect detection and prediction, product inspection, and quality prediction.

Cement

Cement production accounts for roughly 8% of the world's total CO_2 emissions, and is a major hurdle for a greener industry, given its ubiquitous use.[241] A number of organizations, however, are working to reduce the impact of the cement production and optimize the process with AI.

- **AICrete**'s operating platform, AICreteOS, uses AI, machine learning, and computer vision to generate factory insights that help producers optimize concrete mix designs and operations, which lower production costs, increase profit margins, and reduce overall carbon footprints.[242]
- **Carbon Re's Delta Zero Cement** uses AI and machine learning to help manufacturers identify ways to make the manufacturing process more energy-efficient, reduce production costs, and lower carbon emissions.
- **Cemex** uses machine learning to advance the function of ball mills, specifically—the most energy-intensive part of the production process—by collecting data in real time and making adjustments automatically based on that data, resulting in lower energy consumption and a higher quality product.[243]
- **Concrete.ai'**s Concrete Copilot helps industry stakeholders optimize their mix designs—using AI to identify solutions that not only reduce material costs and predict material performance,[244] but also reduce carbon production by an average of 30%.[245]

» **Predictive maintenance.** Detecting potential problems and reducing inspection and maintenance needs.

» **Human-robot collaboration and ergonomics.** Providing human support and improving safety.

"Industry 4.0," the disruptive technology and digitization expected to define the next phase of the manufacturing sector is an approach to optimize each of these pathways. Industry 4.0 is characterized by big data, cloud computing and computational power, analytics and AI, human-machine interaction, advanced engineering, and IoT.[228] It is already driving multifaceted improvements and increased sustainability across industry: decreasing waste when building semiconductors, reducing energy usage and CO_2 emissions at utility companies, and minimizing fuel usage of construction vehicles.[229] In particular, digital twins are allowing for the testing of new products, designs, and materials without use of the existing physical system, thereby saving time, money, materials, and waste.[230]

AI's application for manufacturing is typically clustered under four main domains: scheduling, quality, monitoring, and failure.[231] Scheduling and quality control are part of "AI for optimization" by better using the large amount of data collected from manufacturing digitalization. Monitoring and failure apply AI for prediction and early warnings. AI, leveraging the system-wide data warehouse, can take a holistic view to provide system-level optimization including decision support, layout planning, future product design, and market competitiveness, which are hard to perform using conventional algorithms.

AI and other smart technologies are also being used to optimize transportation logistics within industry.[232] In addition to improving operational efficiency and lowering costs in manufacturing and warehousing, machine learning algorithms are used for transportation scheduling, demand and response prediction, and supporting autonomous vehicles both inside and outside the facilities, helping to lower the environmental impact of industry overall.[233]

Heavy Industry

AI can play an important role in both optimizing existing heavy industry production and discovering new materials for replacement. For example, in the steelmaking process, AI can help reduce costs and emissions for electric arc furnaces, which are mostly used for secondary steelmaking using recycled steel scraps.[234] Unlike primary steel production processes using iron ores (which can facilitate quality control with stable raw material feeds), recycling must deal with highly uncertain scraps from various sources, which requires the application of additives to account for impurities. To ensure the highest quality of the final product, however, expensive additives are typically overused, contributing to higher costs and more emissions from those additives. AI optimization can support steelmakers by identifying the best additive solutions specialized for each batch of product, automating the additive adjustment process, and adapting to existing infrastructure hardware. Additionally, AI can make faster and better adjustments to the volatility of feedstocks, provide higher

INITIATIVE HIGHLIGHTS

Fero Labs

Fero Labs' explainable AI is enabling circular manufacturing workflows to decarbonize the steel, chemicals, and cement industries. Their "Profitable Sustainability Platform" maps the entire factory workflow, from variable feedstocks to final quality metrics, enabling real-time optimization of the production process end-to-end. Fero's focus on AI models that provide confidence bands and explainable insights enables manufacturers to cut costs, reduce energy consumption, improve recycled material usage, minimize waste, and improve the production throughput.

Atlas AI

Atlas AI has developed a number of AI-driven geospatial tools that assist infrastructure actors in historically untapped, underserved markets. Among many operational benefits, they can be used to select and monitor sites (which is especially useful in remote areas or conflict-prone regions), forecast product demand and supply, manage logistics, and optimize transportation routes and networks. Their GeoAI platform is capable of generating socio-demographic data and location insights for any location, helping to monitor economic development in emerging markets and strengthen industrial operations in data-sparse regions. Moreover, their analytical and workflow tools can assist industry actors to make their businesses more efficient, reduce waste, lower energy consumption, and ultimately become more sustainable.

The Materials Project

It takes an extraordinary amount of time and money to synthesize, characterize, and experimentally validate new materials in the physical world. The Materials Project makes the process virtual with AI and machine learning—training models on vast amounts of data (such as crystal structure and chemical composition of existing materials in its datasets) which then generate novel materials and predict their properties. Their web-based suite of apps can be used to predict charge densities, generate novel chemical structures, and even train and evaluate other machine learning models on the path toward creating cheaper, more efficient, and more sustainable materials.

quality control, improve energy and material efficiency, and help heavy industry achieve a circular economy. Similar approaches exist for steelmaking,[235] cement clinker making,[236] plastic recycling,[237] and petrochemical productions such as ethylene.[238]

AI can also help in the discovery of new materials for industrial production. Rapid developments in construction design are demanding novel formulations of concrete, for example, to translate those challenging new designs into actual buildings. The traditional experimental or simulation methods to predict mechanical properties of new types of concrete, which are both expensive and slow, can be supplanted by AI. Using the established rich database of concrete properties, AI can more quickly predict the highly non-linear mechanical performance of new mixes of concrete[239] and thereby suggest better formulations for construction to reduce energy consumption and emissions from upstream productions. In addition, within a given concrete formula, AI can identify and suggest different replacements for individual materials, such as recycled concrete aggregates, less energy-intensive natural aggregates, fly ash, recycled plastic, etc.[240] In many cases, heavy industrial production uses energy- and emission-intensive materials that are both unnecessary and not optimized for efficiency. AI can improve industrial production by identifying less emission-intensive alternative materials and by optimizing the production process to reduce emissions from current use.

ENDNOTES: INDUSTRY

217 "Sources of Greenhouse Gas Emissions," United States Environmental Protection Agency, updated February 23, 2024, https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#:~:text=Industry%20(23%25%20of%202021%20greenhouse,produce%20goods%20from%20raw%20materials.

218 Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change Summary for Policymakers*, (Geneva: Intergovernmental Panel on Climate Change, 2022).

219 "Concrete Needs to Lose Its Colossal Carbon Footprint," Columbia University Libraries, Nature, September 28, 2021, https://www.nature.com/articles/d41586-021-02612-5.

220 Mark Fischetti, Nick Bockelman, and Wil V. Srubar, "Solving Cement's Massive Carbon Problem," Scientific American, February 1, 2023, https://www.scientificamerican.com/article/solving-cements-massive-carbon-problem.

221 "Industry," Systems Change Lab, accessed March 7, 2024, https://systemschangelab.org/industry.

222 Rohit Batra, Le Song, and Rampi Ramprasad, "Emerging Materials Intelligence Ecosystems Propelled by Machine Learning," *Nature Reviews Materials* 6, no. 8 (2021): 655-678.

223 Kai Guo et al., "Artificial Intelligence and Machine Learning in Design of Mechanical Materials," *Materials Horizons* 8, no. 4 (2021): 1153-1172.

224 Lara Waltersmann et al., "Artificial Intelligence Applications for Increasing Resource Efficiency in Manufacturing Companies—A Comprehensive Review," *Sustainability* 13, no. 12 (2021): 6689.

225 Ricardo Silva Peres et al., "Industrial Artificial Intelligence in Industry 4.0: Systematic Review, Challenges and Outlook," *IEEE Access* 8 (2020): 220121-220139.

226 Massimo Bertolini et al., "Machine Learning for Industrial Applications: A Comprehensive Literature Review," *Expert Systems with Applications* 175 (August 2021): 114820.

227 Nadia Khan and Syed Ali Ammar Taqvi, "Machine Learning an Intelligent Approach in Process Industries: A Perspective and Overview," ChemBioEng Reviews 10, no. 2 (April 2023): 195–221.

228 "What are Industry 4.0, the Fourth Industrial Revolution, and 4IR," McKinsey & Company, August 17, 2022, https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-are-industry-4-0-the-fourth-industrial-revolution-and-4ir.

229 Leila Farahzadi and Mahdi Kioumarsi, "Application of Machine Learning Initiatives and Intelligent Perspectives for CO_2 Emissions Reduction in Construction," *Journal of Cleaner Production* 384 (2023): 135504.

230 Zohaib Jan et al., "Artificial Intelligence for Industry 4.0: Systematic Review of Applications, Challenges, and Opportunities," *Expert Systems With Applications* 216 (2023): 119456.

231 Alican Dogan and Derya Birant, "Machine Learning and Data Mining in Manufacturing," *Expert Systems with Applications* 166 (March 2021): 114060.

232 Sai-Ho Chung, "Applications of Smart Technologies in Logistics and Transport: A Review," *Transportation Research Part E: Logistics and Transportation Review* 153 (2021): 102455.

233 Sai-Ho Chung, "Applications of Smart Technologies in Logistics and Transport: A Review," *Transportation Research Part E: Logistics and Transportation Review* 153 (2021): 102455.

234 David B. Sandalow et al., "Artificial Intelligence for Climate Change Mitigation Roadmap," (2023). https://doi.org/10.7916/cfn0-xj39

235 Vaso Manojlović et al., "Machine Learning Analysis of Electric Arc Furnace Process for the Evaluation of Energy Efficiency Parameters," *Applied Energy* 307 (February 2022): 118209.

236 Asem M. Ali, Juan David Tabares, and Mark W. McGinley, "A Machine Learning Approach for Clinker Quality Prediction and Nonlinear Model Predictive Control Design for a Rotary Cement Kiln," *Journal of Advanced Manufacturing and Processing* 4, no. 4 (October 2022): e10137.

237 Hon Huin Chin et al., "Plastic Circular Economy Framework Using Hybrid Machine Learning and Pinch Analysis," *Resources, Conservation and Recycling* 184 (September 2022): 106387.

238 Diogo A.C. Narciso and F.G. Martins, "Application of Machine Learning Tools for Energy Efficiency in Industry: A Review," *Energy Reports* 6 (November 2020): 1181–99.

239 Wassim Ben Chaabene, Majdi Flah, and Moncef L. Nehdi, "Machine Learning Prediction of Mechanical Properties of Concrete: Critical Review," *Construction and Building Materials* 260 (November 2020): 119889.

240 Debasis Sau, Tumpa Hazra, and Amit Shiuly, "Assessment of Sustainable Green Concrete Properties Using Recycled Plastic Waste as Replacement for Fine Aggregate Using Machine Learning Technique," *Composites: Mechanics, Computations, Applications: An International Journal* 14, no. 2 (2023): 1–12.

241 Leah D. Ellis, "Toward Electrochemical Synthesis of Cement—An Electrolyzer-Based Process for Decarbonating CaCO3 While Producing Useful Gas Streams," *Proceedings of the National Academy of Sciences* 117, no. 23 (2020): 12584-12591.

242 "FAQs," AICrete, accessed February 14, 2024, https://www.aicrete.com/faq-01/.

243 "Improving Cement Production through Artificial Intelligence," Cemex, November 18, 2021, https://www.cemex.com/w/improving-cement-production-through-artificial-intelligence.

244 "Optimize Your Mix Designs with AI," ConcreteAI, accessed February 14, 2024, https://www.concrete.ai/.

245 "Concrete.ai Applies Generative AI Solution to Carbon-Wise Mix Designs," Concrete.ai, January 24, 2024, https://www.concrete.ai/news/concrete-ai-applies-generative-ai-solution-to-carbon-wise-mix-designs/.

246 "Cities Key to Solving Climate Crisis," The World Bank, May 18, 2023, https://www.worldbank.org/en/news/press-release/2023/05/18/cities-key-to-solving-climate-crisis.

CURRENT APPLICATIONS IN AI

Cities + Built Environment

Urban areas are both a major driver of climate change and highly vulnerable to it. Currently home to 50% percent of the global population (with an expected rise to 70% by 2050),[246] urban areas account for more than 70% of global CO2 emissions.[247] Buildings in urban areas also contribute 6% of total anthropogenic GHG emissions.[248]

Strategies to cut down urban emissions and increase sustainability include optimizing building energy use, retrofitting existing buildings and infrastructure, decarbonizing heating and cooling appliances, reducing waste, and improving urban planning and design through strategies such as greening and investing in energy-efficient infrastructure.

AI can accelerate the potential for cities and the built environment to become solutions to mitigate and adapt to climate change, and conserve nature. By leveraging a broad range of sensors in smart cities and buildings, AI can help increase energy efficiency and optimize energy use to reduce GHG emissions. More broadly, AI can support the improvement of quality of life in cities by optimizing the built environment in a number of ways, including enhancing green design and improving building quality, traffic flows, and waste management. When applying AI technologies, it is critical to remember that cities are also homes, which means that climate and nature solutions must be centered on people, in all of their complexity. Approaches to address the sustainability of cities must be multilevel and multifaceted, integrating sociocultural, economic, and behavioral needs of each population.

Smart Cities and Buildings

Smart cities are urban centers that effectively incorporate digital solutions into their infrastructure, networks, and services. They strive to be both smart and sustainable, leveraging information and communication technologies to boost quality of life, efficiency, and economic competitiveness. Smart cities employ a range of advanced technologies to deliver smart services to residents including IoT technologies, data analysis capabilities, edge computing, regional data hubs, advanced 5G communication networks, cloud-based computing solutions, and cutting-edge innovations in AI and machine learning.[249] In addition, these cities are increasingly automating sensor data collection to monitor and optimize systems—optimizing traffic flows, congestion, emissions, parking, public transport, energy consumption, waste management processes, and utility management.[250]

AI is starting to be deployed to improve energy efficiency across several cities' public buildings and housing projects, such as in Barcelona, Spain.[251] AI monitors and controls energy consumption, reduces waste and lowers carbon emissions. These initiatives prioritizes interventions in lower-income neighborhoods, ensuring equitable access to energy savings and helping contribute to the overall resilience of the community.

Optimization and Building Decarbonization

- **BrainBox AI** uses autonomous AI technology to proactively optimize the energy consumption of buildings, reducing carbon emissions while generating significant energy savings. Solutions include HVAC optimization, energy management, and decarbonization and offsets.
- **Delve**, developed by Google DeepMind and Labs, is a machine learning platform that assists with the design and construction of buildings. It can make adjustments to designs based on many different parameters, including building height and sun exposure.
- **Mortar IO** uses an AI-driven simulation platform to help users decarbonize buildings by generating virtual models of thousands of buildings within minutes, aiding with quick and efficient retrofitting planning in the real estate decarbonization space.
- **Building X** is an open platform that takes data from one-off events (such as construction) in addition to continuous monitoring of building activities (via sensors). Both the data as well as insights generated from it by the platform are made available to users, helping them make informed decisions and create smart solutions for their buildings.
- **BlocPower** aims to reduce carbon emissions in US buildings by leveraging AI for targeting and planning. It has built a database of 125 million buildings, and employed physics-based bottom-up simulation engines, AI, and machine learning models to generate digital twins of these buildings (which are bias-corrected against real-world data). BlocPower has also developed a Scope of Work Recommendation Engine that identifies buildings needing energy conservation, using factors like topology and energy consumption to assess the feasibility of energy conservation measures.

Energy Consumption Forecasting

Buildings account for a significant part of global energy use and emissions. Monitoring interior data (temperature, electricity consumption, occupancy, etc.) and exterior data (solar availability, weather conditions, etc.) can help us understand real-time trends and determine optimizations based on forecasted changes in the environment (such as cloud cover), neighborhood (occupancy), or transportation network. AI is also increasingly used to optimize operational energy efficiency of heating, ventilation, and air conditioning (HVAC) systems within buildings. These algorithms identify patterns and opportunities for improvement or intervention, detect potential vulnerabilities or flaws that may pose a risk to the longevity of the unit, and automatically alter settings based on previous learning.[252]

Cities are increasingly using digital models of the physical and functional features of the built environment and buildings to develop digital twins. These models can provide detailed information about buildings—such as HVAC systems, thermal properties of windows, energy use, etc.—which then can be leveraged using AI to further model the environment in and around the building and determine opportunities for optimization.[253]

Construction and Material Manufacturing

AI, especially generative AI, is currently being used to create new, more circular construction materials, a key element of cities' environmental footprint.[254,255] Cement is a focus: AI can automate material testing and quality monitoring efforts, reduce costs of production, and lower CO_2 byproducts (see *Industry*). In addition, AI and sensor use have proven helpful in analyzing data collected by in-transit monitoring systems, actively adjusting the cement trucks' spin rates and optimizing the retention of material during transportation.

Urban Planning and Greening

AI can assist in designing and optimizing urban layouts to make them more sustainable and reduce their carbon footprints. It is already being leveraged in many locations around the world to understand urban grid dynamics, efficiency of city services, and water resource planning.[256,257]

Moreover, it is well established that tree canopies and urban forests can offset the heat island effects that have been exacerbated by climate change.[258] Policymakers recognize the need to protect, expand, and improve accessibility to urban trees,[259] but the success of these greening initiatives hinges on accurate, up-to-date tree inventories, which are costly and time-consuming to collect manually. AI is

INSTITUTE HIGHLIGHTS

Urban AI

Urban AI is a think tank focused on conducting research that can assist city leaders, urban planners, and policy-makers in understanding the state of urban technologies, AI models that are currently applied to cities and the built environment, and the potential for AI to make urban life safer and more sustainable. Urban AI describes itself as the "crossroads" between AI and Smart Cities.

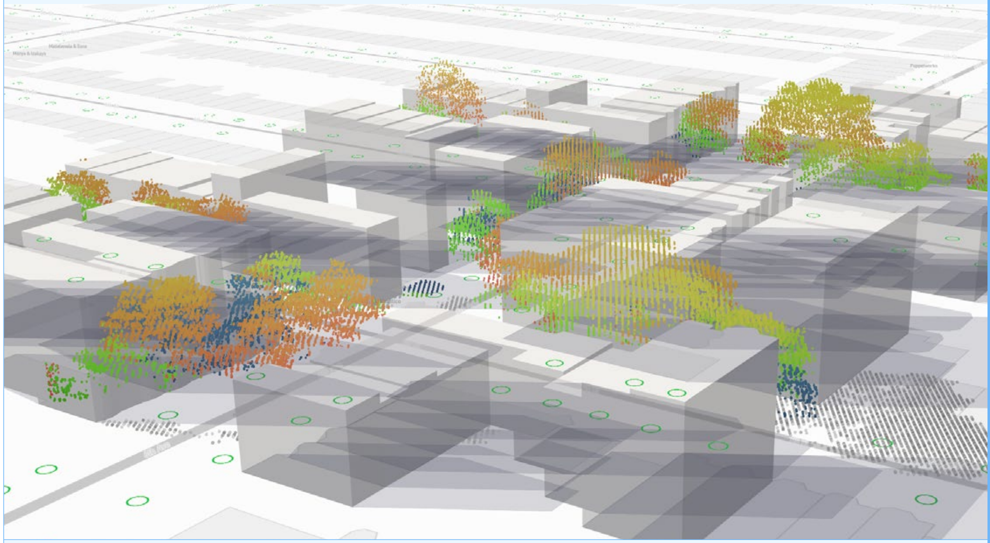
University of Virginia Link Lab

The Link Lab at UVA Engineering is a multidisciplinary consortium of faculty and graduate students conducting research in Smart and Connected Health, Hardware for IoT, and Smart Cities.[272] Their work prioritizes real-world impact of cyber-physical systems, including enabling connected transportation services to meet the needs of all commuters and travelers, using machine learning models to make smart services more efficient, and imagining smart buildings that are not only more sustainable but also improve occupant health and comfort.[273] They work closely with industry to advance their technology, as well as local government for case studies.

INITIATIVE HIGHLIGHTS

Tree Folio NYC

The result of a multi-year collaboration between Cornell University's Design Across Scales Lab and Cornell Tech's Urban Tech Hub, Tree Folio NYC is a digital twin of New York City's tree canopy. Utilizing traditional satellite technology and LiDAR data to model NYC trees and quantify the amount and quality of shade each provides. Machine learning algorithms were used to fill the gaps between the satellite and LiDAR information sources and apply those learnings elsewhere. The tool can be used to make informed decisions on urban planning and management, especially in making the city more sustainable and resilient to warmer weather and extreme heat.



Google's Environmental Insights Explorer

Environmental Insights Explorer is a freely available data and insights tool that uses exclusive data sources and modeling capabilities to help cities and regions measure emissions sources, run analyses, and identify strategies to reduce emissions—creating a foundation for effective climate action at the urban level. In addition to building and transportation emissions, the tool can monitor air quality, solar rooftop potential, and tree canopy coverage.

Greyparrot

Greyparrot works on waste intelligence to improve recycling and help address the global waste crisis. Their computer vision AI waste analytics platform creates a live stream of insight on the material passing through a recycling sorting facility to monitor, audit, and sort waste at scale, through robotics or optical sorters, enabling for more resource recovery and greater diversion to landfills.

a powerful tool for efficiently identifying trees across large areas and providing communities with impactful insights that can be used to strategically plan and enhance urban green spaces. Using data sourced primarily from the United States and China, AI is already showing promise in planning and managing urban forests,[260] and it has also been used both to analyze public opinion on urban green spaces[261] as well as to evaluate the effect of those spaces on particulate matter and ozone formation.[262] Data like this can help shape, optimize, and improve sustainable city planning, urban development, and local policy.

Waste Management and Composting

As cities grow larger in size and population, so do their waste and management needs. Since the greatest proportion of urban solid waste is organic[263] and requires significant labor to sort,[264] optimization of the management chain is an excellent application of AI and new technologies. Computer vision and deep learning have been successfully used in solid-waste classification and segregation,[265] and machine learning models have proven highly effective at detecting the maturity of compost; this is data that can inform operational practices but has not yet been used on a large scale.[266] Developing and scaling up such technologies could dramatically accelerate waste recycling and composting for cities, leading to a significant reduction in our environmental footprint.

Quality of Life

AI can help improve city residents' access to government and city services by efficiently sorting information for residents as well as ensuring optimal communication between leaders and residents. In New Orleans, for instance, AI is used to translate 911 calls to improve communication, especially non-English-speaking callers.[267] Additionally, AI is capable of optimizing urban planning by analyzing vast amounts of data to inform the design of more livable and sustainable cities.[268] For instance, AI is able to help optimize park layouts, public transport networks, and residential areas to reduce pollution, enhance green spaces, and improve accessibility.[269] This can lead to healthier and more livable urban environments.

AI also has the capacity to help monitor environmental risk such as air and water quality, tracking and identifying pollution sources and enabling rapid action to mitigate risk.[270,271] This is especially beneficial in underserved communities that are often disproportionately affected by environmental hazards.

ENDNOTES: CITIES + BUILT ENVIRONMENT

247 "Climate Change," UN-Habitat, accessed November 17, 2023, https://unhabitat.org/topic/climate-change.

248 Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change Summary for Policymakers*, (Geneva: Intergovernmental Panel on Climate Change, 2022).

249 "Smart Cities," National Geographic, accessed November 17, 2023, https://education.nationalgeographic.org/resource/smart-cities/.

250 Liz Louw, "The Future of Blockchain-Based Intelligent Transportation Systems - 5 Things to Look Forward To," BSV Blockchain, February 28, 2024, https://www.bsvblockchain.org/news/the-future-of-blockchain-based-intelligent-transportation-systems-5-things-to-look-forward-to.

251 "Increasing Energy Efficiency in Buildings Using AI," BABLE, accessed April 4, 2024, https://www.bable-smartcities.eu/explore/use-cases/use-case/increasing-energy-efficiency-in-buildings-using-ai.html.

252 Jianli Chen et al., "A review of Computing-Based Automated Fault Detection and Diagnosis of Heating, Ventilation and Air Conditioning Systems," *Renewable and Sustainable Energy Reviews* 161 (2022): 112395.

253 Stephen Xia et al., "RECA: A Multi-Task Deep Reinforcement Learning-Based Recommender System for Co-Optimizing Energy, Comfort and Air Quality in Commercial Buildings," In *Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, 99–109. Istanbul Turkey: ACM, 2023.

254 Hossein Adel, Majid Ilchi Ghazaan, and Asghar Habibnejad Korayem, "Machine Learning Applications for Developing Sustainable Construction Materials," In *Artificial Intelligence and Data Science in Environmental Sensing*, 179–210. Elsevier, 2022.

255 Konstantinos Stergiou et al., "Enhancing Property Prediction and Process Optimization in Building Materials through Machine Learning: A Review," *Computational Materials Science* 220 (March 2023): 112031.

256 Awari Mahesh Babu, T. Sunil Kumar, and Sarangam Kodati, "Construction Method of Urban Planning Development Using Artificial Intelligence Technology," *Design Engineering* (2021): 782-792.

257 Xiaojun Xiang et al., "Urban Water Resource Management for Sustainable Environment Planning Using Artificial Intelligence Techniques," *Environmental Impact Assessment Review* 86 (2021): 106515.

258 "Using Trees and Vegetation to Reduce Heat Islands," United States Environmental Protection Agency, updated October 31, 2023, https://www.epa.gov/heatislands/using-trees-and-vegetation-reduce-heat-islands.

259 Marc Heller, "Biden Releases $1B for Urban Trees," E&E News, April 12, 2023, https://www.eenews.net/articles/biden-releases-1b-for-urban-trees/.

260 Henrique César de Lima Araújo et al., "Artificial Intelligence in UrbanForestry—A Systematic Review," *Urban Forestry & Urban Greening* 66, (2021): 127410.

261 Ghahramani Mohammadhossein et al., "Leveraging Artificial Intelligence to Analyze Citizens' Opinions on Urban Green Space," *City and Environment Interactions* 10 (2021): 100058.

262 Shuhui Yu et al., "Artificial Intelligence and Urban Green Space Facilities Optimization Using the LSTM Model: Evidence from China," *Sustainability* 15, no. 11 (2023): 8968.

263 Lalit Mohan Joshi, Rajendra Kumar Bharti, and Rajesh Singh, "Internet of Things and Machine Learning- Based Approaches in the Urban Solid Waste Management: Trends, Challenges, and Future Directions," *Expert Systems* 39, no. 5 (2022): e12865.

264 A. Jamali and Z. F. A. Misman, "Food Waste Management: A Case Study of the Employment of Artificial Intelligence for Sorting Technique," In *Natural Food Products and Waste Recovery*, pp. 185-205. Apple Academic Press, 2021.

265 Saswati Kumari Behera, L. Vasundhara, G. Saisudha, and N. C. Haariharan, "AI Based Waste Classifier With Thermo-Rapid Composting," In *2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, pp. 1-4. IEEE, 2020.

266 Yalin Li et al., "Prediction of Composting Maturity and Identification of Critical Parameters for Green Waste Compost Using Machine Learning," *Bioresource Technology* 385 (2023): 129444.

267 Thad Rueter, "New Orleans Embraces Multilingual Emergency Dispatch," Government Technology, December 7, 2023, https://www.govtech.com/biz/new-orleans-embraces-multilingual-emergency-dispatch#:~:text=The%20general%20idea%20is%20to,via%20transcriptions%20on%20their%20screens.

268 Tim Heinrich Son et al., "Algorithmic Urban Planning for Smart and Sustainable Development: Systematic Review of the Literature," *Sustainable Cities and Society* (2023): 104562.

269 Yiwen Liu et al., "Exploring the Layout Optimization of Commercial Service Space Affecting Energy Consumption in Communities Using Machine Learning," *Buildings* 14, no. 1 (December 31, 2023): 108.

270 Xiaojun Xiang et al., "Urban Water Resource Management for Sustainable Environment Planning Using Artificial Intelligence Techniques," *Environmental Impact Assessment Review* 86 (2021): 106515.

271 Akshara Kaginalkar et al., "Review of Urban Computing in Air Quality Management as Smart City Service: An Integrated IoT, AI, and Cloud Technology Perspective," *Urban Climate* 39 (2021): 100972.

272 "Link Lab: Multidisciplinary Cyber-Physical Systems Research at the University of Virginia," University of Virginia, accessed February 13, 2024, https://engineering.virginia.edu/link-lab.

273 "Developing Technologies for Smart Cities," University of Virginia, accessed February 13, 2024, https://engineering.virginia.edu/labs-groups/link-lab/research/smart-cities.

CURRENT APPLICATIONS IN AI

Transport

Transportation accounts for 17% of total GHG emissions and is responsible for about a fourth of CO_2 emissions globally, making the transportation sector a major contributor to climate change.[274, 275, 276] Road transport alone is responsible for 72% of those GHG emissions.[277] Similarly, sectors that have historically been considered "hard to decarbonize"—such as shipping and aviation,[278] which contribute roughly 3%[279] and 2.4%[280] of global GHG emissions, respectively—must see technological and operational interventions to reduce their burden on the climate.

AI technologies can play a substantial role in greening transportation. For example, they can make electric vehicle batteries more efficient[281] as well as hasten the production of newer, greener battery materials.[282] They can predict traffic[283] and time traffic signals to reduce congestion and therefore minimize the time vehicles spend on the road.[284] AI is already being used in autonomous vehicles, where machine learning models assist with the mapping of roadways as well as vehicle perception and decision-making.[285] And in industry, AI can make operations more efficient, predict demand for goods, and make supply chain management more sustainable.[286]

The emissions resulting from traffic congestion are significant drivers of climate change. Traffic management systems incorporating AI have enormous potential to reduce congestion through traffic flow prediction, anomaly detection, traffic collision prevention and mitigation, intelligent traffic light optimization, traffic flow smoothing, and routing.

Traffic Management

Reducing traffic is a key priority to reduce carbon emissions. AI can leverage satellite and other remote sensing data to map transportation routes and networks, a key step in route optimization, and it can gather information on traffic flow patterns, congestion, and accidents by collating additional sensor and GPS data.[287] AI can then optimize those traffic networks to reduce congestion and cut wait time and emissions, such as by changing traffic signals in real-time or redirecting drivers to less-congested roadways through their smartphones or car navigation systems.[288, 289] Google Map and DeepMind have implemented GNN-based traffic prediction algorithms, which can improve the accuracy of estimated time-of-arrival up to 50%.[290] AI can also optimize the flow of transportation on city roads by applying active traffic signal timing control.[291] When "non-recurrent" traffic incidents happen, the previously settled traffic signals are no longer viable for optimizing traffic streams, causing significant travel delays that in turn increase passenger waiting time and emissions. AI algorithms are faster and better adapted to updating optimal traffic signal timing in real-time when such incidents occur.

In addition to improving and optimizing traffic streams on our roadways, AI can be used to predict and optimize air traffic, which can have the dual benefit of minimizing delays and avoiding accidents.[292] Air traffic control has always been necessary to ensure that airplanes operate safely both in the air and on the ground, but the impact of delays has been hard to predict and optimize. Now AI can leverage large amounts of historical data to recommend optimal traffic control strategies by minimizing anticipated delays while preserving required safety protocols. By analyzing both air and ground traffic data in real-time, AI algorithms can adjust traffic to reduce accident risk as well as improve traffic flow and traffic conditions in response to accidents, thus enhancing overall safety and efficiency. The use of AI to manage traffic logistics can be widely applied to other transportation sectors, such as shipping berth allocation and control.[293]

Autonomous Vehicles

More than in any other area, AI has been essential to the development of autonomous vehicles (AVs). It is widely used throughout a comprehensive autonomous driving system that consists of multiple subsystems, including motion planning, vehicle localization (position identification), environment detection (pedestrian, traffic sign, road-marking), parking, cybersecurity, and system fault detection.[294] The use of AI allows AVs to perceive the surrounding environment and determine a drivable path by identifying and classifying objects as obstacles and signals. Furthermore, while they are operating, AVs benefit from AI's computation abilities to improve the execution time for any safety-related adjustments needed to protect both passengers and pedestrians. AV's reliance on AI to optimize routes and avoid collisions can reduce emissions by smoothing traffic flow.

As vehicles become "smarter," intelligent transportation systems and smart transport infrastructures—characterized by embedded sensor technologies and digital connectivities—are also quickly expanding,[295] and AI plays an important role in maximizing the healthy interaction between those systems and AVs. AI can process real-time data quickly and with high granularity; automatically enable dynamic traffic light sequencing (system action); and suggest alternative routes (vehicle action).

AI can also play an important role in demand prediction and automatic vehicle resource allocation for shared mobility or public transport. AI-guided autonomous public transit can improve operational efficiency and expand the extent of public transit routes, making public transport both more accessible and perhaps preferable, which would reduce private driving needs. Autonomous driving system fault detection can also perform predictive maintenance that will enable cars to stay on the road longer and therefore increase economic efficiency.

While AVs are a leading application of AI in the transport sector, they could be counterproductive in terms of climate change goals and actually increase GHG emissions if they were viewed as reducing barriers to travel in individual vehicles. It will be important to pair the promotion of AV use to the public with an emphasis on increased use of public transportation to prevent unintended negative consequences from this exciting technology.

Electric Vehicles

Electric Vehicles (EVs) can contribute to lower fuel consumption and cost, reduced emissions, and an improved fuel economy,[296] but one of the main challenges to their adoption by the general public is the lack of infrastructure.[297] AI is being used to improve existing infrastructure and optimize the placement of new EV charging stations.[298] AI is also being used to enhance energy capacity of batteries, making EVs more efficient by reducing charging frequency and bolstering the processing capacity of battery disposal systems.[299] According to the literature, AI is also capable of optimizing energy systems and predicting battery capacity.[300,301]

INITIATIVE HIGHLIGHTS

Green Light

Green Light, a Google Research initiative, optimizes traffic lights to reduce vehicle emissions. It is currently underway across a dozen cities in North America, South America, Europe, and Asia. Green Light reports that pollution is 29 times higher at city intersections than open roads, in part due to acceleration after stopping.[302] It leverages AI in conjunction with Google Maps data to analyze and predict traffic behaviors, understanding intersections, measuring traffic trends, developing recommendations for the city, and analyzing impact—all delivered through a user-friendly recommendation interface.

Chemix's MIX™ Platform

Chemix, a California tech startup, is using its MIX™ Platform to apply AI and machine learning to EV battery design. Battery design has always been challenging: producing highly complex objects made of a selection of nearly infinite available materials, it is a demanding effort with typically long and slow testing times. With AI, however, Chemix can accelerate battery development and performance through new material discovery and predictive modeling. It helps identify better-performing and/or lower-carbon battery materials, and it speeds up the battery-testing process through digital simulations.

Project Contrails

Google Research teamed up with American Airlines and Breakthrough Energy to study the development of contrails. Condensation trails (contrails) form when water vapor condenses around soot and other pollutant particles emitted by airplane engines. Contrails can persist as cirrus clouds and account for approximately 35% of aviation global warming impact. By combining massive quantities of weather data, satellite data, and flight data, Project Contrails used AI to create state-of-the-art predictions of when and where contrails are likely to form. Pilots and dispatchers can use that information to adjust the altitudes of their flights, with initial findings suggesting that following the recommended routes can reduce contrails by 54%.[303]

Parallel Systems

Parallel Systems, a startup founded by SpaceX engineers, builds modular electric freight cars (below), which are much cleaner than traditional railcars, with fully-automated systems that use machine learning to help optimize routes, energy consumption, and scheduling. Their goal is to make railways cheaper, safer, and more profitable, and eventually get railways to net zero emissions.

ENDNOTES: TRANSPORT

274 World Resources Institute, *State of Climate Action 2021: Systems Transformations Required to Limit Global Warming to 1.5*, (Washington, DC: World Resources Institute, 2021), https://www.wri.org/research/state-climate-action-2021.

275 Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change Summary for Policymakers*, (Geneva: Intergovernmental Panel on Climate Change, 2022).

276 Intergovernmental Panel on Climate Change, *Climate Change 2022: Mitigation of Climate Change Summary for Policymakers*, (Geneva: Intergovernmental Panel on Climate Change, 2022).

277 "Transport," Systems Change Lab, accessed March 7, 2024, https://systemschangelab.org/transport.

278 "Transport," Systems Change Lab, accessed March 7, 2024, https://systemschangelab.org/transport.

279 "How Much Does the Shipping Industry Contribute to Global CO2 Emissions," Sinay Maritime Data Solution, September 22, 2023, https://sinay.ai/en/how-much-does-the-shipping-industry-contribute-to-global-co2-emissions/.

280 Jeff Overton, "Issue Brief: The Growth in Greenhouse Gas Emissions from Commercial Aviation (2019, Revised 2022)," Environmental and Energy Study Institute, June 9, 2022, https://www.eesi.org/papers/view/fact-sheet-the-growth-in-greenhouse-gas-emissions-from-commercial-aviation.

281 Wei Li, "Intelligent Optimization Methodology of Battery Pack for Electric Vehicles: A Multidisciplinary Perspective," *International Journal of Energy Research* 44, no. 12 (2020): 9686-9706.

282 Wuxin Sha et al., "Artificial Intelligence to Power the Future of Materials Science and Engineering," *Advanced Intelligent Systems* 2, no. 4 (2020): 1900143.

283 Mahmuda Akhtar and Sara Moridpour, "A Review of Traffic Congestion Prediction Using Artificial Intelligence," *Journal of Advanced Transportation* 2021 (2021): 1-18.

284 Vishal Mandal et al., "Artificial Intelligence-Enabled Traffic Monitoring System," *Sustainability* 12, no. 21 (2020): 9177.

285 Yifang Ma et al., "Artificial Intelligence Applications in the Development of Autonomous Vehicles: A Survey," *IEEE/CAA Journal of Automatica Sinica* 7, no. 2 (2020): 315-329.

286 Mehrdokht Pournader et al., "Artificial Intelligence Applications in Supply Chain Management," *International Journal of Production Economics* 241 (2021): 108250.

287 Kenneth Li-Minn Ang et al., "Emerging Technologies for Smart Cities' Transportation: Geo-Information, Data Analytics and Machine Learning Approaches," *ISPRS International Journal of Geo-Information* 11, no. 2 (2022): 85.

288 Palwasha W. Shaikh et al., "A Review on Swarm Intelligence and Evolutionary Algorithms for Solving the Traffic Signal Control Problem," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 1 (2020): 48-63.

289 Srishti Dikshit et al., "The Use of Artificial Intelligence to Optimize the Routing of Vehicles and Reduce Traffic Congestion in Urban Areas," *EAI Endorsed Transactions on Energy Web* 10 (2023).

290 Oliver Lange, "Traffic Prediction With Advanced Graph Neural Networks," September 3, 2020, https://deepmind.google/discover/blog/traffic-prediction-with-advanced-graph-neural-networks/.

291 Tuo Mao et al., "Boosted Genetic Algorithm Using Machine Learning for Traffic Control Optimization," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 7 (2022): 7112–41.

292 Noboru Takeichi et al., "Prediction of Delay Due to Air Traffic Control by Machine Learning," In *AIAA Modeling and Simulation Technologies Conference*, p. 1323. 2017.

293 Lorenz Kolley, Nicolas Ruckert, and Kathrin Fischer, "A Robust Berth Allocation Optimization Procedure Based on Machine Learning," In *Logistics Management: Contributions of the Section Logistics of the German Academic Association for Business Research, 2021, Dresden, Germany*, pp. 107-122. Springer International Publishing, 2021.

294 Mrinal R. Bachute and Javed M. Subhedar, "Autonomous Driving Architectures: Insights of Machine Learning and Deep Learning Algorithms," *Machine Learning with Applications* 6 (2021): 100164.

295 David B. Sandalow et al., *Artificial Intelligence for Climate Change Mitigation Roadmap* (Innovation for Cool Earth Forum, 2023) https://doi.org/10.7916/cfn0-xj39.

296 "Electric Vehicle Benefits and Considerations," U.S. Department of Energy, accessed March 6, 2024, https://afdc.energy.gov/fuels/electricity_benefits.html#:~:text=All%20forms%20of%20electric%20vehicles,fuel%20costs%2C%20and%20reduce%20emissions.

297 Steve Russell, "The Main Challenges Facing EVCS Today (and Some Ways to Solve Them)," Environment, December 7, 2023, https://environment.co/evcs-challenges-and-solutions/.

298 Ahmed, Moin, Yun Zheng, Anna Amine, Hamed Fathiannasab, and Zhongwei Chen. "The role of artificial intelligence in the mass adoption of electric vehicles." *Joule* 5, no. 9 (2021): 2296-2322

299 Moin Ahmed et al., "The Role of Artificial Intelligence in the Mass Adoption of Electric Vehicles," *Joule* 5, no. 9 (2021): 2296-2322.

300 Mekyung Lee, "An Analysis of the Effects of Artificial Intelligence on Electric Vehicle Technology Innovation Using Patent Data," *World Patent Information* 63 (2020): 102002.

301 Rui Xiong et al., "Key Technologies for Electric Vehicles," *Green Energy and Intelligent Transportation* 1, no. 2 (2022): 100041.

302 "Green Light: Using Google AI to Reduce Traffic Emissions," Google Research, accessed December 28, 2023, https://sites.research.google/greenlight/.

303 "Project Contrails: A cost-effective and scalable way AI is helping to mitigate aviation's climate impact," Google Research, accessed April 19, 2024, https://sites.research.google/contrails/

CURRENT APPLICATIONS IN AI

Greenhouse Gas Emissions

Over the period of 2013 to 2022, fossil carbon dioxide (CO_2) emissions had reached 9.6(±0.5) gigatons of carbon per year.[304] Land-use change (mainly deforestation) accounted for 1.3(±0.7) gigatons of carbon per year. Methane—mostly caused by agriculture, fossil fuels, and landfill decomposition—is also a major contributor to GHG emissions and global warming: even though the magnitude of natural and anthropogenic emissions of methane is much less than that of CO_2, methane is 28 times more potent (global warming potential over 100 years) than CO_2 in terms of trapping heat in the atmosphere.[305]

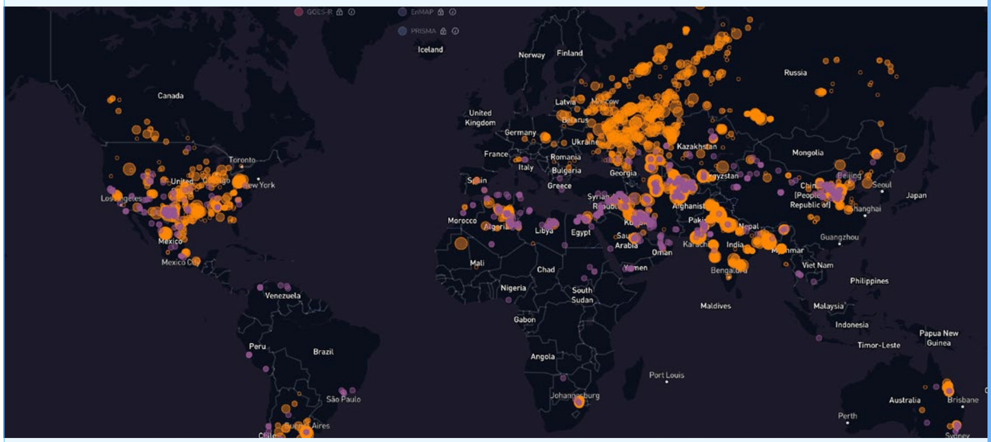
AI can be leveraged for carbon and methane emissions monitoring (assessing and predicting GHG emissions as well as evaluating the effectiveness of interventions), reduction (reducing carbon production at the household or industry level), and removal (sequestering existing carbon from the atmosphere).

GHG Emissions Monitoring

A substantial fraction of GHG emissions monitoring can now be accomplished by AI and machine learning algorithms. These algorithms use data acquired by aircraft, unmanned aerial vehicles (UAVs), satellites, and remote sensing to provide near real-time GHG monitoring capacity. For example, these tools can be used to measure emissions, identifying high- and ultra-methane-emitters (such as the oil and gas industry, which alone represents as much as 12% of global methane), and tracking plumes of atmospheric methane due to point source emissions.[306] AI is also used to measure and upscale point estimates of carbon emissions from anthropogenic sources (e.g., power plants or vehicles)[307] or to improve estimates of wildfire emissions using satellite data.[308]

Other traditional emissions monitoring methods, such as fuel consumption-derived emissions monitoring, naturally aggregate lower-resolution data and are subject to delays caused by the low reporting frequency. AI-powered emissions monitoring is more accurate and less biased than traditional reporting and monitoring, and it can deliver

INITIATIVE HIGHLIGHTS



Kayrros Methane Watch Map. Source: https://methanewatch.kayrros.com/map

Kayrros and Climate TRACE

Kayrros is an environmental intelligence company that measures the effect of human activity on the environment at a global level. Using science, AI, and realtime satellite imagery, Kayrros aims to reduce GHG emissions through measurement and attribution, manage energy transitions, and protect populations, ecosystems, and assets—modeling both climate risk as well as biomass and biodiversity for voluntary carbon credits. Their products include Methane Watch for monitoring super emitters, Carbon Watch (used to provide information on carbon credits), as well as Forest Carbon Monitor and Wildfire Risk Monitor, among others.

Leveraging technology from Kayrros, **Climate TRACE** is a nonprofit coalition that aims to empower climate action through radical transparency. Climate TRACE uses satellites, remote sensing technology, and AI to collect data from an extensive array of sources to provide an up-to-date snapshot of GHG emissions on a global scale. Their AI models are trained on those data to accurately predict actual activity at the ground level and cross-check that information with individual emitting facilities, farms, forests, and other assets in their database to produce a detailed global inventory of emissions. Their data, as well as the methodology and research that informs their models, is publicly available online.[335]

Perennial

Perennial is the leading measurement, reporting, and verification platform for soil-based carbon removal. Perennial—in partnership with Descartes Labs—developed the highest-ever resolution map of soil organic carbon for the continental USA.[336] Its evaluations rely on land remote sensing technology, statistical quantification, an archive of in-situ soil samples of wide-ranging origin, and machine learning algorithms to map and predict the carbon content within soil over time.

Heriot Watt University ECO-AI

ECO-AI is a UKRI funded project to address key barriers for large scale Carbon Capture and Storage (CCS) implementation including: a) high energy demands of the capture process, b) high cost for predicting and monitoring , and c) uncertainties in financing CCS projects and lack of understanding of the impact of regulatory and/or market interventions. The project aims to address the barriers by developing: AI materials discovery pipeline for energy efficient CO_2 capture; AI-solvers for modeling CO_2 flow in geological storage formations; or modeling CO_2 target progress coupled with innovation trajectories for each industrial sector.

near real-time emissions data as well as carbon credit verification with higher spatial granularity.[309] For example, AI can track traffic and shipping routes by combining satellite imaging with GPS data, which enables it to pin-point exactly where and when emissions occur. Such high transparency and near real-time tracking can support technical improvements to reduce emissions as well as inform policy proposals to address their abatement. Moreover, it can help us understand the rapid effects of policies and global or regional events on the carbon cycle, such as pandemics, disasters, and conflicts.[310]

AI can also improve the monitoring of carbon sequestration efforts and the integrity of carbon markets, critical for mitigating climate change.[311,312] AI is used to validate and enhance the monitoring, reporting, and verification systems for carbon markets and addresses challenges related to over-crediting and inaccuracies in emission reductions. Through AI models and the integration of diverse datasets, a more reliable and transparent framework for assessing and managing carbon offsets is emerging.[313] This framework can not only better support and validate reforestation efforts, but can even ensure the credibility of diverse initiatives in the Voluntary Carbon Market, such as clean cookstove projects.[314] Important uncertainties however remain in those estimates and further refinement of the methodologies will be necessary.

INITIATIVE HIGHLIGHTS

Argonne National Laboratory

The Argonne National Laboratory is using AI to identify new materials for carbon capture through generative AI to dream up previously unknown building block candidates, machine learning, and high-throughput screening of candidate materials. They are working on metal-organic frameworks, which is a porous material that can selectively adsorb carbon dioxide.

CarbonCure

CarbonCure Technologies develops innovative concrete solutions aimed at reducing carbon emissions. Their AI-enabled system precisely controls the injection of carbon dioxide into concrete, where it mineralizes and permanently embeds, decreasing the concrete's carbon footprint without affecting its performance. This process not only contributes to the reduction of greenhouse gases but also enhances the sustainability of the building materials industry.

Stanford University CCSNet

CCSNet creates digital twins for carbon capture and storage. It provides a deep learning modeling suite for CO2 storage predictions for 2D and 3D saline reservoirs with a wide range of reservoir condition, injection design, rock properties, and permeability maps. This work was carried out in partnership with the California Institute of Technology, Purdue University and NVIDIA and supported by the Stanford Center for Carbon Storage and ExxonMobil through the Strategic Energy Alliance at Stanford University.

Carbon Sinks

The ocean and land biosphere have naturally sequestered about 56% of the annual CO_2 and land use emissions into the atmosphere during the period from 2013 to 2022.[315] The biosphere's ability to remove carbon will likely exceed the capacities of technological carbon removal, so it should be a first-order priority to quantify and monitor naturally occurring carbon sinks like the biosphere, despite the difficulty of traditional data collection.

The ocean carbon sink can be reconstructed from sparse surface ocean pCO_2 (partial pressure of CO_2) data using a variety of AI algorithms.[316] Ocean pCO_2 data is measured on-ship, but these data cover only about 2% of the ocean surface; AI can combine these data with satellite coverage of sea-surface properties (e.g., temperature, salinity), and extrapolate global pCO_2 from there. For example, deep learning–based methods developed for reconstructing pCO_2 data in the Southern Ocean found that surface layer pCO_2 in that region changes seasonally and has increased since 1998.[317] With limited observational data, AI can identify a main carbon sink area and seasonally variable patterns, as well as provide high resolution reconstruction. AI can also provide more accurate quantification of ocean carbon uptake,[318] greatly improving limited observation-based data products.

Similarly, the land carbon sink can be modeled by upscaling point data from flux measurements.[319,320] AI algorithms are then used to model the long-term regional and global carbon sinks and their variability to extreme events like heatwaves and droughts. AI can also be used to monitor land-use and land-cover change (LULCC), which is closely related to agricultural production and land carbon sink quantification.[321] LULCC detection and modeling through remote sensing is computationally expensive due to massive data quantity and complex data types. AI is rapidly becoming a critical tool in the analysis of LULCC monitoring and modeling because it excels at image classification and segmentation. It can also provide information on soil carbon content during agricultural activity[322] and quantify forest carbon sinks,[323] which can inform efforts to maximize carbon sink potential.

Together these AI efforts can support better estimation of natural carbon solutions (NCS), while potentially addressing other challenges such as environmental and societal problems. However, substantial uncertainties remain in the estimates of NCS, in a changing climate. For instance, terrestrial belowground carbon, which is critical for correct estimates of NCS, remains poorly observed and AI has therefore limited leverage to provide more accurate quantitative assessment of terrestrial ecosystem NCS.

Technological Carbon Removal, Capture, and Sequestration

Technological carbon removal aims to remove CO_2 from the atmosphere and sequester it in long-term storage solutions, such as secure geological formations. Carbon capture and sequestration (CCS) aims to capture CO_2 emissions from sources like power plants or industrial facilities, and then store or sequester that CO_2 safely. So far, AI has mostly been utilized in the optimization of carbon capture within plant operations.[324] One digital recreation of a coal-fired power plant developed by the University of Surrey, for example, showed that applying AI to the plant's carbon capture reactor increased its capture rate by 17% and decreased its reliance on the UK's National Grid by 36%.[325] Broadening AI use in production plants beyond digital simulations could lead to significant reductions in material and energy consumption and provide real-time operation response; for example, AI might minimize human bias in determining the suitability of GHG removal technologies (capabilities that have already been demonstrated in forestation, enhanced weathering, direct air carbon capture, and storage and biochar).[326]

Material creation and testing is benefiting from AI technologies, too, including in the development of materials that can selectively adsorb CO_2 to assist the carbon removal process. Both Berkeley National Laboratory as well as Argonne National Laboratory, for example, have early evidence that metal-organic frameworks (MOFs)—a class of porous polymers with large chemical versatility—have great potential for use in numerous cost-effective applications to support novel carbon capture technology.[327, 328, 329] AI can predict MOF material properties and help design specific MOF structures.[330] It can also bridge the gap between computational and experimental efforts in MOF material developments and, with limited data, highlight subdomains as material synthesis conditions. In addition to MOFs, AI can help other carbon capture technology developments (such as membranes[331]) and predict subsurface CO_2 sequestration mechanisms in saline aquifers,[332] evaluating the performance of existing materials and processes[333] or modeling subsurface CO_2 sequestration.[334]

AI can not only optimize deployment of carbon capture, utilization, and sequestration technologies, but can also optimize their operation to enhance their efficiency and reduce costs. It can define optimal conditions for carbon capture or optimize routes for CO_2 transport. It can also help identify pathways for converting captured CO_2 into valuable products, considering factors like market demand, production costs, and environmental impact.

ENDNOTES: GREENHOUSE GAS EMISSIONS

304 Pierre Friedlingstein et al , "Global Carbon Budget 2023," Earth System Science Data 15, no 12 (2023): 5301-5369

305 "Importance of Methane," United States Environmental Protection Agency, updated November 1, 2023, https://www.epa.gov/gmi/importance-methane#:~:text=Methane%20is%20the%20second%20most,trapping%20heat%20in%20the%20atmosphere.

306 Sudhanshu Pandy et al., "Daily Detection and Quantification of Methane Leaks Using Sentinel-3: A Tiered Satellite Observation Approach with Sentinel-2 and Sentinel-5P" *Remote Sensing of Environment* 296 (2023): 113716.

307 Douglas P. Finch, Paul I. Palmer, and Tianran Zhang, "Automated Detection o f Atmospheric NO2 Plumes From Satellite Data: A Tool to Help Infer Anthropogenic Combustion Emissions," *Atmospheric Measurement Techniques* 15, no. 3 (2022): 721-733.

308 Piyush Jain et al., "A Review of Machine Learning Applications in Wildfire Science and Management," *Environmental Reviews* 28, no. 4 (2020): 478-505.

309 Sandalow, David B., McCormick, Colin, Kucukelbir, Alp, Friedman, Julio, Nagrani, Trishna, Fan, Zhiyuan, Halff, Antoine M., et al. "Artificial Intelligence for Climate Change Mitigation Roadmap," 2023. https://doi.org/10.7916/CFN0-XJ39.

310 Bowen Wang et al., "Crises and Opportunities in Terms of Energy and AI Technologies During the COVID-19 Pandemic" Energy and AI 1 (2020: 100013.

311 Ballian Chen et al., "Geologic CO_2 Sequestration Monitoring Design: A Machine Learning and Uncertainty Quantification Based Approach," *Applied Energy* 225 (September 2018): 332–45.

312 Surojit Gupta and Lan Li, "The Potential of Machine Learning for Enhancing CO_2 Sequestration, Storage, Transportation, and Utilization-Based Processes: A Brief Perspective," *JOM* 74, no. 2 (February 2022): 414–28.

313 Collins Matiza et al., "A Systematic Review of Remote Sensing and Machine Learning Approaches for Accurate Carbon Storage Estimation in Natural Forests," *Southern Forests: A Journal of Forest Science* 85, no. 3–4 (October 2, 2023): 123–41.

314 Susann Stritzke et al., "Impact Financing for Clean Cooking Energy Transitions: Reviews and Prospects," *Energies* 16, no. 16 (August 15, 2023): 5992. https://doi.org/10.3390/en16165992.

315 Pierre Friedlingstein et al., "Global Carbon Budget 2023," *Earth System Science Data* 15, no. 12 (2023): 5301-5369.

316 Peter Landschützer et al., "Recent Variability of the Global Ocean Carbon Sink," *Global Biogeochemical Cycles* 28, no. 9 (2014): 927-949.

317 Wang, Yanjun, Xiaofeng Li, Jinming Song, Xuegang Li, Guorong Zhong, and Bin Zhang. "Carbon Sinks and Variations of p CO 2 in the Southern Ocean From 1998 to 2018 Based on a Deep Learning Approach." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14 (2021): 3495–3503. https://doi.org/10.1109/JSTARS.2021.3066552.

318 Gloege, L., M. Yan, T. Zheng, and G. A. McKinley. "Improved Quantification of Ocean Carbon Uptake by Using Machine Learning to Merge Global Models and pCO 2 Data." Journal of Advances in Modeling Earth Systems 14, no. 2 (February 2022): e2021MS002620. https://doi.org/10.1029/2021MS002620.

319 Martin Jung et al., "The FLUXCOM Ensemble of Global Land-Atmosphere Energy Fluxes" *Scientific Data* 6, no. 1 (2019): 74.

320 Juan Nathaniel, Jiangong Liu, and Pierre Gentine, "Metaflux: Meta-Learning Global Carbon Fluxes from Sparse Spatiotemporal Observations," *Scientific Data* 10, no. 1 (2023): 440.

321 Wang, Junye, Michael Bretz, M. Ali Akber Dewan, and Mojtaba Aghajani Delavar. "Machine Learning in Modelling Land-Use and Land Cover-Change (LULCC): Current Status, Challenges and Prospects." Science of The Total Environment 822 (May 2022): 153559. https://doi.org/10.1016/j.scitotenv.2022.153559.

322 Wang, Jin, Qingguan Wu, Yong He, Yawei Li, Junzeng Xu, and Qianjing Jiang. "Maximizing the Carbon Sink Function of Paddy Systems in China with Machine Learning." Science of The Total Environment 909 (January 2024): 168542. https://doi.org/10.1016/j.scitotenv.2023.168542.

323 Zhao, Junbin, Holger Lange, and Helge Meissner. "Estimating Carbon Sink Strength of Norway Spruce Forests Using Machine Learning." Forests 13, no. 10 (October 19, 2022): 1721. https://doi.org/10.3390/f13101721.

324 Simon Fahle, Christopher Prinz, and Bernd Kuhlenkötter, "Systematic Review on Machine Learning (ML) Methods for Manufacturing Processes–Identifying Artificial Intelligence (AI) Methods for Field Application," *Procedia CIRP* 93 (2020): 413-418.

325 Oliver J. Fisher et al., "Responsive CO 2 Capture: Predictive Multi-Objective Optimisation for Managing Intermittent Flue Gas and Renewable Energy Supply," *Reaction Chemistry & Engineering* 9, no. 2 (2024): 235-250.

326 Jude O. Asibor et al., "A Machine Learning Approach for Country-Level Deployment of Greenhouse Gas Removal Technologies," *International Journal of Greenhouse Gas Control* 130 (2023): 103995.

327 Hyun Park et al., "A Generative Artificial Intelligence Framework Based on a Molecular Diffusion Model for the Design of Metal-Organic Frameworks for Carbon Capture," *Communications Chemistry* 7, no. 1 (February 14, 2024), https://doi.org/10.1038/s42004-023-01090-2.

328 Julie Chao, "A Sponge to Soak Up Carbon Dioxide in the Air," U.S. Department of Energy Office of Science, August 17, 2021, https://www.energy.gov/science/articles/sponge-soak-carbon-dioxide-air.

329 Jared Sagoff, "Argonne Scientists Use AI to Identify New Materials for Carbon Capture," Argonne National Laboratory, February 14, 2024, https://www.anl.gov/article/argonne-scientists-use-ai-to-identify-new-materials-for-carbon-capture.

330 Chong, Sanggyu, Sangwon Lee, Baekjun Kim, and Jihan Kim. "Applications of Machine Learning in Metal-Organic Frameworks." Coordination Chemistry Reviews 423 (November 2020): 213487. https://doi.org/10.1016/j.ccr.2020.213487.

331 Barnett, J. Wesley, Connor R. Bilchak, Yiwen Wang, Brian C. Benicewicz, Laura A. Murdock, Tristan Bereau, and Sanat K. Kumar. "Designing Exceptional Gas-Separation Polymer Membranes Using Machine Learning." Science Advances 6, no. 20 (May 15, 2020): eaaz4301.

332 Song, Youngsoo, Wonmo Sung, Youngho Jang, and Woodong Jung. "Application of an Artificial Neural Network in Predicting the Effectiveness of Trapping Mechanisms on CO_2 Sequestration in Saline Aquifers." International Journal of Greenhouse Gas Control 98 (July 2020): 103042. https://doi.org/10.1016/j.ijggc.2020.103042.

333 Wesley J. Barnett et al., "Designing Exceptional Gas-Separation Polymer Membranes Using Machine Learning," *Science Advances* 6, no. 20 (2020): eaaz4301.

334 Youngsoo Song et al., "Application of an Artificial Neural Network in Predicting the Effectiveness of Trapping Mechanisms on CO_2 Sequestration in Saline Aquifers," *International Journal of Greenhouse Gas Control* 98 (2020): 103042.

335 "Approach," Climate Trace, accessed February 14, 2024, https://climatetrace.org/approach.

336 "Ground-Breaking Without Breaking Ground: Perennial Uses the World's Most Advanced Remote Measurement Technology for Soil Carbon Sequestration and Emissions," Perennial, accessed February 14, 2024, https://www.perennial.earth/technology.

CURRENT APPLICATIONS IN AI

Climate Impacts

Climate change is driving an increase in the severity and frequency of extreme weather events;[337] as land and ocean temperatures rise, so do torrential storms, intense heat waves, flooding, and drought.[338] Low- and middle-income countries, vulnerable populations, and historically marginalized communities are most at risk—and they are already suffering serious and detrimental consequences of climate change.[339,340]

Current AI investments are mostly focused on climate mitigation, but it is clear that we also need to invest in climate *adaptation*—increasing our ability to predict future climate extremes and protect human life, and limit the impact on infrastructures and assets from the changes that are already occurring.

Monitoring

AI can assist with early detection and real-time monitoring of the environment through its ability to process large amounts of high dimensional and multivariate data, especially coming from satellite imagery. AI has been used to monitor floods in near-real-time, merging data from different satellites (with different frequencies and resolutions)—which has, in turn, supported the development of parametric insurance, especially in floodplains, home to about 1.5 billion inhabitants.[341]

The California Department of Forestry and Fire Protection is now using AI to improve wildfire suppression through prediction, early detection, guidance of firefighting efforts, and post-fire restoration and analysis.[342] Agencies monitoring droughts, and their spatio-temporal evolutions, now use AI to handle large volumes of diverse data with high uncertainty, such as through the European Drought Observatory for Resilience and Adaptation.[343,344] IBM and NASA recently collaborated to develop an open-source foundation model for geospatial satellite data that has many applications, including the monitoring of natural disasters.[345,346]

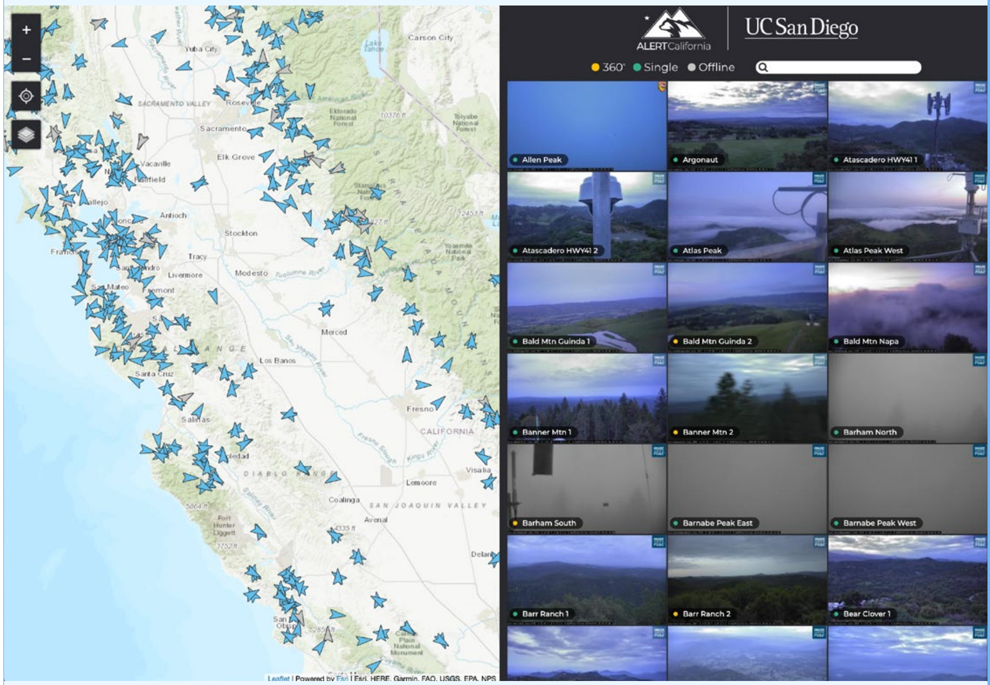
AI in Climate Modeling

While the use of AI in climate modeling has grown in popularity over the last few years, applications that address climate change adaptation have remained relatively limited. Just as mitigation efforts benefit from machine learning's flexibility in usage—used to identify a host of climate solutions tailored to specific communities, regions, and landscapes—so too can it be leveraged to determine key elements for adaptive interventions. Policy stands a great deal to gain from such approaches, allowing decision makers to customize policies to maximize efficient, equitable allocation of resources. This area contains one important caveat, however: adaptation efforts often do not involve easily reduced, simple datasets that are easily digested and analyzed by standard machine learning methods.

Preventing, Detecting, and Monitoring Wildfires

Traditionally, wildfires have been identified through 911 calls, airplanes, and lookout towers. Too often, however, detection comes too late.[355] Identifying flammable, at-risk vegetation is similarly inefficient, laborious, and offers too little information too late; requiring fire agencies to take tree samples by hand from forested areas and measure the water contained within them by drying out the sample in an oven and comparing weights.[356] Now AI is being used comprehensively for wildfire tracking.

The **California Forest Observatory** uses AI to identify at-risk land vulnerable to wildfires and works to improve resilience in those areas.[357] **ALERTCalifornia**, a program out of UC San Diego with the California Department of Forestry and Fire Protection and Digital Path, developed an AI platform that provides early wildfire confirmation and actionable real-time data to rapidly scale fire resources, helps evacuations through enhanced situational awareness, and monitors fire behavior. In its first year of operation it detected over 1,200 fires, beating 911 calls 30% of the time. It also proved to be effective at spotting anomalies in remote areas and at night.



ALERTCalifornia monitoring feeds. Source: https://cameras.alertcalifornia.org/

Prediction

"The impact of numerical weather prediction is among the greatest area of physical science."[347] Catalyzed by private sector interest and investment, AI has very recently been incredibly successful at leveraging observational data to generate faster and more accurate weather forecasts.[348,349] In fact, AI-based weather forecasting is now on par or even better than traditional physics-based forecasts, yet can be simulated at greater speed (1,000–10,000x faster).

A noticeable challenge in this category is climate predictions and projections—i.e., forecasting on the order of years and decades—despite these long-term projections being critical for many decisions. The lack of data is central; for instance, very few El Niño events (drivers of seasonal weather patterns and extreme rainfall and drought conditions) have been observed, so the dataset is insufficient to train high-dimensional AI models. There are efforts, however, to develop hybrid approaches (i.e., physics plus AI) to address this data gap and leverage historical or high-fidelity simulation data to inform the future.

Disaster Risk and Recovery

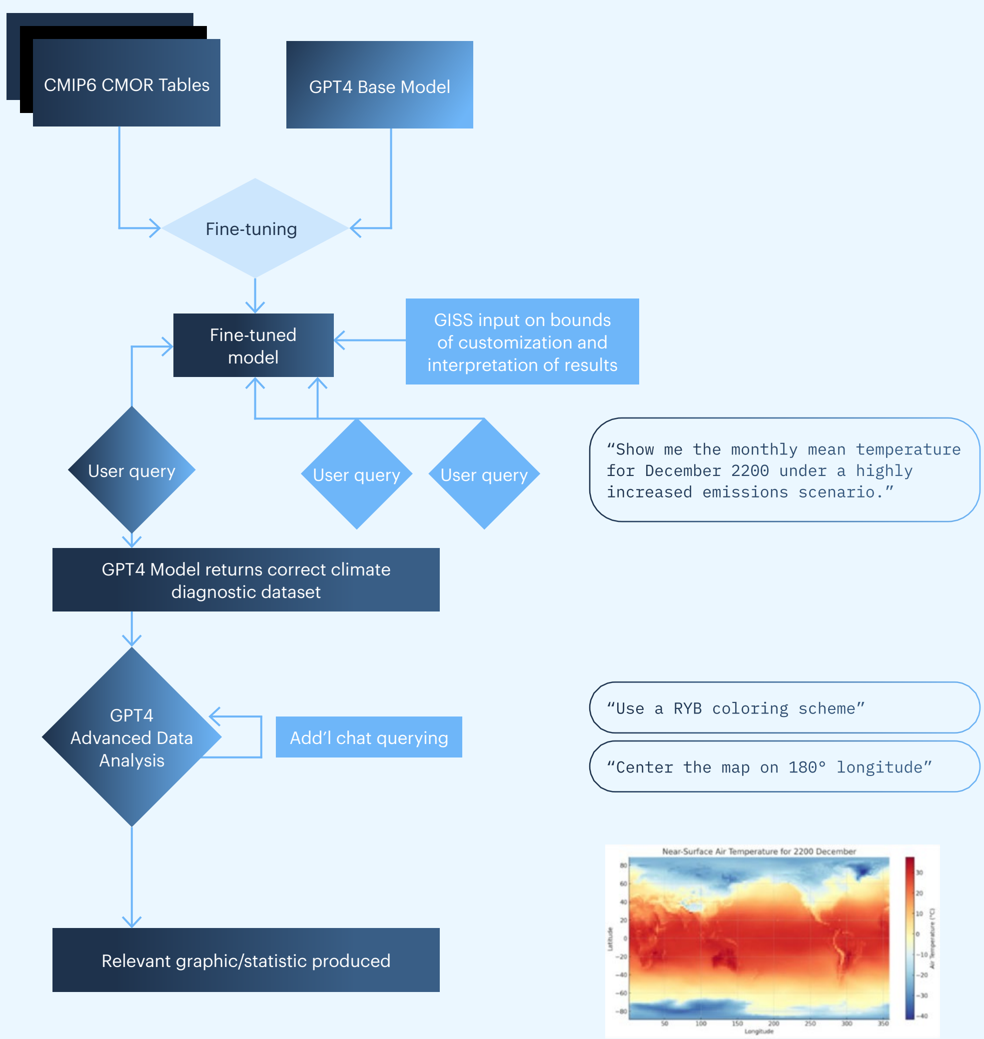
AI can play a crucial role in both identifying areas with a higher likelihood of damage before a natural disaster strikes, as well as managing disaster relief efforts after one has taken place. After a disaster strikes, assessors need to determine the level of damage and where it has occurred to move forward with disaster recovery efforts and prioritize heavily-damaged areas. This can be a challenging and time-consuming process that can lead to delayed response, especially in remote areas of the Global South. Through satellite imagery analysis, however, AI has helped to expedite damage assessment after hurricanes and earthquakes, identify the potential of cascading risks (such as landslides), and better coordinate response efforts.[350,351]

Used in tandem with drone and satellite imagery, AI can efficiently (and non-invasively) identify which communities are more likely to incur damage from an impending disaster event and, once the event occurs, can also be used for confirmatory analysis and prioritization of high damage areas. Similarly, through

An opportunity for Large Language Models in the co-production of climate impacts?

Researchers at the NASA Goddard Institute for Space Studies have asked: Can the skill of LLMs at interpreting natural language and building code enable users to generate individually tailored climate impact diagnoses based on simple queries?[358]

Source: Michael Hendrickson, project lead



the collection and analysis of images from different sources, this technology can support rapid post-disaster housing assessments, thereby providing policy makers with new tools to determine levels of need and eligibility for a disaster declaration from the relevant government. Reducing the time needed for such assessments from months to weeks has the potential to improve disaster recovery worldwide—and subsequently save lives.

AI can also be used for preemptive intervention and disaster response by predicting disaster impacts, optimizing evacuation routes, and coordinating relief efforts, such as with drones or UAVs. Drones can also help deliver aid and perform search and rescue missions in hazardous conditions.

Recovery efforts can also be targeted more effectively by disaster managers when vast data points of environmental sensor data (satellites and IoT) are combined with social media inputs or rapid crowd-sourced data.[352] Still, while multimodal approaches to assessing disaster risk and recovery are vital, special attention will need to be paid to the diversity of ingested data to ensure ethical use.[353]

The progress AI has already brought to natural disaster preparedness, early warning, and relief may be greatly accelerated in the near future with the emergence of collaborative working groups, such as the International Telecommunication Union, World Meteorological Organization, and United Nations Environment Programme's Focus Group on AI for Natural Disaster Management—which aims to lay the groundwork for establishing the best practices of AI disaster management—ultimately integrating the technology into the modus operandi of the sector.[354] There is great potential to leverage AI for disaster documentation in multiple languages, especially in terms of the development of preparedness exercises and simulations and assorted documentation (situation manuals, player handbooks, etc), which have typically been very time consuming despite being fairly standardized. While planning meetings, stakeholder engagement, and editing tasks will not disappear entirely, AI can be leveraged in ways that significantly reduce the heavy burden involved with the production of documentation. It will always be important, however, for human actors to view the AI-produced materials as a starting point requiring additional review and revision.

INITIATIVE HIGHLIGHTS

Google DeepMind's GraphCast

DeepMind's GraphCast is a machine learning-based weather forecasting method that seeks to improve weather forecasting and reduce their computational cost—the latest version can be run at a fraction of a standard weather forecasting model and on a personal computer. The GraphCast approach enables ten-day weather predictions at "unprecedented accuracy" in less than a minute and opens up new possibilities that have historically been computationally too expensive to be mainstream.[359] Its predictive ability and forecasts are more supportive of severe weather events and natural disasters including tropical storms and extreme heat.[360]

ClimaX (UCLA and Microsoft)

Recent advancements in climate modeling primarily rely on physics-informed numerical atmospheric models. While this translates to an increased ability to model more complex, nonlinear interactions among multiple variables, they demand significant computational resources. Machine learning is an essential step in solving forecasting problems.[361] ClimaX attempts to fill that gap through a flexible deep learning model that can be used on a wide variety of heterogeneous datasets while streamlining computing costs and maintaining generalizable usage.

NASA Earth System Digital Twin

NASA's Earth System Digital Twins efforts focus on developing novel technologies for integrating diverse Earth and human activity models, continuous observations and information system capabilities to provide unified, comprehensive representations and predictions that can be utilized for monitoring as well as for developing actionable information and supporting decision making. NASA's Earth System Digital Twins include a continuously updated digital replica of the Earth System, dynamic forecasting models, and impact assessment capabilities.

xView2

A collaborative effort backed by the Defense Innovation Unit of the Pentagon and Carnegie Mellon University's Software Engineering Institute, xView2 brought together various research partners, including Microsoft and the University of California, Berkeley to rapidly identify and categorize the severity of damage to buildings and infrastructure in disaster-affected areas. By leveraging machine learning algorithms in tandem with satellite imagery from multiple sources, xView2 is able to generate critical information significantly faster than conventional methods.

This technology played a pivotal role in supporting disaster logistics and on-the-ground rescue operations after Turkey's devastating earthquake in February 2023, garnering praise for its usefulness in locating otherwise unknown damaged areas.

Islahiye, Turkey - Satellite imagery from Maxar Technologies (left) and the output from xView2 (right), attributed to UC Berkeley/Defense Innovation Unit/Microsoft. Source: https://www.technologyreview.com/2023/02/20/1068824/ai-actually-helpful-disaster-response-turkey-syria-earthquake/

ENDNOTES: CLIMATE IMPACTS

337 "Extreme Weather and Climate Change," NASA, accessed February 15, 2024, https://climate.nasa.gov/extreme-weather/.

338 Deborah Block, "Record Temperatures in Warming Oceans Causes Chaotic Weather Patterns," Voa News, July 2, 2023, https://www.voanews.com/a/record-temperatures-in-warming-oceans-causes-chaotic-weather-patterns-/7162523.html.

339 Sahrish Saeed et al., "Climate Change Vulnerability, Adaptation, and Feedback Hypothesis: A Comparison of Lower-Middle, Upper-Middle, and High-Income Countries," *Sustainability* 15, no. 5 (2023): 4145.

340 Thierry Coulibaly, Moinul Islam, and Shunsuke Managi, "The Impacts of Climate Change and Natural Disasters on Agriculture in African Countries," *Economics of Disasters and Climate Change* 4 (2020): 347-364.

341 Mitchell Thomas et al.,. "A Framework to Assess Remote Sensing Algorithms for Satellite-Based Flood Index Insurance," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 16 (2023): 2589-2604.

342 "Research Development and Innovation," California.gov, accessed December 27, 2023, https://www.fire.ca.gov/what-we-do/research-and-development.

343 "EDORA - European Drought Observatory for Resilience and Adaptation," European Commission, accessed December 27, 2023, https://edo.jrc.ec.europa.eu/edora/php/index.php?id=201.

344 Colin Brust et al., "DroughtCast: A Machine Learning Forecast of the United States Drought Monitor," *Big Data* 4 (2021): 773478.

345 Josh Blumenfeld, "NASA and IBM Openly Release Geospatial AI Foundation Model for NASA Earth Observation Data," NASA, August 3, 2023, https://www.earthdata.nasa.gov/news/impact-ibm-hls-foundation-model.

346 Grey Nearing et al., "Global Prediction of Extreme Floods in Ungauged Watersheds," *Nature* 627, no. 8004 (March 21, 2024): 559–63.

347 Peter Bauer, Alan Thorpe, and Gilbert Brunet, "The Quiet Revolution of Numerical Weather Prediction," *Nature 525, no. 7567 (2015): 47-55.*

348 Carissa Wong, "DeepMind AI Accurately Forecasts Weather - On a Desktop Computer," *Nature* (2023).

349 Paul Voosen, "AI is Set to Revolutionize Weather Forecasts," *Science* 382, no. 6672 (2023): 748-749.

350 "How AI Can Boost Disaster Response and Recovery," Development Asia, March 22, 2021, https://development.asia/insight/how-ai-can-boost-disaster-response-and-recovery.

351 Yangbing Bai et al., "Building Damage Assessment in the 2015 Gorkha, Nepal, Earthquake Using Only Post-Event Dual Polarization Synthetic Aperture Radar Imagery," *Earthquake Spectra* 33, no. 1 (2017): 185-195.

352 So-Min Cheong, Kris Sankaran, and Hamsa Bastani, "Artificial Intelligence for Climate Change Adaptation," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 12, no. 5 (2022): e1459.

353 USAID, *Artificial Intelligence Ethics Guide*, (USAID, 2023), https://www.usaid.gov/sites/default/files/2023-12/_USAID%20AI%20Ethics%20Guide_1.pdf.

354 "Focus Group on AI For Natural Disaster Management (FG-AI4NDM)," International Telecommunication Union, accessed March 12, 2024, https://www.itu.int/en/ITU-T/focusgroups/ai4ndm/Pages/default.aspx.

355 Lily Nelson, "Using AI to Fight Wildfires—Prevention, Detection, & Monitoring with Computer Vision," Xyonix, August 30, 2021, https://www.xyonix.com/blog/using-ai-to-fight-wildfires.

356 Josie Garthwaite, "Tracking the Tinderbox: Mapping Dry Wildfire Fuels with AI and New Satellite Data," Stanford University, May 21, 2020, https://sustainability.stanford.edu/news/tracking-tinderbox-mapping-dry-wildfire-fuels-ai-and-new-satellite-data.

357 Lily Nelson, "Using AI to Fight Wildfires—Prevention, Detection, & Monitoring with Computer Vision," Xyonix, August 30, 2021, https://www.xyonix.com/blog/using-ai-to-fight-wildfires.

358 Gavin A. Smith, et al., "Development of Digital Twin Technologies for Climate Projections," (poster, 23rd Meeting of the American Geophysical Union, San Francisco, December 2023). https://ntrs.nasa.gov/citations/20230011589

359 Remi Lam, "GraphCast: AI Model for Faster and More Accurate Global Weather Forecasting," Google DeepMind, November 14, 2023, https://deepmind.google/discover/blog/graphcast-ai-model-for-faster-and-more-accurate-global-weather-forecasting/.

360 Remi Lam et al., ""Learning Skillful Medium-Range Global Weather Forecasting," Science (2023): eadi2336.

361 Tung Nguyen et al., "Climax: A Foundation Model for Weather and Climate," *arXiv preprint arXiv:2301.10343* (2023).

Barriers to Progress

Data

Equity

Trust

Workforce

Policy + Governance

Deployment

While this Landscape Assessment highlights the tremendous opportunities presented by the use of AI in addressing the climate and nature crises, significant challenges remain for broader adoption and transformative changes.

Data

Despite explosive growth in data collection and new developments in modern hosting infrastructure, there remain critical data issues that both limit the operation and performance of current and future AI systems, and also hamper AI innovation in climate and nature solutions. These issues—including data gaps, imbalances and scarcity of data from particular regions (e.g., Africa or South America), multimodality (i.e., multiple data types and sources), and generalizability (given that climate change is a never-before-seen phenomenon)—are among the primary challenges to AI innovation in the climate and nature domain.

» **Gaps and scarcity.** When the status of many threatened species is not well understood because of a lack of relevant data[362] or when most of our observations of the terrestrial carbon sinks are located in the Global North and not in climate-critical regions such as tropical rainforests, the need for more widespread and better data is readily apparent. Additional and more evenly distributed data will help ensure that AI models capture the planet's diversity, in turn allowing them to perform more accurately across the globe. The collection of larger datasets from a wider range of sources also expands the scope of potential issues beyond technical questions of gathering and curation methods into thornier questions of privacy and data integrity, all of which require thorough consideration.

Moreover, data storage in the climate and nature domain tends to be siloed and is often laboratory or institution-specific. Data sharing is still uncommon, although efforts to open data are underway (e.g., AWS open-data support). Collaboration and data sharing are further inhibited by various factors, including data formats, the agency or company responsible for the acquisition, and even domain culture: while open datasets are common in the field of computer science, among others, they are less common in climate and nature applications. Nevertheless, these open datasets with clear benchmark definitions are a main driver of AI innovation and will be crucial for building out new and larger models. Indeed, one of the primary mechanisms to get the AI and machine learning community involved in climate and nature applications is to have easily accessible and usable datasets (equivalent to ImageNet) and clear benchmarks and metrics of success. Developing such datasets and benchmarks is a critical path to acceleration of AI use in the climate and nature space.

As with other areas of climate and nature, data scarcity negatively impacts the development of AI applications in climate modeling and disaster risk reduction. Climate data is often sparse, obtained from disparate sources of varying quality, and accompanied by a high level of uncertainty that is not explicitly accounted for by many AI algorithms. This poses a significant challenge to building globally applicable AI and machine learning models, as different geographic regions face different environmental conditions. And, given that uncertainties can dominate the prediction, without data from certain regions models must rely on extrapolation for predictions that may not prove correct; this both

Strategies to address data scarcity

Several things can be done to help mitigate the negative impact of data scarcity on AI models and solutions. One such solution is the use of data augmentation, which is the process of using synthetic data to artificially inflate a data set to generate new data from existing sources. This enhances models' performance, reduces data dependency, mitigates overfitting in training data, and improves data privacy.[368]

Efforts to develop standards and centralization for data through central data hubs and data-sharing pathways is another strategy to accelerate AI progress, facilitate collaboration, and help the rapid development of new AI tools and interventions.

threatens the equity of AI solutions in low- and middle-income countries and can also perpetuate challenges in combating bias in AI solutions.

While vast quantities of data about the planet exist, licensing restrictions, storage formats, acquisition difficulties, technical costs, and other limitations create barriers both to data availability and to the awareness and accessibility of that data for a wider audience. In addition, the scarcity of labeled data (e.g., hand-labeled land cover classes used for classification and segmentation) across several sectors poses difficulties in training machine-learning models effectively. For example, the small number of labeled underwater image and video datasets that currently exist lack standardized formats and are seldom shared between organizations; this hampers both the study of aquatic environments and the development of new AI models to address relevant problems. In short, barriers to good quality data, coupled with insufficient and inconsistent data labeling, contribute to the frequent scarcity of good, reliable, and usable data required for AI to thrive.

Perhaps paradoxically, sometimes the challenge is in the abundance of data rather than its scarcity. For example, the vast amount of data generated by satellites can be difficult to process and label accurately, making it less useful than it otherwise could be. To address these issues and enhance the overall effectiveness of AI interventions, we need to promote open-source datasets, facilitate data sharing among organizations, and encourage cross-sectoral collaboration. Additional investment in the labor-intensive process of dataset labeling is also needed.

» **Multimodality.** AI applications in nature require the integration of data from disparate data streams with varying spectral frequencies, resolutions, and projections, which can be challenging. For example, the fusion of satellite data observing the same location on Earth is challenging when that data differs in terms of its time of acquisition, spatial and spectral resolution, or noise. Additionally, experts in data science and climate and nature solutions emphasize that further innovation in the field will require the capacity to integrate data across different formats and sources. For example, foundation models are overwhelmingly text-oriented, and while this has led to significant advances in language-based applications like ChatGPT, there is a need for many more vision- or video-based and multimodal models (e.g., DALL-E[363]) to address non-text-based problems, such as geospatial Earth data.

DATA WISHLIST

Climate Change AI's Dataset Wishlist

In 2020, Climate Change AI created a "Dataset Wishlist" for enabling identification of which datasets needed to become available to enable AI technologies to address climate change.[369] They're given various classifications based on perceived problems or needs within each specific field of data:

1 public, needs structure **2 private, needs to be released** **3 scattered, needs collation**
4 proxies, needs to be inferred **5 scarce, needs collection**

Data Category	Data	Data Type
Overarching Datasets	Satellite imagery for remote sensing	2 3
	LiDAR data for topography	1 2 3 4 5
	Data for materials design	1 2 3
Electricity Systems	Power grid systems	1 2 5
	Solar power production for forecasting	1 2 3 4 5
	Wind power production for forecasting	1 2 3 4 5
	Aggregated electricity demand for forecasting	1 2 3
	Power grid data for predictive maintenance	2
Disruptive Future Technologies	Nuclear fusion data for disruption detection	2 3
	Battery operation and optimization	3
Transportation	Transportation arrival statistics for infrastructure design	1 2 3
	Freight activity for optimizing transport	3 5
	Traffic counts for infrastructure design	1 3 5
	Electric vehicle charging data for infrastructure design	5
	Urban mobility data for infrastructure design	1 2 3 4 5
Buildings and Cities	Building level energy consumption for demand management	2 4 5
	Building thermal dynamics for optimal energy management	1 2 3
	Building information for urban planning	1 2 3 4 5
	Urban mobility data for infrastructure design	1 2 3 4 5
	City-level energy and GHG-emissions data	1 3 4 5
Industry	Product-specific GHG emissions for informed consumption	2 4 5
	Electrocatalysis data for lowering the temperature of industrial process	2 5
	Factory power for increasing energy efficiency and demand response	2 3 4 5
	Methane leak data for detection/prevention	2 3 4
Climate Mitigation	Geophysical data for CO_2 sequestration site suitability/subsurface identification	2 3
Climate Prediction	Climate model outputs for fast approximation	1 2 3
Societal Impacts	Water treatment data for predictive maintenance	2
	Flood maps for infrastructure design and urban planning	3
	High-resolution crop yield for food security	3
	Social media posts for disaster relief	3
	Forest fire	3
	Occurrence of landslides to detect new landslides due to extreme weather events	1 2
Individual Actions and Collective Decisions	Consumer climate preferences for facilitating behavior change	2
	Global climate policy dataset	1 3

» **Generalizability.** The complexity of environmental data (characterized by numerous variables within intricate ecological systems), coupled with the constant climate and anthropogenic changes present in a dynamic environment, makes it difficult for AI models to generalize for climate, land, freshwater, and ocean ecosystems. Similarly, the different environmental conditions and geographies that affect complex and context-specific agricultural data limit both the transferability and the generalized application of solutions in that field. Nevertheless, there is promise in the idea that this gap in model generalizability may be mitigated by the strategic use of transfer learning (the transfer of knowledge from a data-rich to data-poor domains) and meta-learning ("learning to learn" across different tasks and domains), especially in the Global South.[364]

» **Data sustainability.** AI models require large volumes of high-quality data to train effectively. In the context of environmental and climate issues, consistent, long-term and comprehensive data can be rare, particularly in developing regions. Historical data may even not be digitized or accessible and might need to be processed to be useful for AI. Ensuring long-term sustainability of climate and nature data (i.e., ensuring the accessibility and ongoing maintenance of datasets) is a major challenge that is still under-appreciated and largely underfunded. The lack of a viable "business-model" for data sustainability presents an opportunity for philanthropy to ensure the sustainability of open climate and nature datasets, which would tremendously accelerate AI progress.

Equity

Equity considerations—including data and algorithm biases, unequal accessibility of data, and insufficient data from certain regions of the globe—present important gaps in the application of AI for climate and nature. For example, the recent explosion of data acquisition has primarily been concentrated in the Global North, leaving the Global South at a disadvantage. However, even in the Global North, there are still important gaps in terms of data acquisition and AI adoption that are typically restricted to the most well off. Similarly, currently, only a small fraction of the population have the means to afford climate actions. More inclusive data acquisition and incentives for financial support to underserved communities would ensure large-scale impact. Furthermore, the substantial internet bandwidth and computing capacity required to download large datasets presents under-developed regions with another hurdle to achieving equity. There are alternatives such as modern cloud infrastructures and cloud-proximate computing that can reduce this infrastructure gap. Yet, those platforms need financial support, which could be in-kind or sponsored through pay-to-play services whose revenues could support the cost for those who cannot bear it.

The proliferation of large and start-up firms and not-for-profit initiatives in AI presents an equity issue as well. For example, AI has garnered proof of concept and profitability—such as for optimization of large-scale farming practices—but many initiatives appear best geared towards large-scale, private applications. Furthermore, advanced AI sensors, UAVs, and public remote sensing imagery for monitoring can be expensive and difficult to acquire and implement. Without a viable business model for financing smaller operations, AI applications may remain out of reach for millions of small-scale stakeholders, especially throughout the Global South.

The high cost and time-consuming initial setup of new technologies are particularly limiting for vulnerable smallholder farmers or farmers in low-income communities, for example, despite the broader objective of AI innovations in food and agriculture to improve their access to those technologies and expand to a wider range of crops. That said, the emergence of new start-ups aimed specifically at reaching those underserved communities (e.g., through smartphone technology or other means) is a positive development in this area.

Trust

As questions of privacy and safety persist with respect to AI use, trust in the technology more generally remains a notable challenge, especially given the difficulty of explaining and interpreting AI models for a general audience. For example, a general lack of trust and transparency in data collection and usage presents a major challenge to the adoption and use of AI applications in cities and built environments, which require an abundance of sensor usage to collect data that are inextricably linked to personal behavior, such as GPS coordinates, commuting patterns, and activities within the home. While the ease with which Internet of Things technologies can be adapted to urban environments has generated a great deal of excitement, the practice itself still presents concerns that must be addressed before such technologies are implemented.

Across applications—and especially as more cross-disciplinary, collaborative work is undertaken to address climate and nature problems through AI—there is a need for new and deeper understanding of domain-specific challenges to building trust.For example, a lack of trust in the technology may explain the hesitance of utility companies to apply AI to grid-based systems, given their high need for reliable, consistent performance. Similarly, the relative opacity of AI and machine learning algorithms fails to instill confidence in policymakers and practitioners, as they see the potential hazards and lack of interpretability of AI tools as outweighing the promise of rewards from broader AI adoption.[365]

More research on transparency is required to combat skepticism and reluctance to fully embrace AI. Practitioners need to understand these tools in order to use them successfully. For example, disaster managers using AI tools to predict wildfires need to know the reasons behind a prediction and trust the data provided in order to evaluate whether to integrate it into their decision-making. Similarly, policy makers must understand the opportunities and challenges associated with the use of AI before they can craft appropriate policies that will enable, rather than constrain, advances in the field.

Workforce

To best leverage the power of AI, it has to be targeted at important problems with plentiful data. This requires interdisciplinary training with both AI and domain-specific knowledge. Several training programs at the interface between disciplines have been emerging over the last few years and aimed at creating a new workforce capable of tackling these critical environmental problems with modern tools. However, it takes time to train scientists or develop curricula in these interdisciplinary domains, so that workforce development is still lagging behind societal needs.

While new educational initiatives with a focus on interdisciplinarity are emerging to increase the future talent pool, there is a critical need to support the development of an entire workforce able to perform roles at the intersection of AI, climate, and nature beyond university education. There is a limited subset of people with AI expertise working on climate and nature solutions relative to the number of climate experts generally. A study released in 2022 suggested that AI specialists worldwide amounted to just over 22,000, with the growth of AI job openings outpacing the supply of skilled workers.[366]

WORKFORCE DEVELOPMENT HIGHLIGHT

Investing in the next generation of AI for climate and nature workforce

Several initiatives are underway to develop interdisciplinary curricula to facilitate the convergence of AI and domain-specific science:

- The Oxford Intelligent Earth AI Centre for Doctoral Training in AI for the Environment brings together academics from AI and Earth applications with non-academic partners to train a new generation of quantitative environmental data scientists equipped to tackle the most pressing environmental issues.
- The National Science Foundation Learning Earth with Artificial Intelligence and Physics (LEAP) Center is training scientists at the interface of climate change and AI, to dramatically improve near-term climate projections to support adaptation and resilience.
- The National Science Foundation AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography is a convergent center that will create trustworthy AI for environmental science, revolutionizing the prediction and understanding of extreme weather and ocean hazards.
- The University of Southampton AI Centre for Doctoral Training in AI for Sustainability will train PhD students in sustainable AI, focusing on renewable energy and carbon emissions reduction efforts.
- University at Albany's Institute for Artificial Intelligence and AI Plus takes an innovative and holistic approach to teaching and learning about AI to ensure that every graduate is prepared to live and work in a world that will continue to be radically changed by the technology. This philosophy drives UAlbany to incorporate foundational and applied concepts of AI into new curricula in disciplines such as climate science, semiconductor design, anthropology, cybersecurity, social welfare, and health data analytics.

Workforce strengthening

Recognizing workforce gaps, BlocPower, an AI-powered building retrofitting company, runs programs to upskill candidates from vulnerable communities with AI- and ML-based construction training that incorporates both AI theory and applied learning through augmented reality technology. Workforce participants have also driven data collection for air quality that feeds back into targeting models.

Policy and Governance

While policy and governance have been cited as constraints for AI integration into climate and nature solutions, we will not realize the potential of AI to contribute to climate mitigation and adaptation without supportive policies and effective governance. Companies can be spurred to act when new policies alleviate roadblocks to the adoption of new technologies or require new methodologies aimed at addressing climate and nature challenges.

Consider the power industry; compared to other sectors, power companies have typically preferred caution over innovation in the adoption of new approaches and technologies. This is also because the sector is heavily regulated in the United States, and utility companies use compliance with regulations as a shield against rapid change in what has historically been a secretive industry. Opportunities to challenge the *status quo* do exist, however. For example, enacting evidence-based renewable energy policies that require companies to make better use of AI-informed resources or risk penalties could force companies to adopt new climate-forward technologies. Similarly, decision makers and legislators in cities need to understand how mandating the incorporation of AI advancements into their infrastructure and traffic systems would provide long-term benefits to the health and well-being of their constituents. Furthermore, they need to be made aware of the powerful contribution

Sidewalk Labs in Toronto

When Sidewalk Labs, a subsidiary of Google, launched its ambitious initiative to build a sustainable, tech-forward community in 2017, it envisioned Quayside as a beacon of urban innovation in Toronto, Canada.[370] Intending to construct buildings from mass timber, reduce GHGs, and implement advanced systems such as an automated vacuum waste collection system and a data-driven infrastructure to optimize housing and traffic, Sidewalk Labs expected to see substantial economic and environmental benefits that would make Quayside a potential template for modern, sustainable cities.

Quayside was discontinued in May 2020. While the economic impacts of COVID-19 were cited as the primary driver of the decision, underlying issues of trust and transparency (particularly concerning data privacy and the use of resident information) also seemed to have played a significant role.[371] The abrupt and unexpected end of the Quayside experiment raises doubts about the feasibility of such futuristic urban developments.

Still, there are crucial lessons to learn from Quayside. Building technology-driven sustainable communities requires balancing data for efficiency and environmental benefits with residents' privacy and trust. Future projects would do well to prioritize transparency, involve community input, and ensure a clear understanding among all constituents as to how data will be used. This balance is delicate but vital for developing smart cities that are not only technologically advanced, but also socially responsible and trusted by their inhabitants.

AI could make to mitigation planning and strategy, as the multimodal nature of climate change mitigation is well suited to its use.

On the climate mitigation side, new regulations such as the Californian climate disclosure laws Climate Corporate Data Accountability Act (SB-253) and Greenhouse Gases: Climate-Related Financial Risk Act (SB-261), requiring public and private US companies (and other business entities) that do business in California—whether or not they are physically present in the state, to disclose their climate-related risks. Moreover, Local Law 97 in New York City will require buildings to meet ambitious energy efficiency and GHG emissions limits with the aim to reduce emissions of the largest buildings by 40% by 2030 and reach net zero by 2050.[367] Such policies can greatly push the adoption of AI-based estimates of emissions and climate risk.

Finally, AI can help process near real-time observations to directly and rapidly inform legislators on the successes or failures of enacted policies, allowing for better, and faster, data-driven decisions.

Deployment

Beyond the previously mentioned issues of data availability and quality, potential geographical biases, ethical considerations and regulatory challenges, there are important challenges related to scalability and integration with existing systems.

Existing systems are often composed of a mix of old and new technologies; integrating AI algorithms requires ensuring that they are compatible with legacy systems, which may not have been designed with AI integration in mind. This might involve retrofitting older processes and algorithms or developing bridges that can interface AI algorithms with older technologies.

AI solutions must also be scalable in terms of data handling, computational requirements, or integration with existing processes. As entities expand or modify their processes, algorithms might need to be adjusted or adapted to handle vast amounts of data while maintaining integration. This scalability is crucial for the efficiency and effectiveness of AI. It's also worth noting that the integration of AI into traditional industries can disrupt established workflows and require changes to employee roles and responsibilities. Effective changes and management strategies—training staff to work with new AI tools, understanding new interfaces, and adapting to new decision-making protocols based on AI—are needed to ensure a smooth transition. •

ENDNOTES: BARRIERS TO PROGRESS

362 Devis Tuiaet al., "Perspectives in Machine Learning for Wildlife Conservation," *Nature communications* 13, no. 1 (2022): 792.

363 Aditya Ramesh et al., "Hierarchical Text-Conditional Image Generation With Clip Latents," *arXiv preprint arXiv:2204.06125* 1, no. 2 (2022): 3.

364 Gabriel Tseng, Hannah Kerner, and David Rolnick, "Timl: Task-Informed Meta-Learning For Agriculture," *arXiv preprint arXiv:2202.02124* (2022).

365 John Zerilli, Umang Bhatt, and Adrian Weller, "How Transparency Modulates Trust in Artificial Intelligence," *Patterns* 3, no. 4 (2022).

366 "Skills Gaps Are Slowing down AI-Workforce Integration,"Deloitte, accessed April 18, 2024, https://action.deloitte.com/insight/2295/skills-gaps-are-slowing-down-ai-workforce-integration#.

367 "Local Law 97," City of New York - Sustainable Buildings, accessed May 7, 2024, https://www.nyc.gov/site/sustainablebuildings/ll97/local-law-97.page.

368 "What is Data Augmentation," Amazon Web Services, accessed December 12, 2023, https://aws.amazon.com/what-is/data-augmentation/.

369 "Climate Change AI Dataset Wishlist," accessed February 12, 2024, https://www.climatechange.ai/dataset-wishlist.pdf.

370 Bennat Berger, "Sidewalk Labs' Failure and the Future of Smart Cities," Triple Pundit, June 16, 2020, https://www.triplepundit.com/story/2020/sidewalk-labs-failure-smart-cities/120616.

371 "Sidewalk Toronto," Sidewalk Labs, accessed October 19, 2023, https://www.sidewalklabs.com/toronto.

Opportunities

Foundational Advances in AI

Untapped or Underfunded Areas

The Environment Enabling AI Solutions

AI is already making substantial advances in many areas of climate and nature, but important gaps to advance climate and nature solutions remain. Opportunities for investment and development in this space fall within three main categories: foundational advances in AI, untapped and underfunded areas of opportunity, and the enabling environment for AI solutions in climate and nature.

Foundational Advances in AI

The following focus areas were identified as integral to enabling the foundational advances in AI necessary to realize transformative change in climate and nature solutions.

» **Critical data gathering and infrastructure.** The validity of versatile foundation models relies on the abundance of datasets such as large-scale image or video datasets. Building up data infrastructure for AI —including creating these large-scale datasets, as well as collecting, gathering, curating, labeling, and using them, especially for climate and nature applications—is a critical area for future AI research.

» **Multimodal capability.** Vision-language models represent the current state-of-the-art in multimodal AI. For climate and nature solutions, advances beyond current AI foundation models that can incorporate multimodal analysis (e.g., acoustic, satellite imagery, multispectral, point cloud) are needed to better combine and analyze the data coming from different and heterogeneous sources in order to provide a holistic understanding of ecosystems, support more accurate environmental monitoring, and produce more robust and reliable predictions.

» **Unified data platform.** The absence of a centralized and unified data platform is a major barrier to progress in the use of AI to develop climate and nature solutions. The ideal platform would host most key climate and nature datasets in one place to allow AI models to be trained on the largest amounts of data coming from a wide range of sources supplying data from multiple data streams (e.g., from many different satellites).

» **Open data.** Well-organized and open data following FAIR (Findable, Accessible, Interoperable, Reusable) data principles is needed to upscale the use and reuse of data. For example, the value of free, open, well-structured data is clearly illustrated by the experience of the US Landsat satellite program, which saw a more than 100x increase in the use of its data shortly after it became free and open in 2008.[372] That same data had existed for three decades, but was only put to limited use by the specialized community that had access to it.

» **Open codes.** Open codes can foster valuable partnerships and collaborations between academic institutions and public and private entities, and are therefore critical to accelerating progress for AI solutions. Achieving open code sharing, however, will require—at a minimum—a myriad of policy and management changes, including innovative legal solutions to address inter-country regulations.

» **Open-source models.** Open-source LLMs like Meta's Llama or the recent Mixtral model by Mistral are leading to rapid innovations, iterations, and collaborations between industries and the public sector (academia in particular). This openness may lead to a virtuous and more equitable circle of innovation that allows for the development of new applications and domains by innovators who might not otherwise have the capacity to develop or leverage those models internally.

» **Domain-specific data for training.** Foundation models often lack domain-specific knowledge required for certain applications, and adapting these models to new domains in the climate and nature context may require additional model training. For instance, in some parts of the Global South, a dearth of essential ground truth data can limit the development of new energy and power systems. This data, which would be readily available in other regions, is necessary to leverage AI for such potential applications as geo-located rural infrastructure (e.g., household access, farm mechanization, diesel use at businesses). Similarly, access to the requisite power and extensive technical expertise to maintain sensors in natural ecosystems hinders the development of important solutions in the developing world.

» **Privacy-preserving data sharing.** Mechanisms to upload and share data with the ability to control acceptable privacy protection levels are needed. Such data needs to be used for training AI models with maximum utilities for public good. Combining those datasets while respecting issues of privacy, trust, and security is critical to accelerate progress on climate and nature AI solutions. Rainfall is an example where there is a patchwork of data around the globe–weather station data, radar data, and privately held microwave data from cellular communication towers. Being able to fuse those datasets while sharing them securely and publicly would dramatically accelerate applications of AI to climate and nature solutions.

Untapped or Underfunded Areas

There are still areas of opportunity where AI is still relatively absent and could be leveraged to accelerate progress as well as instances where AI is currently underfunded. This section focuses on areas of opportunity, in no intentional order, that are both scalable and particularly suitable for the integration of AI to lead to dramatic improvement.

» **AI for energy management.** AI can be leveraged and scaled up across many aspects of modern energy management, including grid energy storage optimization; prediction enhancement; and the optimization and integration of renewable and mixed energy resources. These innovations align with climate change mitigation goals by contributing to the decarbonization of the energy sector. AI is therefore pivotal to the transition toward a more sustainable, reliable, and efficient energy infrastructure system.

» **Carbon capture and storage.** Carbon capture and storage (CCS) remain key solutions for efficient mitigation and reaching net-zero goals, yet those solutions are not ready to be brought to scale. AI can accelerate the development and optimization of CCS technologies by: identifying the most efficient ways to capture, transport, and store carbon; advancing materials and optimizing site locations and characteristics to accelerate sequestration; and optimizing the logistics and deployment of CCS.

» **AI for soil health and carbon sequestration.** Substantial work has been done in mapping above-ground biomass using AI that can now be done at the individual tree level; but soil carbon quantification remains an open problem due to lack of observations and scientific investment in this field. This is a major impediment to arriving at correct estimates of carbon storage and requires additional investment. With proper funding, AI, supplemented by more data acquisition to complement the currently limited datasets,[373] could assist in the understanding of soil carbon storage potential by analyzing and combining various sources of data from in situ, drones, and satellites. This could support land restoration efforts, promote sustainable soil health, and help prevent soil degradation to enhance carbon sequestration for more informed natural carbon solutions. The potential of AI in enhancing soil health and optimizing carbon sequestration is vast yet underexplored, especially when compared to more visible climate solutions like renewable energy.

» **Climate prediction analysis and modeling.** Support is needed for AI projects that focus on improving climate data analysis and predictive modeling. These projects can offer insights into changing climate patterns, extreme weather events, and long-term climatic changes so our society can minimize the cost associated with climate change. If properly funded, these projects will support better planning and decision-making for mitigation and adaptation strategies as well as early warning systems for climate events such as inundation and wildfires. This would allow for efficient resource allocation to combat climate change and minimize the impact of disasters on vulnerable communities.

» **Biodiversity mapping and species protection.** As discussed in this report, biodiversity mapping and species protection is already using AI extensively with computer vision and acoustic data. Substantial work is still needed, however, to share and unify the different datasets used, develop methods for rare and endangered species, reduce biases due to acquisition focused on specific regions of the world and predict threats from human activities and environmental changes. In addition, leveraging low-technology citizen-science solutions can be used to expand the reach of conservation interventions.

» **AI for small farmers.** While AI is already being used for large-scale agriculture, it has substantial potential to benefit small farmers as well, especially in the Global South. Data from high-resolution satellites can now be used at low cost to help inform the decisions small farmers make and lead to increased yield and reduced vulnerability to natural climate variability and pests. This result would be transformative for small farmers who lack the capacity to invest in expensive, large-scale solutions.

» **Environmental justice and inclusive climate action.** Climate impact is tightly connected to social inequity and racial redlining, as underserved communities are typically most vulnerable to—and simultaneously least responsible for—climate change. AI can be used to address environmental justice and ensure inclusive climate action and adaptation policies, yet this is still an emerging field. For instance, AI can be used to identify the impact of extreme events—such as heat waves or inundation—on vulnerable communities and determine how best to adapt to these negative impacts at reduced cost.

» **Behavioral change and public engagement.** Maybe one of the most important steps towards broad climate and nature solutions is fundamentally rooted in behavior. AI can support new initiatives aimed at promoting sustainable behaviors and increasing public engagement and awareness in climate and sustainability actions. Indeed, AI can develop personalized recommendations and targeted communication in many languages that can potentially change individuals' actions in ways that promote positive climate and nature impacts. The use of AI to translate recommendations and communications in different languages and even dialects could further extend the scale and reach of those communications.

The Environment Enabling AI Solutions

» **Datasets and benchmarks.** One of the primary enablers of AI innovations is the availability of open datasets and clear benchmarks such as ImageNet. There are already several examples of community datasets and benchmarks in the climate

Eight Spotlight Initiatives from AI for Climate & Nature Workshop Report

In October 2023, the Bezos Earth Fund held an AI for Climate and Nature Workshop in collaboration with Foresight Institute to stimulate dialogue by providing critical insights to decision makers and key stakeholders in the AI, climate, and nature space.[374] The participants collectively identified 59 opportunity spaces at the nexus of climate/nature challenges and AI capabilities. In addition, participants voted on promising opportunity areas to deep dive on where AI could tackle specific climate and nature challenges, and developed the eight spotlight initiatives listed below. Other gaps, challenges, and opportunities raised during the workshop have been integrated elsewhere in this report.

- **Characterizing emissions: A global, accurate, and authoritative account of greenhouse gas flux, separated out by origin and owner.** The objective of this initiative is to reduce uncertainties in global emissions accounting, provide full coverage, and assign mitigation responsibility. The ultimate goal is to provide a reliable resource for greenhouse gas emissions, aiding in the development of effective mitigation plans and aligning human emissions with the Earth's carbon absorption capacity, in line with international accords like the Paris Agreement.
- **Optimization of clean energy systems: AI-accelerated building decarbonization.** This initiative aims to accelerate and revolutionize the decarbonization of buildings, focusing on strategies such as building-by-building recommendations that encompass energy efficiency, optimized deployment of clean energy technologies, and energy forecasting for tailored individual user decisions and policymakers decision-making.
- **Biodiversity data infrastructure: Unleashing AI-enabled decisions for a thriving planet through the Data Mesh.** Aimed at revolutionizing biodiversity and climate monitoring, this initiative aspires to create an intricate "data mesh" that seamlessly integrates an array of existing data sources—from hardware and datasets to human expertise and species information—to provide an efficient platform to aid decision makers in devising and refining robust biodiversity and climate strategies.
- **Ecosystem mapping + geospatial models: Transforming access to geospatial information that accelerates pathways from data to insight to impact/action.** The primary aim of this initiative is to empower users to quickly and effectively engage with generative models trained on multifaceted geospatial data sourced from various origins using natural language queries.
- **Sensors: The Trillion Sensor Challenge.** This initiative aims to integrate vast, smart, and affordable sensors into both land and aquatic ecosystems to grasp each ecosystem's vitality, focusing on individual species' behaviors. A key element is its global inclusivity, aiming to democratize big data beyond traditionally data-rich regions like the US and Europe, and to build transparency and trust in conservation efforts.
- **Restoration: Trees for Life.** This initiative aims to utilize equitable AI to promote the restoration of forests and grasslands in Africa. A distinctive feature is its emphasis on community-focused restoration, determining which trees to plant where and collaborating with communities for mutual benefits.
- **Incorporating local and tribal knowledge: Advancing Climate Justice through Decolonization of Data.** This initiative aims not just at technological progress but at enabling local communities to incorporate traditional knowledge with modern data science to champion climate justice. The plan involves using AI to enable localized data collection, access new knowledge sources, and combine existing knowledge systems, all within a responsible AI framework mindful of cultural contexts and potential risks.
- **Decision-making: ClimatePolicyTracker 2.0.** The primary aim of this initiative is to connect decision-making with practical, on the ground climate- and nature-focused actions. ClimatePolicyTracker 2.0 serves as a user-friendly interface connecting a live global map of climate and nature regulations with their real-world impacts, supported by a thorough set of evidence-based decision-making tools.

and nature space such as WeatherBench, used to define a benchmark for weather forecasting and that has helped the AI community center the weather forecasting realm at unprecedented pace and with great success. More datasets and benchmark creation should be supported by the community and funding agencies, as they are tremendous leverage for AI yet are often tedious to put together and require deep domain expertise.

» **Interdisciplinary collaboration.** Addressing challenges in nature and climate domains requires collaboration among AI researchers and practitioners and domain experts. This includes computational scientists, experimentalists, and those working in industry and policy, as well as experts in meteorology, ecology, and environmental science. Bridging the gap among these disciplines—each with its specialized knowledge and terminology—is important for the proposed models and solutions to be successful and impactful.

» **Educational training and workforce development.** The scalability of AI solutions in nature and climate critically depends on the quality and performance of the trained workforce. Funding should support innovative educational solutions to train a new generation of scientists and engineers well versed in both AI and domain applications (in nature as well as climate). Given the global nature of those problems, online education seems particularly well suited to training the broadest community of experts across the globe, especially in the currently underserved Global South.

» **Public education.** Public education and the demystification of the science of AI will allow individuals to understand the power of AI to improve outcomes, which would likely lead to more acceptance of the use of AI in a wide variety of contexts.

» **Optimal policy and strategy formulation**. AI can support optimal and effective climate strategies by providing stakeholders with simulations and projections of climate impacts under different policy scenarios that are tailored to their needs. Mitigation strategies are by definition multimodal and multi-agent as they need to deal with various objectives and stakeholders. AI can strive to define policies to reach the most efficient results. This can help in formulating policies that are both optimal and realistic.

ENDNOTES: OPPORTUNITIES

372 Earth Resources Observation and Science Center, "Free, Open Landsat Data Unleashed the Power of Remote Sensing a Decade Ago," United States Geological Survey, April 17, 2018, https://www.usgs.gov/news/free-open-landsat-data-unleashed-power-remote-sensing-decade-ago#:~:text=All%20that%20changed%20in%20January,images%20free%20to%20the%20public.

373 Ana Carolina S. Ferreira et al., "Predicting Soil Carbon Stock in Remote Areas of the Central Amazon Region Using Machine Learning Techniques," *Geoderma Regional* 32 (2023): e00614.

374 Bezos Earth Fund, *AI for Climate & Nature Workshop: Summary Report* (Bezos Earth Fund, 2023), https://www.bezosearthfund.org/ai-climate-nature.

Conclusion + Appendices

AI holds immense potential for driving positive change in the world. Still, it is a tool, not a panacea. As with any transformative technology, safeguards are needed to ensure that solutions leveraging that technology are enabling ethical, equitable, and actionable decision-making, while still providing assurances that insights and recommendations will lead to positive impacts with few unintended consequences.

More broadly, AI solutions for climate and nature need to be advocated alongside large-scale innovation and policy overhauls aimed at changing the underlying socio-economic and political systems that enable and perpetuate the climate and nature crises. AI technologies and approaches alone cannot solve these challenges; new collaborations, more and different kinds of data, and openness are just a few of the things required to solve these inherently complex and multidisciplinary problems.

AI has already transformed many aspects of science and society, and it offers us a way to dramatically accelerate the pace of solutions to our most intractable problems. There is much we can celebrate, but still much to be done.

Contributors

LEAD AUTHOR
Pierre Gentine, *Columbia Engineering and Columbia Climate School, Columbia University*

COLUMBIA UNIVERSITY AUTHORS
Geneva List, *Columbia Climate School*
Kyoko Thompson, *Columbia Engineering*
Zhiyuan Fan, *Columbia University*
David Sandalow, *Center on Global Energy Policy, Columbia University*
Neal Ma, *Columbia Engineering*

UNIVERSITY AT ALBANY, STATE UNIVERSITY OF NEW YORK AUTHORS
Thenkurussi (Kesh) Kesavadas, *Division for Research and Economic Development*
Theresa Pardo, *Division for Research and Economic Development*
Jeanette Altarriba, *College of Arts and Sciences*
Xin Li, *College of Nanotechnology, Science, and Engineering*
George Berg, *College of Emergency Preparedness, Homeland Security and Cybersecurity*
Zheng Wu, *Department of Atmospheric and Environmental Sciences*
Tianning Huang, *Division for Research and Economic Development*
Aidai Kokonova, *Division for Research and Economic Development*
Battulga Buyannemekh, *Division for Research and Economic Development*

ESRI AUTHORS
Lauren Bennett, *Spatial Analysis and Data Science*
Steve Kopp, *Spatial Analysis and Data Science*
Gina O'Neil, *Data Science*

CARTOGRAPHY AND VISUALS
Jared Kohler, *Esri, Professional Services*

PRODUCTION
Darrel Frost and Susan Tilson

ACKNOWLEDGMENTS
The authors acknowledge the important contributions from Maria João Sousa who provided a comprehensive review of the full report and critical feedback.

The team is grateful for the Columbia University subject matter advisors who reviewed and provided content to draft versions of this report. Subject matter expert reviewers include: Dan Beinstock, Logan Brenner, Thomas Chandler, George Deodatis, Sharon Di, Jessica Fanzo, Galen McKinley, Duncan Menge, Vijay Modi, Oscar Nordness, Matthias Preindl, Michael Puma, Andrew Smyth, Jeffrey Schlegelmilch, Dan Steingart, Maria Uriarte, and Bolun Xu.

The team would like to acknowledge the key stakeholders who provided their insights to this report through consultations, including Marlene Kretschmer, Carl Boettiger, Steve Brumby, Marcus Noack, Vasant Honovar, Elizabeth Barnes, Pin-Yu Chen, Katie Zacarian, Evan Tachovsky, Tanya Berger-Wolf, Anna Michalak, Amy Luers, Keith Brown, Evan Rapoport, Justin Kitzes, and Sara Beery.

The authors are also grateful for the direction and valuable contributions from the Bezos Earth Fund team members including Andrew Steer, Amen Ra Mashariki, Kelly Levin, Erin Jones, Noel Bakhtian, Adrienne Schmoeker, Stacie Cobos, Rocio Lower, and Claire Pfitzinger. Invaluable support has also been provided by Columbia University's Farhana Mather, Samar Kaukab, and Vanessa Lau.

Methods and Systems Change Lab

The application and use of AI across a broad range of domains, as well as basic AI research and development, are advancing at an extremely rapid pace. This Landscape Assessment was conducted with this dynamic context in mind. While traditional approaches used to review cutting-edge research and practice within and across disciplines (e.g., literature reviews) are necessary, they were also deemed insufficient for this work. Engaging AI- and thematic-subject-matter experts as thought leaders was key to the thoroughness and forward-looking aspect of this assessment. Three primary data collection strategies informed this Landscape Assessment.

First, the teams conducted literature reviews of peer-reviewed journal articles on the use of AI in climate and nature from 2015 to the present. Search terms included AI and machine learning with each of the Systems Change Lab-designated global systems further broken down into their "shifts" when warranted. Climate modeling and prediction search terms, as well as biodiversity and conservation, were added to the list. The articles were reviewed to emphasize key messages, applications and AI technologies, gaps or challenges, opportunities, and recommendations.

Second, the project teams scanned the internet, both manually and with the assistance of generative AI-tailored applications, to identify key stakeholders and initiatives encompassing a broad range from pilot projects, university institutes, non-profits, start-ups, and large companies. Key initiatives were also gleaned from the literature and conversations with experts in the field.

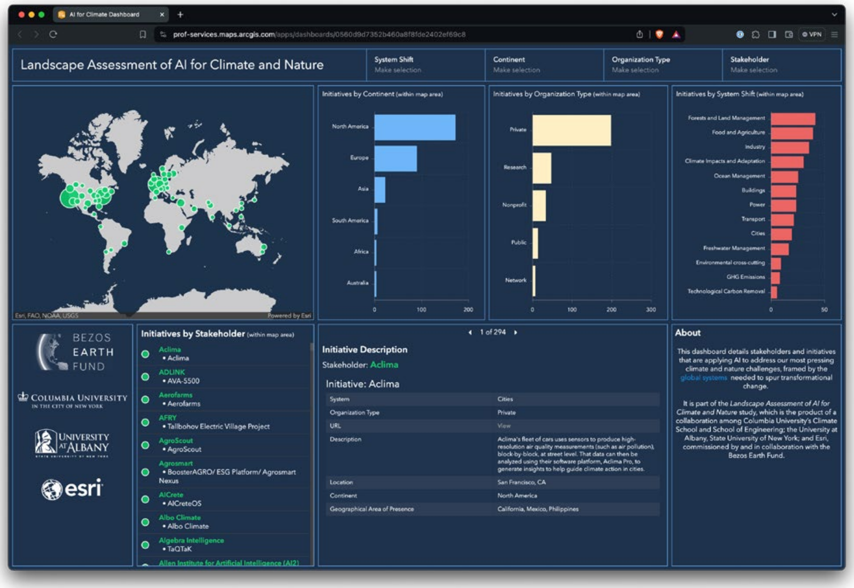
Third, the teams consulted with experts—with representation from academia, industry, and government and non-profit organizations—to conduct additional research and to confirm findings from the literature reviews and scans. Data were collected through qualitative surveys (n=14) and semi-structured interviews (n=31) with key stakeholders in the space of climate, nature, and AI. Questions included requests for information on the grand challenges and known applications of AI across the respondents' and stakeholders' fields of expertise, key stakeholders in the area, as well as the main gaps, challenges, opportunities for scaling, and risks. Additionally, this report underwent thorough expert review, revisions, and feedback throughout the writing process.

One of the main limitations to the data collection is a strong geographical concentration of data collection in North America, as well as the restriction of our review to English-only literature and internet searches.

Stakeholders and Initiatives

The Landscape Assessment team identified key stakeholders and major initiatives that are applying AI technologies in the field of climate and nature. Using the Systems Change Lab global systems as a guide, the review targeted the following focus areas: Forests and Land Management, Freshwater Management, Oceans Management, Food and Agriculture, Power, Industry, Cities, Buildings, Transport, and Technological Carbon Removal. In addition to these ten global systems, and to correspond to the outline of this Landscape Assessment report, initiatives have also been identified in two additional areas: climate impacts and GHG emissions. Finally, key initiatives that are cross-cutting but leveraging AI to address environmental issues have been coded under Environmental cross-cutting.

Nearly 300 key stakeholders and major initiatives were identified and are listed below. This data is publicly available in an interactive dashboard on Esri's ArcGIS platform (linked at right).



Stakeholders and Initiatives Dashboard

This stakeholder and initiative data is publicly available in an interactive dashboard on Esri's ArcGIS platform at https://prof-services.maps.arcgis.com/apps/dashboards/0560d9d7352b460a8f8fde2402ef69c8.

Methodology

The stakeholders and initiatives list is composed of the global system or chapter identifier, stakeholder, initiative name (if different from stakeholder), organization/initiative website, organization type, description of the stakeholder/initiative, and the geographic location of the stakeholder's headquarters.

For the purposes of this list, "stakeholder" refers to an organization that has deployed AI technology in the focus areas, and "initiative" refers to a publicized, named AI application or project under the stakeholder's management. Stakeholders are sorted into the following organization types: Private, Public, Nonprofit (including non-governmental organizations), Research (including centers within academic institutions), and networks (encompassing collaborations and hubs). The list also includes a list of models and databases that are utilized for AI applications in climate and nature (coded under *Research*).

To produce the key stakeholder and major initiative list, the research team identified stakeholders and initiatives through consultations with subject matter experts, literature reviews, as well as internet scans supported by generative AI technologies from September 2023 to April 2024. The objective was to reach a minimum of 20 initiatives per focus area (i.e., 20 initiatives over 12 focus areas). In some focus areas this was easily achieved. In these instances the active search for additional initiatives and stakeholders ceased after reaching 20; however, throughout the course of the project, when the research team organically came across important stakeholders or initiatives, they were added. Often the descriptions used to describe the stakeholders and initiatives are directly copied from the company's website.

The key initiatives and stakeholders that have been featured in this report were selected based on the authors' understanding of the AI for climate and nature space, and the assessment of the initiatives' innovation or potential for impact.

Limitations

The stakeholders and initiatives list is not meant to be a comprehensive or exhaustive representation of the AI landscape globally. Importantly, the search was limited to stakeholders and initiatives featured only in English literature, media and/or websites. In addition, AI applications in climate and nature are evolving and growing rapidly. The scan may have failed to capture emerging major initiatives and key stakeholders. The coding of the stakeholders and initiatives may contain inaccuracies due to misinterpretation or human error. The codes and descriptions reflect the judgment of the authors and do not necessarily reflect the views of the collaborating institutions that produced the Landscape Assessment study.

Despite these potential caveats, the list should be a valuable starting point to better understand AI applications in the climate and nature domains as well as to highlight opportunities to address gaps, scale applications, and increase impact.

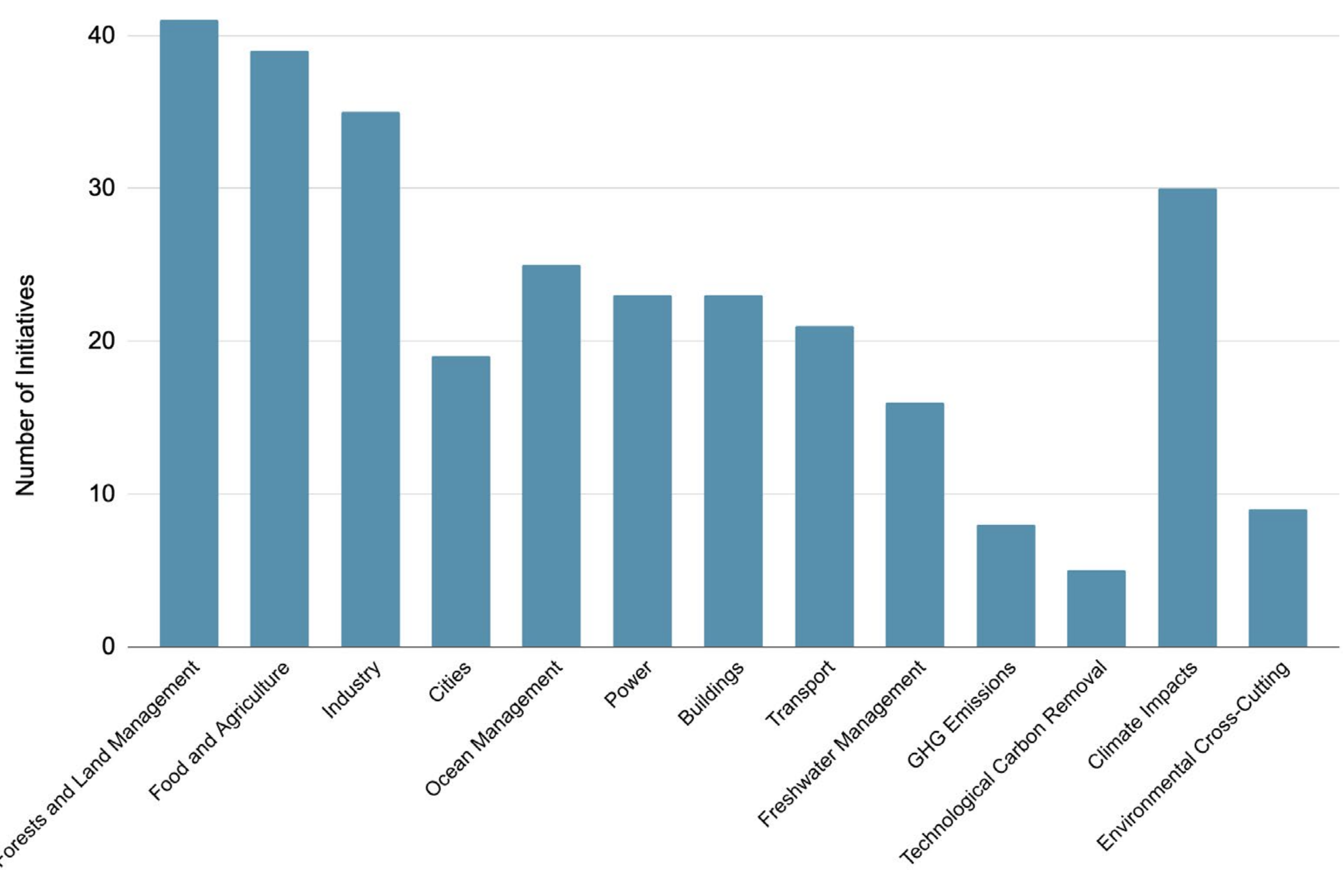
Summary of Findings

The review conducted for this Landscape Assessment determined that there are significant AI initiatives in forests and land management, food and agriculture, and industry; with relatively fewer, in comparison, in GHG emissions monitoring and technological carbon removal (Figure 1).

The stakeholders managing these AI initiatives are found largely in the Global North and western hemisphere (Figure 2 and 3). This is likely because: (a) wealthier economies drive advanced technological innovations and have more access to infrastructure, data, and capital, (b) there is a high concentration of tech startups, and especially climate tech startups, in the Silicon Valley/ Bay area, and (c) the scan was conducted in English only, which will naturally bias towards, and potentially oversaturate, results for English-speaking countries (see *Limitations*).

The scan demonstrated that most AI initiatives in climate and nature are globally active or at least globally available. For those

Fig. 1 — Area of Application Initiatives



not implemented or available on a global scale, implementation tends to be concentrated in North America and Europe—reflecting stakeholder location. The scan found relatively little AI deployment concentrated only in Asia, Africa, South America, and Australia, although many global initiatives may work in these regions.

The vast majority of stakeholders applying AI to climate and nature solutions are in the private sector (67%), followed by research (16%) and nonprofits (11%), with stakeholders in the public sector and networks (usually a nonprofit or research collaboration) amounting to 4% and 2% respectively. However, public sector funding supports a number of the research and nonprofit efforts listed here.

The private sector comprises the largest share of stakeholders across most systems and is the main organization type for food and agriculture, and industry (Figure 4). From the initiatives found in our scan, only the private sector is working on buildings and transport. Nonprofits are more prominent in forests and land management, and ocean management as well as environmental cross-cutting (i.e., working across environmental sectors). Research institutions are also quite active in forests and land management, climate impacts and adaptation, and technological carbon removal, despite there being relatively few initiatives found in that area.

The initiative scan aimed to provide a useful overview of the stakeholders and initiatives currently in place. Findings suggest that many areas are already demonstrating viable business models for AI applications and have thus seen widespread private sector involvement (e.g., optimization for reduced energy use, carbon emissions, or waste). The findings also point to the opportunity to expand the development and implementation of AI solutions for climate and nature to the Global South.

Fig. 2 — Initiatives by Location

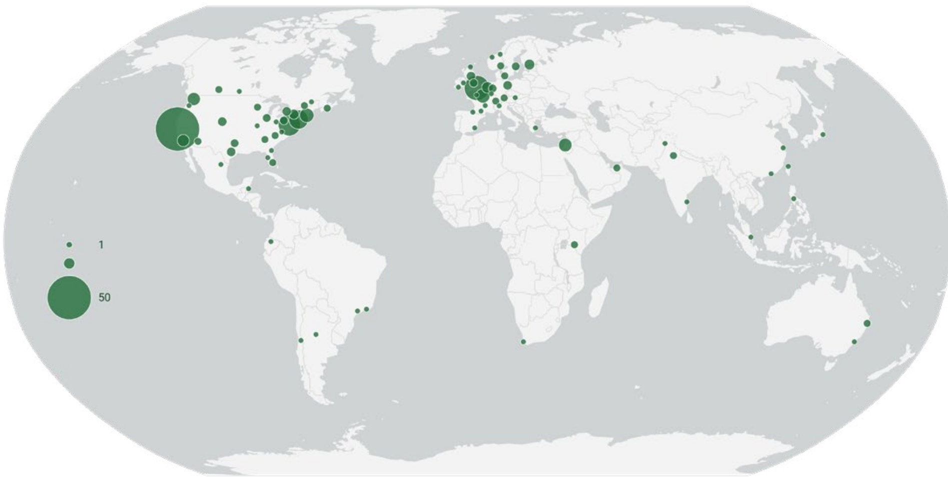


Fig. 3 — Initiative Organization Location

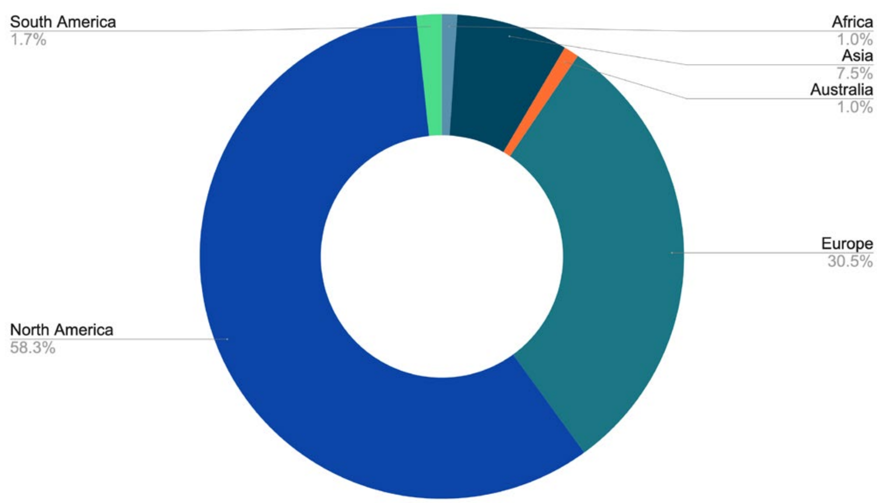
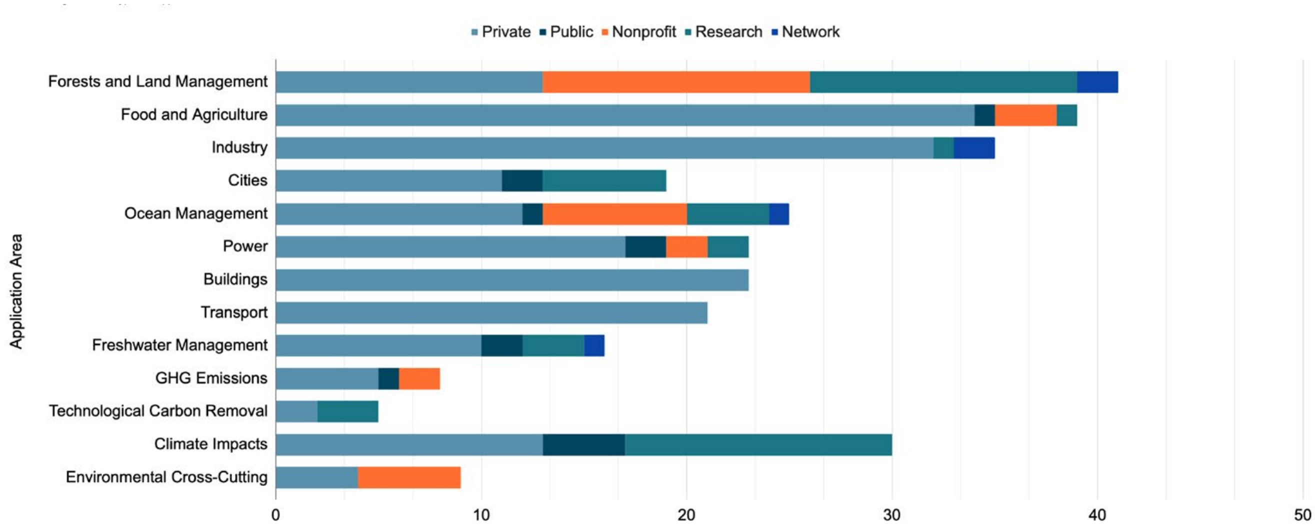


Fig. 4 — Initiatives by Organization Type



Buildings

AFRY: Tallbohov Electric Village Project

afry.com

HEADQUARTERS: Stockholm, Sweden
ORGANIZATION TYPE: Private
AFRY is helping Tornet, a public housing company in Sweden, to nudge residents of a pilot village project to adopt more sustainable, eco-friendly behaviors using AI and machine learning. The digital platform is brought to residents through the user interface TORNA—a smartphone app connected to the building's energy system. In the future, it could also be integrated into, for example, a smart mirror in the apartment.

Arup

arup.com

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Arup is a global network of designers, engineers, and creators committed to sustainable development that support organizations and government agencies in various projects. One ability they have is to use AI to help design buildings, making them more sustainable by enhancing their energy efficiency. In collaboration with Hong Kong Polytechnic University, they optimized the energy efficiency of the structure's ventilation system using sensors and machine learning algorithms.

Autodesk: Autodesk Forma

autodesk.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Autodesk Forma (formerly Spacemaker) is cloud-based, AI-powered software that helps architects in the building design process. Using machine learning, it can create 3D design possibilities for a given location or space within minutes, adjust based on architects' inputs, and solve problems such as reducing a potential building's environmental impact and help ensure compliance.

BlocPower

blocpower.io

HEADQUARTERS: Brooklyn, NY
ORGANIZATION TYPE: Private
BlocPower aims to reduce carbon emissions in US buildings by leveraging AI for targeting and planning. It has built a database of 125 million buildings and employed physics-based bottom-up simulation engines, AI, and machine learning models to generate digital twins of these buildings. These twins have highly accurate simulated energy profiles that are bias-corrected against real-world data. BlocPower has also developed a Scope of Work Recommendation Engine that identifies buildings needing energy conservation, using factors like topology and energy consumption to assess the feasibility of energy conservation measures (ECMs). Future enhancements to the engine will consider energy and cost savings, which will build upon the existing AI- and heuristic-based models, enabling the estimation of the energy savings potential of implementing ECMs at the building level.

BrainBox AI

brainboxai.com/en/

HEADQUARTERS: Montreal, Canada
ORGANIZATION TYPE: Private
BrainBox autonomous AI technology proactively optimizes the energy consumption of buildings and reduces carbon emissions while generating significant energy savings. Solutions include HVAC optimization, energy management, and decarbonization and offsets.

Bricsys: BricsCAD

bricsys.com

HEADQUARTERS: Ghent, Belgium
ORGANIZATION TYPE: Private
Bricsys uses its AI and machine learning platform, BricsCAD, to help designers and architects streamline the design of buildings, automating formerly time-consuming tasks to model 3D structures with many different geometries at a level of detail previously unattainable, making the planning of greener buildings and outdoor spaces easier than ever.

CIM

cim.io

HEADQUARTERS: Sydney, Australia
ORGANIZATION TYPE: Private
CIM's SaaS platform uses AI, machine learning, and mechanical engineering to help make buildings more efficient, sustainable, and comfortable by optimizing HVAC and other mechanical systems.

Contilio

contilio.com

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Contilio is an AI-driven platform for construction and contractors that generates insights to help cut emissions, costs, and time in the construction process.

DeepMind: Delve

sidewalklabs.com/products/delve

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Private
Developed by Google DeepMind and Sidewalk Labs, Delve is a machine learning platform that assists with the design and construction of buildings. It can make adjustments to designs based on many different parameters, including building height and sun exposure. In one real-life case of a large building constructed in Wembley Park, Delve improved daylight access, sun hours, and open space available to the building and its occupants.

Google: Nest Learning Thermostat

Nest Learning Thermostat in Google Store

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Private
Developed by Nest Labs, the Nest Thermostat (later acquired by Google) uses AI to acclimate to individual voices and voice commands, predict temperature preferences, and program itself automatically according to those preferences. This can help users cut down their energy usage by automating heat and cooling systems (and helps them control temperature when away from home to reduce energy waste).

Honeywell

honeywell.com

HEADQUARTERS: Charlotte, NC
ORGANIZATION TYPE: Private
Honeywell helps make buildings more efficient and sustainable with AI- and machine learning-powered hardware, software, and data analytics.

IBM: Envizi ESG Suite

ibm.com/products/envizi

HEADQUARTERS: Armonk, NY
ORGANIZATION TYPE: Private
IBM's Envizi is a SaaS platform that uses machine learning and robust data analytics to monitor building operations and identify opportunities to lower carbon footprints.

Infogrid

infogrid.io

HEADQUARTERS: Chelmsford, UK
ORGANIZATION TYPE: Private
Infogrid is an energy management and analytics platform that helps commercial real estate and facility managers reduce their buildings' contribution to GHG emissions and make their buildings more sustainable by optimizing energy usage.

IRT Surveys

irtsurveys.co.uk

HEADQUARTERS: Dundee, UK
ORGANIZATION TYPE: Private
IRT Surveys uses AI to analyze thermal imaging data to identify excessive heat and energy use to help inform building residents about their heat portfolio and how they can reduce energy consumption. IRT Surveys has been acquired by Mears Group.

Johnson Controls

johnsoncontrols.co.uk

HEADQUARTERS: Cork, Ireland
ORGANIZATION TYPE: Private
Johnson Controls uses AI and machine learning to predict buildings' energy consumption, detect defaults in building equipment (chillers, cooling towers, lights, appliances, etc.), predict and schedule maintenance, and optimize HVAC operations to reduce energy consumption.

Maximpact

maximpact.com

HEADQUARTERS: Cape Town, South Africa
ORGANIZATION TYPE: Private
Maximpact offers technological solutions, consulting services, and training to help municipalities, communities, and companies become more efficient. They can use AI to monitor, evaluate, and manage energy usage in buildings and factories. Their technology identifies problems, detects potential equipment failure and needed repairs, and reduces energy consumption during peak hours.

Buildings (continued)

measurable.energy

measurable.energy

HEADQUARTERS: Reading, UK
ORGANIZATION TYPE: Private
measurable.energy created and sells plug sockets that use machine learning to identify small power waste in plugged-in devices automatically, and can help reduce electricity costs of users by a minimum of 20%.

Mortar IO

mapmortar.io

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Mortar IO uses an AI-driven simulation platform to help users decarbonize buildings by generating virtual models of thousands of buildings within minutes, aiding with quick and efficient retrofitting planning in the real estate decarbonization space.

Phyn

phyn.com

HEADQUARTERS: Torrance, CA
ORGANIZATION TYPE: Private
Phyn, a Belkin International subsidiary, uses sensors and cloud AI to monitor water pressure, flow, and temperature in residential plumbing systems. Users can use it to identify water usage trends and find actionable insights into how to reduce water use (and maintain their systems to reduce water waste overall).

Saint-Gobain

saint-gobain.com/en

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
Saint-Gobain designs, manufactures, and distributes materials and services for the construction and industrial markets. A large organization with wide-reaching applications, it is involved in the renovation and construction of public and private buildings to improve buildings' energy efficiency, retrofitting buildings to new uses, integrate new construction materials, and support innovative solutions within architecture.. Its efforts in industry and mobility complement its built environment endeavors—which recently have shifted to incorporate AI technologies to improve the company's sustainability, such as through enhanced building material for light construction, optimized retrofitting, or optimizing supply chain so that the company can achieve its carbon neutrality goal by 2050.

Siemens: Building X

siemens.com/global/en/products/buildings/building-x.html

HEADQUARTERS: Munich, Germany
ORGANIZATION TYPE: Private
Building X is an open platform consisting of applications and connectivity solutions. It takes data from one-off events (such as construction) and continuous monitoring of building activities (via sensors). Both the data and insights generated by the platform are made available to users, helping them make informed decisions and create intelligent solutions for their buildings, making them more efficient and sustainable.

WINT

wint.ai

HEADQUARTERS: Goshen, NY
ORGANIZATION TYPE: Private
WINT's water management system uses AI to identify leaks within a water system and automatically turn off water when leaks take place, helping buildings and businesses become more sustainable by lowering water waste and improving their water footprint.

Yord

yord.ch

HEADQUARTERS: Fribourg, Switzerland
ORGANIZATION TYPE: Private
Yord's optimizer hardware can be installed in buildings to help make heating and cooling systems in buildings more energy-efficient and the buildings themselves more sustainable.

Cities

Aclima

aclima.io

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Aclima's fleet of cars uses sensors to produce high-resolution air quality measurements (such as air pollution), block-by-block, at street level. That data can then be analyzed using their software platform, Aclima Pro, to generate insights to help guide climate action in cities.

BuntPlanet: BuntBrain

buntplanet.com

HEADQUARTERS: Donostia-San Sebastian, Spain
ORGANIZATION TYPE: Private
BuntBrain is AI-driven software developed by BuntPlanet to address water scarcity, helping utilities monitor their water distribution networks and identify solutions to water losses. They claim it can cut commercial water loss by as much as half. In December 2023, Siemens acquired BuntPlanet.

CANN Forecast: InteliSwim/InteliPipes

www.cannforecast.com/en/

HEADQUARTERS: Montreal, Canada
ORGANIZATION TYPE: Private
Cann Forecast develops decision tools leveraging artificial intelligence and machine learning for municipal water management. The products include predictive machine learning models to predict the concentration of E. coli in urban water bodies (InteliSwim) and also AI-based algorithms to help identify at-risk pipes before they break (IntenliPipes).

ClimateIQ

climateiq.org

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Research
ClimateIQ is an AI-driven, multi-hazard exposure assessment tool leveraging Machine Learning, Big Data, and multiple climate hazard model environments. The tool aims to aid communities in accessing high-resolution hazard exposure information and to advance risk assessment in urbanized regions worldwide. It was supported through a google.org Impact Challenge on Climate Innovation, which is the collaboration of many partners led by the Urban Systems Lab at the New School in New York City.

Cornell University: Tree Folio NYC

labs.aap.cornell.edu/daslab/projects/treefolio

HEADQUARTERS: Ithaca, NY
ORGANIZATION TYPE: Research
Tree Folio NYC is a digital twin of New York City's tree canopy—utilizing traditional satellite technology and LiDAR data to model NYC trees and quantify the amount and quality of shade each provides. Machine learning algorithms were used to fill the gaps between the satellite and LiDAR information sources and apply those learnings elsewhere. The tool can be used to make informed decisions on urban planning and management, especially in making the city more sustainable.

Digital Water Solutions: hydrant.AI

digitalwater.solutions/device-and-platform/

HEADQUARTERS: Ontario, Canada
ORGANIZATION TYPE: Private
Digital Water Solution's hydrant.AI uses artificial intelligence and sensors to monitor acoustic, pressure, and temperature data in water systems to detect leaks early and help systems reduce water loss.

Cities (continued)

Digital-Water.City (DWC): DWC

digital-water.city

HEADQUARTERS: Berlin, Germany
ORGANIZATION TYPE: Private
DWC develops digital solutions for urban environments to support European water and sewage infrastructure in reducing water waste, improving water quality, optimizing maintenance,

Google: Environmental Insights Explorer

insights.sustainability.google

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Private
Environmental Insights Explorer is a freely available data and insights tool that uses exclusive data sources and modeling capabilities to help cities and regions measure emissions sources, run analyses, and identify strategies to reduce emissions — creating a foundation for effective action.

Greyparrot: Analyzer

www.greyparrot.ai

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Greyparrot's Analyzer is an AI waste analytics platform that creates a live stream of insight on the material passing through a recycling sorting facility to enable more resource recovery.

Indian Institute of Technology Jammu: Centre of Excellence in Artificial Intelligence

iitjammu.ac.in/aicpmu/

HEADQUARTERS: Jammu, India
ORGANIZATION TYPE: Public
In late 2023, the Indian government issued a call for proposals to establish a Centre of Excellence in AI focused on developing AI solutions for sustainable cities and smart cities. Including Forecasting and modeling for urban sustainability, sustainable infrastructure and resource planning, analysis and monitoring, sustainable applications for mobility, urban development, and resilience using AI SAMUDRA, generating casual AI-powered digital twin with reinforcement learning for sustainable urban transformation, and AI-powered sustainable cities.

Masdar City

masdarcity.ae

HEADQUARTERS: Abu Dhabi, United Arab Emirates
ORGANIZATION TYPE: Private
Masdar City is a sustainable urban community in the United Arab Emirates. Its focus is innovation and creating scalable solutions for climate change in cities that can be used worldwide, leveraging AI when possible. They claim that buildings within Madar City use 90% recycled aluminum and use 40% less energy and water than typical buildings.

MIT: Department of Urban Planning

dusp.mit.edu/urban-science

HEADQUARTERS: Cambridge, MA
ORGANIZATION TYPE: Research
Researchers at MIT are combining sensors, AI, visualization, and data analysis to develop solutions for city planners, designers, and policymakers to make cities more sustainable.

New York City Office of the Mayor: The New York City Artificial Intelligence Action Plan

The New York City Artificial Intelligence Action Plan

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Public
This multi-pronged AI action plan for NYC has stakeholders across sectors and industries and intends to identify opportunities for AI integration and in-house tool development, scale in-house projects, and determine and support agency needs. These efforts can impact the city's carbon footprint by increasing the capability of the city government to make managing buildings and transportation more sustainable.

Replica

replicahq.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Web-based interface for engineers, investors, city planners, and decision-makers working in urban infrastructure and transportation. It can be used to help gain insights and plan active transportation, EV infrastructure, and public transit within a city—including evaluating interventions to reduce the impact of these activities on climate change.

Stevens Institute of Technology

www.stevens.edu/news/nasa-funds-stevens-ai-to-help-monitor-nyc-water-supply

HEADQUARTERS: Hoboken, NJ
ORGANIZATION TYPE: Research
SIT was funded by NASA to develop a tool that uses satellite data, remote sensing, and hydraulic modeling to optimize reservoir management in watersheds in the northeast and manage the water supply sent to New York City residents during cold seasons. The effort is meant to optimize reservoir inflow and reduce water waste.

University of Virginia: Link Lab

engineering.virginia.edu/link-lab

HEADQUARTERS: Charlottesville, VA
ORGANIZATION TYPE: Research
The Link Lab at UVA Engineering is a multidisciplinary consortium of faculty and graduate students conducting research in Smart and Connected Health, Hardware for IoT, and Smart Cities. Their work prioritizes the real-world impact of cyber-physical systems, including enabling connected transportation services to meet the needs of all commuters and travelers, using machine learning models to make smart services more efficient, and imagining smart buildings that are not only more sustainable but also improve occupant health and comfort. They work closely with industry to advance their technology, as well as local government for case studies.

University of Waterloo

uwaterloo.ca/news/news/ai-could-help-cities-better-detect-water-leaks

HEADQUARTERS: Waterloo, Canada
ORGANIZATION TYPE: Research
Engineering researchers at the University of Waterloo have developed leak detection technology in partnership with industry actors. The technology, published in the Urban Water Journal, uses acoustic sensors to detect leaks and can help municipalities identify leaks and emergencies in real time and cut down on water losses.

Urban AI

urbanai.fr

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
Urban AI is a think tank focused on conducting research that can assist city leaders, urban planners, and policy-makers in understanding the state of urban technologies, AI models that are currently applied to cities and the built environment, and the potential for AI to make urban life safer and more sustainable. Urban AI describes itself as the "crossroads" between AI and Smart Cities.

UrbanFootprint

urbanfootprint.com

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Private
UrbanFootprint offers resilience insights to urban communities, utility companies, government agencies, and private companies. The "world's first urban intelligence platform" helps identify solutions to make urban environments more sustainable.

Climate Impacts

Allen Institute for Artificial Intelligence (AI2): Climate Modeling

allenai.org/climate-modeling

HEADQUARTERS: Seattle, WA
ORGANIZATION TYPE: Research
AI2 is building modern machine learning into current climate models to improve their performance in key areas and ultimately to refine climate change predictions. The ML is trained on ultra-realistic 'digital twin' simulations of the Earth's atmosphere that exploit the world's fastest supercomputers.

Allen Institute for Artificial Intelligence (AI2): Wildlands

allenai.org/wildlands

HEADQUARTERS: Seattle, WA
ORGANIZATION TYPE: Research
They are applying machine learning to support wildland fire management and research workflows. Wildlands focuses on ground-level fuels that are not measurable with current satellite technology and are currently a neglected research area in wildfire research and management. The project uses current low-tech methodologies and applies computer vision to amplify its impact.

Atmo AI

www.atmo.ai

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Atmo AI is a deep learning model and platform for weather prediction to improve meteorology worldwide in the face of climate change.

AtmoRep

atmorep.org

HEADQUARTERS: Bonn, Germany
ORGANIZATION TYPE: Research
AtmoRep uses large-scale representation learning from artificial intelligence to determine a general description of the highly complex, stochastic dynamics of the atmosphere.

CLINT

climateintelligence.eu

HEADQUARTERS: Milano, Italy
ORGANIZATION TYPE: Research
CLINT uses machine learning algorithms and AI-enhanced climate science to monitor and analyze large climatological datasets to learn from and forecast the impact of weather events (including extreme events such as tropical cyclones, heat waves, and droughts).

Department of Defense's Defense Innovation Unit: xView2

xview2.org

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Public
The Pentagon's Defense Innovation Unit, in collaboration with Carnegie Mellon University, created the xView2 challenge, releasing a massive dataset of high-resolution satellite imagery for public use to encourage the computer vision community to help automate and improve building damage assessment after environmental disasters. While accuracy is dependent on cloud-free days, the technology has proven successful in supporting humanitarian relief efforts (for example, it was used to aid logistics and rescues in Turkey).

European Drought Observatory for Resilience and Adaptation: The European Drought Impacts database

http://edid-test.eu/#/home

HEADQUARTERS: Brussels, Belgium
ORGANIZATION TYPE: Public
The European Drought Impacts database includes a compilation of data on the impact of droughts between 1977 and 2022. The Drought Risk Atlas uses machine learning to simulate the effect that an increase in temperature of +1.5, 2, and 3 Degrees Celsius can have in the future. Developed by scientists at the Commission's Joint Research Centre, the projections show in which regions of the European Union water will become scarcer than elsewhere and which economic sectors and subsectors will be most affected.

Excarta

excarta.io

HEADQUARTERS: San Carlos, CA
ORGANIZATION TYPE: Private
Excarta uses AI research to produce best-in-class weather forecasts to make businesses more resilient to volatile weather.

Floodbase: Floodbase

www.floodbase.com

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Private
Floodbase uses satellites and AI to track floods in near real-time anywhere on Earth for parametric flood insurance products.

FuXi

charts.ecmwf.int/?facets=%7B%22Product%20type%22%3A%5B%22Experimental%3A%20Machine%20learning%20models%22%5D%7D

HEADQUARTERS: Shanghai, China
ORGANIZATION TYPE: Research
FuXi is a high-accuracy machine learning weather forecasting model developed in 2023, capable of interpreting up to 15-day predictions of global forecasts.

Google DeepMind: GraphCast

deepmind.google/discover/blog/graphcast-ai-model-for-faster-and-more-accurate-global-weather-forecasting

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
DeepMind's GraphCast is a machine learning-based weather forecasting method that seeks to improve weather forecasting and reduce their computational cost (the latest version can be run at a fraction of a standard weather forecasting model and thus can even be run on a personal computer). The GraphCast approach enables ten-day weather predictions at "unprecedented accuracy" in less than a minute and, therefore, opens up new possibilities for weather forecasting that have historically been computationally too expensive to be mainstream.

Google Research: Flood Hub

research.google/floodforecasting

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Private
Google Research's Flood Hub uses two AI models to simultaneously assess and forecast water flow (such as within a river) and predict water levels along areas of the waterway. With this system, entire populations can be alerted to impending floods—thereby limiting environmental and property damage and preventing fatalities.

Huawei: Pangu-Weather

HEADQUARTERS: Shenzhen, China
ORGANIZATION TYPE: Private
Huawei's Pangu-Weather Model, available on the European Centre for Medium-Range Weather Forecasts (ECMWF) website, offers 3D high-resolution medium-range global weather forecasting. Using AI, Pangu-Weather is more than 10,000 times faster than ECMWF's Integrated Forecasting System and is available for free, public use.

IBM's PAIRS Geoscope: IBM Environmental Intelligence Suite

ibm.com/products/environmental-intelligence-suite

HEADQUARTERS: Armonk, NY
ORGANIZATION TYPE: Private
The IBM Environmental Intelligence Suite empowers AI-driven solutions with vast geospatial data storage, curation, and model libraries tailored to specific business needs and workflows. Built on rich data sets, including historical, current, and forecast weather data and remote-sensing imagery.

Kayrros: Wildfire Risk Monitor for Insurance

kayrros.com

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
Kayrros's Wildfire Risk Monitor uses AI, satellite imagery, data fusion, and machine learning to evaluate wildfire risk, monitor wildfires, and assess damage after a wildfire has ended. Similarly, its Wildfire Risk Monitor for Insurance takes that information to create risk modeling tools to assist the insurance industry in minimizing insurer losses.

NASA: Earth System Digital Twin

esto.nasa.gov/earth-system-digital-twin/

HEADQUARTERS: Greenbelt, MD
ORGANIZATION TYPE: Public
The Advanced Information Systems Technology (AIST) program leads NASA's Earth System Digital Twins (ESDT) efforts, developing novel technologies for integrating diverse Earth and human activity models, continuous observations, and information system capabilities to provide unified, comprehensive representations and predictions that can be utilized for monitoring as well as for developing actionable information and supporting decision making. The three major components of an ESDT are a continuously updated Digital Replica of the Earth System of interest, dynamic Forecasting models, and Impact Assessment capabilities.

Climate Impacts (continued)

National Science Foundation Learning the Earth with Artificial Intelligence and Physics Center (LEAP): LEAP

leap.columbia.edu

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Research
The National Science Foundation Learning the Earth with Artificial Intelligence and Physics Center (LEAP) focuses on improving "near-term climate projections by merging physical modeling with machine learning across a continuum from expertise in climate science and climate modeling to cutting-edge machine learning algorithms." It seeks to use physics and machine learning to advance data science algorithms' ability to address real-world problems.

NVIDIA: Earth Climate Digital Twin

nvidianews.nvidia.com/news/nvidia-announces-earth-climate-digital-twin

HEADQUARTERS: Santa Clara, CA
ORGANIZATION TYPE: Private
NVIDIA and The Weather Company have teamed up to integrate meteorological data with AI tools to provide users with an efficient pathway to building digital twins, providing state-of-the-art diffusion modeling and fine-scale local data to enable high-resolution weather modeling products. Their tools are designed to simulate and visualize weather and climate at an unprecedented scale.

NVIDIA: FourCastNet

docs.nvidia.com/deeplearning/modulus/modulus-sym/user_guide/neural_operators/fourcastnet.html

HEADQUARTERS: Santa Clara, CA
ORGANIZATION TYPE: Private
Model: FourCastNet uses AI and satellite data to generate highly accurate short- to medium-range weather forecasting, which can be leveraged to predict extreme weather events and manage human and environmental preparations.

One Concern: Domino AI / Co-pilot

oneconcern.com/

HEADQUARTERS: Menlo Park, CA
ORGANIZATION TYPE: Private
One Concern uses AI and digital twins to help businesses become more climate resilient by analyzing their infrastructure's climate risk (extreme environmental and climate events). Their mission is to "make disasters less disastrous." Domino AI provides curated physical risk data for precise pricing. Domino Co-pilot provides advanced risk analysis to visualize downtimes.

Salo Sciences, Planet, Vibrant Planet: California Forest Observatory

forestobservatory.com/tour

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Research
The California Forest Observatory, a data-driven forest monitoring system. We map the drivers of wildfire hazards across the state—including forest structure, weather, topography & infrastructure—from space.

Schmidt Futures Multiscale Machine Learning in Coupled Earth System Modeling (M2LInES): M2LInES

m2lines.github.io

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Research
Supported by Schmidt Futures, Multiscale Machine Learning In Coupled Earth System Modeling (M2LInES) is an international collaborative project focused on innovating data and AI to improve climate models, using AI to emulate complex components of the climate system.

Terrafuse AI

terrafuse-ai.com

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Private
Terrafuse AI uses physics-enabled AI models to understand climate-related risk at a hyperlocal level for businesses and organizations interested in understanding the potential impact of climate and weather-related events on their operations. Terrafuse leverages historical wildfire data, numerical simulations, and satellite imagery on Microsoft Azure to model wildfire risk for any location. It also estimates temporal change in carbon density because of fire, deforestation, and other calamities.

The European Centre for Medium-Range Weather Forecasts: ECMWF Charts

charts.ecmwf.int/?facets=%7B%22Product%20type%22%3A%5B%22Experimental%3A%20Machine%20learning%20models%22%5D%7D

HEADQUARTERS: Reading, UK
ORGANIZATION TYPE: Public
ECMWF leverages AI, machine learning, and satellite imagery to monitor data points such as temperature and precipitation—data which can then be used to inform climate change mitigation solutions (such as wildfire predictions).

UC San Diego: ALERTwildfire

alertcalifornia.org

HEADQUARTERS: San Diego, CA
ORGANIZATION TYPE: Research
CAL FIRE, ALERTCalifornia, and industry partner DigitalPath developed a new AI system that provides early wildfire confirmation and actionable real-time data to quickly scale fire resources, helps evacuations through enhanced situational awareness, and monitors fire behavior. The AI platform is a new tool in the toolbox and allows data to drive firefighting decisions, which saves lives, protects habitats, and infrastructure.

UCLA, Microsoft: ClimaX

microsoft.github.io/ClimaX/

HEADQUARTERS: Los Angeles, CA
ORGANIZATION TYPE: Research
ClimaX is the first foundation model designed to perform a wide variety of weather and climate modeling tasks. ClimaX uses numerical models of the atmosphere to generate fast, accurate, data-driven weather forecasts, climate models, and projections that outperform other deep learning-based baselines across all key metrics.

University at Albany: Atmospheric Sciences Research Center (ASRC)

albany.edu/asrc

HEADQUARTERS: Albany, NY
ORGANIZATION TYPE: Research
ASRC is a leading institution fostering collaboration in and outside the university to advance research and technology in atmospheric science. One highlight of ASRC is its xCITE laboratory, directed by Dr. Kara Sulia. xCITE specializes in developing software and AI techniques for weather- and climate-related research. A second highlight is the New York State Mesonet (NYSM), a network of 126 weather stations operated by UAlbany and equipped with automated sensors that collect and disseminate a variety of weather-related data (temperature, humidity, wind speed, and direction, etc.), which is available to emergency managers and the public in real time.

WeatherBench

github.com/pangeo-data/WeatherBench

HEADQUARTERS: Cambridge, MA
ORGANIZATION TYPE: Research
WeatherBench is a benchmark dataset for data-driven weather forecasting.

xBD Dataset

xview2.org/dataset

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Research
The xBD Dataset is an annotated high-resolution satellite imagery for building damage assessment. The xView2 Building Damage Challenge builds on the previous xView 2018 Challenge for Object Detection. It focuses on applying innovative computer vision solutions to a specific problem in Humanitarian Assistance and Disaster Recovery (HADR).

Yokahu

yokahu.co

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Yokahu provides parametric weather insurance for climate risk resilience, having developed AI-driven products for hurricane forecast evacuation cover, wildfire evacuation, and post-wildfire/hurricane rent/mortgage coverage. Their tools are designed to protect climate-vulnerable communities.

Environmental Cross-cutting

Bayanat

bayanat.ohdstaging.com

HEADQUARTERS: Abu Dhabi, United Arab Emirates
ORGANIZATION TYPE: Private
Bayanat leverages AI to enhance its geospatial intelligence services, offering solutions across various sectors, such as smart cities, transportation, and the environment. Their AI-driven platforms integrate data analytics and multi-intelligence technologies to provide advanced geospatial data and analytics services, helping clients in decision-making and operational efficiencies.

BlueSky Analytics: Climate Data Hub/ SpaceTime

blueskyhq.io

HEADQUARTERS: The Hague, Netherlands
ORGANIZATION TYPE: Private
Blue Sky Analytics is a geospatial data intelligence company building an API-based catalogue of Environmental Datasets by leveraging Satellite data, AI, and cloud. Their products are used for ESG reporting, verification and transparency on carbon credits, and climate risk assessments.

Climate Change AI

climatechange.ai

HEADQUARTERS: Pittsburgh, PA
ORGANIZATION TYPE: Nonprofit
Climate Change AI (CCAI) is an organization composed of volunteers from academia and industry who believe that tackling climate change requires concerted societal action, in which machine learning can play an impactful role. Since it was founded in June 2019 (and established as a US domestic non-profit on June 14, 2021), CCAI has led the creation of a global movement in climate change and machine learning, encompassing researchers, engineers, entrepreneurs, investors, policymakers, companies, and NGOs.

Climate Policy Radar

climatepolicyradar.org/

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Nonprofit
Climate Policy Radar is building machine learning models that, with NLP, can parse information from large numbers of documents on climate law and policy worldwide. Its data is open-source, which allows for more democratic information-sharing.

Earth Species Project

earthspecies.org

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Nonprofit
Earth Species' mission is to use AI to decode or deepen the understanding of non-human communication. The work is mainly focused on fundamental research, which gives the basis for the further application of the research outcomes in the climate- and conservation-related domains.

EcoBot

ecobot.com/

HEADQUARTERS: Asheville, NC
ORGANIZATION TYPE: Private
Ecobot uses AI to help businesses manage and meet the requirements of environmental assessments.

Microsoft: Planetary Computer

planetarycomputer.microsoft.com

HEADQUARTERS: Redmond, WA
ORGANIZATION TYPE: Private
Launched in 2020, Microsoft's Planetary Computer unites different tools with AI in a way that not only allows for many different applications of its technology in different areas of climate and nature but also enables partners to build on top of its platform, thereby enhancing the impact of sustainability practitioners. The Planetary Computer contains petabytes of data ranging from satellite imagery and weather data to land cover and species distribution data.

SkyTruth

skytruth.org

HEADQUARTERS: Shepherdstown, WV
ORGANIZATION TYPE: Nonprofit
Skytruth uses AI, satellite data, cloud computing, and data science to generate atmospheric and weather insights and monitor environmental activities. Their mission is to protect the planet, and their catchphrase is "If you see it, you can change it."

World Resources Institute: Resource Watch

resourcewatch.org

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Nonprofit
Resource Watch develops a multitude of AI-powered data insights that can be applied across energy, forests and land management, food and agriculture, ocean and freshwater management, climate monitoring, and urban environments to solve problems caused by human impact on the planet.

Food + Agriculture

Aerofarms

aerofarms.com

HEADQUARTERS: Danville, VA
ORGANIZATION TYPE: Private
Aerofarms creates digital pathways to smart farms, integrating machine vision, machine learning, and Internet of Things technologies to optimize agricultural operations. They utilize integrated algorithms and agSTACK software with integrated PLC and SCADA systems.

AgroScout

agro-scout.com

HEADQUARTERS: Yir'on, Israel
ORGANIZATION TYPE: Private
AgroScout combines AI and machine learning with high-resolution images from the ground (via smartphone), from the air (via drones), and from space (via satellites) to create a desktop and mobile platform for farmers to better monitor their crops. The tool helps growers reduce waste, optimize farm operations (seeding, watering, fertilizing, etc.), and identify anomalies early.

Agrosmart: BoosterAGRO/ ESG Platform/ Agrosmart Nexus

agrosmart.com.br/about

HEADQUARTERS: São Paulo, Brazil
ORGANIZATION TYPE: Private
The largest climate intelligence platform in Latin America, Agrosmart is a private company dedicated to merging big data and analytics with agriculture in a way that helps find routes to more efficient, sustainable, and climate-resilient food systems. They have created a variety of service platforms that, through machine learning algorithms, help farmers and other stakeholders across Central and South America to optimize their production and supply chain operations, give them a competitive advantage, and make them wiser and stronger contributors to the communities they serve.

Alliance for a Green Revolution in AFrica (AGRA): AGRA

agra.org

HEADQUARTERS: Nairobi, Kenya
ORGANIZATION TYPE: Nonprofit
AGRA is an African collaboration of organizations working toward supporting food and agriculture efforts in Africa, addressing food insecurity, and making farming more sustainable and climate resilient. In partnership with Atlas AI, one of its initiatives around predictive analytics for smallholder agriculture is using satellite imagery and machine learning to develop insights for smallholder farmers regarding land use, yields, peak time for harvest, input distribution gaps, and other contextual monitoring aspects.

Food + Agriculture (continued)

Amini

amini.ai

HEADQUARTERS: Nairobi, Kenya
ORGANIZATION TYPE: Private
Amini uses AI and space technologies to collect massive amounts of environmental data that can inform new tools for smallholder farmers and make the farm-to-table supply chain more resilient. It aims to address environmental data scarcity in Africa.

Benson Hill: Cloud Biology/ Crop OS

bensonhill.com

HEADQUARTERS: Saint Louis, MO
ORGANIZATION TYPE: Private
Benson Hill's Cloud Biology converges big data with plant biology. Their CropOS(,Ñ¢) initiative, in tandem, is a crop design platform created to make that data accessible and actionable. It combines AI, machine learning, and data analytics to vastly increase the speed and precision of genomic crop breeding while reducing breeding trade-offs, such as optimizing yield at the expense of nutrition.

Better Origin: X1

betterorigin.co.uk

HEADQUARTERS: Cambridge, UK
ORGANIZATION TYPE: Private
Better Origin's X1s are AI-powered insect farms purchasable by stakeholders within food and agriculture. Food waste is placed into X1s alongside insect larvae; the X1 converts the food waste into larvae feed. Then, the larvae consume the feed and grow over the course of a few weeks, are harvested, and finally delivered directly to agricultural animals as a sustainable form of protein.

Biocraft

biocraftpet.com

HEADQUARTERS: Vienna, Austria
ORGANIZATION TYPE: Private
Biocraft Pet Nutrition leverages AI and machine learning to generate more sustainable and nutritious protein options for pets.

Blue River Technology: See and Spray

bluerivertechnology.com/our-mission/

HEADQUARTERS: Sunnyvale, CA
ORGANIZATION TYPE: Private
Blue River Technology solution leverages deep learning algorithms paired with a computer vision system to create the ultimate virtual field scout for agriculture. Through 5+ years of collecting millions of images of plants and weeds across hundreds of thousands of acres, See & Spray,Ñ¢ is capable of detecting a variety of crops and weeds to provide weed control throughout a growing season.

Cellcraft

cellcraft.com

HEADQUARTERS: Cambridge, UK
ORGANIZATION TYPE: Private
Cellcraft leverages AI to create unique and potentially more sustainable ways to produce meat (i.e., cultivated meat that is grown in labs).

ClariFruit

clarifruit.com

HEADQUARTERS: Rishon Le-zion, Israel
ORGANIZATION TYPE: Private
Clarifruit's quality control platform (along with the parallel mobile application) uses computer vision and machine learning to relieve human inspectors from the time-consuming task of inspecting fruit products by hand. The computer vision models grow increasingly accurate over time, creating an efficient, practical pathway for meeting customer quality standards, reducing waste, and maximizing profit.

Climate AI

climate.ai

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
ClimateAi has several digital platforms that use AI models to gather and assess climate and weather data in order to generate valuable, easy-to-interpret insights for actors across food and agriculture, industry, energy, the public sector, and others to better prepare for and adapt to, the effects of climate change on their respective operations.

Climate LLC: Fieldview

climate.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
FieldView is helping address one of our planet's most pressing challenges, growing more with fewer natural resources. The power of machine learning, artificial intelligence, and data science can help farmers bring a new level of precision to every seed, chemical, machine, and decision. CO_2

Climax Foods: Deep Plant Intelligence Platform

climax.bio

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Private
Climax's Deep Plant Intelligence platform uses machine learning to support the creation of new, plant-based ingredients that can serve as much more sustainable replacements for animal-based products in the food industry.

Cropx

cropx.com

HEADQUARTERS: Netanya, Israel
ORGANIZATION TYPE: Private
CropX is a farm management system that combines farm data, weather conditions, and agronomic knowledge to help farmers make informed decisions that help optimize their operations and increase crop yields.

CULT Food Science

cultfoodscience.com

HEADQUARTERS: Vancouver, Canada
ORGANIZATION TYPE: Private
CULT Food Science leverages AI to create products aimed toward developing sustainable and ethically sourced cellular agriculture ingredients and products and accelerating them to market.

Equinom

equi-nom.com

HEADQUARTERS: Givat Brenner, Israel
ORGANIZATION TYPE: Private
Equinom uses AI to assist with plant breeding, allowing for easier and more efficient creation of plant-based ingredients that are better for the environment as well as human consumers.

Eternal

eternal.bio

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Eternal uses AI to support automatic experimentation and analysis in the creation of alternative proteins for consumption (such as Mycofood, a fungal-based product) to help alleviate energy and water consumption required for animal-based proteins.

FruitCast

fruitcast.co.uk

HEADQUARTERS: Lincoln, UK
ORGANIZATION TYPE: Private
FruitCast uses AI to scan soft fruit crops, predicting and increasing yields and reducing waste.

Ginkgo Bioworks

ginkgobioworks.com

HEADQUARTERS: Boston, MA
ORGANIZATION TYPE: Private
Ginkgo Bioworks uses technology to program cells to create many different types of products—including more sustainable, climate-smart solutions for agriculture.

Harvest CROO

harvestcroorobotics.com

HEADQUARTERS: Tampa, FL
ORGANIZATION TYPE: Private
Harvest CROO Robotics helps strawberry farmers automate their crop management, harvesting, and packing. Their harvesting services, which help reduce food waste and increase crop yields, are estimated to reduce CO_2 emissions. AI and machine learning vision are used to inspect each strawberry for health and ripeness, which then instructs the robot to selectively and gently pick berries. Harvest CROO Robotics is a recipient of the National Science Foundation Award.

IBM: Watson Decision Platform for Agriculture

ibm.com/downloads/cas/0XZ0VRAW

HEADQUARTERS: Armonk, NY
ORGANIZATION TYPE: Private
The Watson Decision Platform combines decades of IBM research, AI, and IoT data to generate predictive insights and a suite of low-cost solutions to help stakeholders across different agricultural roles make more informed decisions. The platform can help them find pathways to increasing the profitability and quality of their produce through data on local weather, soil, farm equipment, workflow, and visuals (satellite and drone images).

Food + Agriculture (continued)

Inari: SEEDesign

inari.com

HEADQUARTERS: Cambridge, MA
ORGANIZATION TYPE: Private
Inari's digital platform, SEEDesign, leverages AI and gene editing to identify gene combinations for more resilient, more nutritious, and more robust crops.

Indigo Agriculture

indigoag.com

HEADQUARTERS: Boston, MA
ORGANIZATION TYPE: Private
Indigo Agriculture uses AI to analyze the microbiome of soil on farms, drawing insights to help farmers optimize their crop yields and land usage.

International Rice Research Institute: Fit-for-Future Genetic Resources unit

irri.org

HEADQUARTERS: Los Banos, Leguna, Philippines
ORGANIZATION TYPE: Research
IRRI's Fit-for-Future Genetic Resources unit has received a *Google.org* grant to integrate AI and high-throughput phenotyping methodologies into IRRI's gene bank, the largest rice gene bank in the world, consisting of over 132,000 types of rice from 132 countries. AI will assess existing rice genotypes for resistance to environmental stressors associated with climate change, such as flooding, drought, and salinity.

Kilimo

kilimo.com

HEADQUARTERS: Cordoba, Argentina
ORGANIZATION TYPE: Private
Kilimo reduces water usage and waste in agriculture by providing farmers with an easy-to-use, machine learning-driven platform where they can review their irrigation data and receive recommendations for cutting back water usage.

Nokia/ Vodafone Foundation: Smart-Agriculture-as-a-service

nokia.com/about-us/newsroom/articles/iot-unlocking-the-potential-of-precision-farming/

HEADQUARTERS: Espoo, Finland
ORGANIZATION TYPE: Private
Links field sensors and Nokia's Worldwide Internet of Things Network Grid (WING) via a mobile network operator to provide information to farmers via mobile and web-based applications. The packages include environmental monitoring and pest management, crop monitoring and management, soil monitoring and management, and an advisory center.

NotCo: The Giuseppe Platform

notco.ai

HEADQUARTERS: Santiago, Chile
ORGANIZATION TYPE: Private
NotCo's Giuseppe Platform is an AI-powered platform that helps discover novel, more sustainable, plant-based products for the food industry.

Plantix: Crop Doctor App

plantix.net/en

HEADQUARTERS: Berlin, Germany
ORGANIZATION TYPE: Private
The Plantix Crop Doctor is the world's most downloaded app for farmers - combining artificial intelligence and the expertise of leading research institutions around the globe. Millions of customers use the Plantix farmers' app to diagnose crop problems and get unbiased recommendations about treatments and the best-suited products at a local store.

Plenty

plenty.ag

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Plenty is a startup seeking to create more sustainable farms. Their two-acre, indoor vertical farm is capable of generating what 720 acres of traditional farmland would yield. It does so by using AI to monitor the farm environment (water use, light, temperature) and determine which combination, to what degree, produces the highest-quality produce (managed by robots). They claim this also reduces typical water use for farming by 95%.

Protein Industries Canada

proteinindustriescanada.ca

HEADQUARTERS: Regina, Canada
ORGANIZATION TYPE: Nonprofit
Protein Industries Canada uses AI to advance agrifood and create sustainable, plant-based food products.

Protera

proterabio.com

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
Protera uses protein engineering and AI to generate more sustainable ingredients that can be used in the food industry.

Shiru: Flourish

shiru.com

HEADQUARTERS: Alameda, CA
ORGANIZATION TYPE: Private
Shiru's AI platform, Flourish, accelerates ingredient discovery for sustainable, functional protein alternatives.

Spoiler Alert

spoileralert.com

HEADQUARTERS: Boston, MA
ORGANIZATION TYPE: Private
Spoiler Alert uses machine learning to help reduce food waste at a high level by optimizing sales, supply chains, and inventory management for brands.

Sprout

sproutprotect.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Sprout offers smallholder farmers climate change protection via their smartphones. The app, which delivers assessments and alerts based on satellite data and machine learning, helps farmers make decisions about their crops based on expected rainfall, temperature, soil moisture, and other data points. They also offer crop insurance and work with insurance companies to connect farmers' products to the local market.

University of Maryland: NASA Harvest

nasaharvest.org/about

HEADQUARTERS: College Park, MD
ORGANIZATION TYPE: Public
NASA Harvest is a global consortium of multidisciplinary experts led by the University of Maryland, aimed at broadening the use of Earth observations to deliver critical food security and agricultural assessments. The program leverages NASA's Earth observations from space to provide data, products, tools, and predictions relevant to agricultural producers, traders, agencies, and others. Many of their projects use AI to enhance their agricultural monitoring and food security applications, such as crop mapping, yield prediction, drought monitoring, or food insecurity mapping

Vertical Future: DIANA

verticalfuture.com

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Vertical Future's vertical farm systems include sophisticated and adaptable lighting, nutrient delivery (aeroponic & hydroponic), effective space utilization, and end-to-end automation (with in-house robotics), eliminating resource-intensive production bottlenecks. Vertical Futures utilizes DIANA, an advanced Software as a Service (SaaS) product that enables operators to control, monitor, and optimize growing conditions. The platform works hand in hand with thousands of sensors to provide a high degree of control and efficiency across the entirety of the growing environment and broader farm operations.

Wadhwani AI: CottonAce

wadhwaniai.org/programs/pest-management

HEADQUARTERS: New Delhi, India
ORGANIZATION TYPE: Nonprofit
CottonAce is an AI-powered early warning system that helps farmers determine optimal pesticide spray times and schedules for their crops, protecting them from pests and increasing crop outputs.

Winnow

winnowsolutions.com

HEADQUARTERS: Milton Keynes, UK
ORGANIZATION TYPE: Private
Winnow's platform uses cameras and VisionAI to help kitchens reduce food waste by monitoring food stores and identifying waste, identifying when food is thrown away, and monitoring costs and trends. This, in turn, helps chefs make informed decisions that help cut down the amount and cost of their food waste.

Forests and Land Management

Allen Institute for Artificial Intelligence (AI2): EarthRanger

allenai.org

HEADQUARTERS: Seattle, WA
ORGANIZATION TYPE: Research
AI2's software product, EarthRanger, helps conservationists, ecologists, biologists, and protected land managers make more informed decisions in wildlife conservation.

Australian Acoustic Observatory (A2O) Queensland University of Technology: Australian Acoustic Observatory (A2O)

acousticobservatory.org

HEADQUARTERS: Brisbane, Australia
ORGANIZATION TYPE: Research
Funded by an Australian Research Council grant, A2O is a continental-scale acoustic sensor network that is recorded for a five-year period across multiple Australian ecosystems. The data are freely available to researchers, citizen scientists, and the general public.

CollectiveCrunch

collectivecrunch.com

HEADQUARTERS: Espoo, Finland
ORGANIZATION TYPE: Private
CollectiveCrunch is an AI as SaaS startup that uses remote sensing along with field and machine data to digitalize forestry—providing critical monitoring analysis data for tens of millions of hectares of forest that can then be used in harvest planning and proposals, supporting forestry practices, improving harvest yields, streamline the forestry supply chain, as well as forestry predictions.

Conservation AI

conservationai.co.uk

HEADQUARTERS: Liverpool, UK
ORGANIZATION TYPE: Nonprofit
Conservation AI uses advanced machine learning techniques to identify a wide range of animal species in different habitats from images. They can also recognize humans and artificial objects, which can support conservation efforts (such as identifying vehicles, which are often used in poaching activities).

Conservation X Labs: Sentinel AI

sentinel.conservationxlabs.com

HEADQUARTERS: Washington, DC **ORGANIZATION TYPE:** Private
Sentinel AI uses wildlife monitoring tools (like trail cameras and acoustic recorders) alongside AI to process environmental data as it is collected in real-time. Satellite and cellular networks allow conservationists to respond rapidly to wildlife-related threats. With it, they can monitor invasive species, poaching and wildlife trafficking, zoonotic diseases, and changing animal behavior.

Cornell University: bioCLIP

imageomics.github.io/bioclip/

HEADQUARTERS: Ithaca, NY
ORGANIZATION TYPE: Research
BioCLIP is a digital platform consisting of a multimodal foundation model trained on a new 10M-image dataset of biological organisms with fine-grained taxonomic labels. It contains 10 million images of about half a million species covering insects, plants, and animals.

Cornell University: BirdNET

birdnet.cornell.edu

HEADQUARTERS: Ithaca, NY
ORGANIZATION TYPE: Research
Cornell's BirdNET is a citizen science platform that leverages AI, low-power microchips, and acoustic sensors to identify bird sounds of specific species.

Cornell University: K. Lisa Yang Center for Conservation Bioacoustics

birds.cornell.edu/ccb

HEADQUARTERS: Ithaca, NY
ORGANIZATION TYPE: Research
Researchers at the Center conduct a broad range of terrestrial, aquatic, and marine bioacoustic research, often at large geographic scales. Many of their projects are applied, featuring a strong focus on the conservation of endangered species. More recently, they have engaged in soundscape ecology research and the development of acoustic metrics to assess biodiversity and ecosystem health. They are also researching new ways to collect and analyze acoustic data sets using autonomous mobile systems and algorithm development.

Cornell University: Merlin

merlin.allaboutbirds.org

HEADQUARTERS: Ithaca, NY
ORGANIZATION TYPE: Research
Co-developed by CalTech and Cornell University, Merlin is a smartphone application that uses an AI model trained on large amounts of visual and audio data to allow its users to identify bird species via recordings or photos.

CTrees

ctrees.org

HEADQUARTERS: Pasadena, CA
ORGANIZATION TYPE: Nonprofit
A nonprofit organization using remote sensing technology for land carbon monitoring, including monitoring, verifying, and reporting carbon stocks and deforestation/land-use monitoring.

Dendra Systems: RestorationOS

dendra.io

HEADQUARTERS: Oxford, UK
ORGANIZATION TYPE: Private
Dendra Systems' RestorationOS is a platform that uses AI to generate ecosystem insights and assist with managing land and environments to support the rehabilitation of ecosystems and restoration of natural landscapes. Applications include aerial seeding services powered by drone technology.

DHI A/S: MUSE

dhigroup.com/technologies/muse

HEADQUARTERS: Hørsholm, Denmark
ORGANIZATION TYPE: Private
Based on artificial intelligence and advanced video analysis, MUSE AI allows for reducing the speed of offshore wind turbines when specific bird species fly by, which is increasingly becoming a regulatory requirement in many countries. The result is optimized capacity utilization and more robust bird protection against wing collision.

GainForest

gainforest.earth

HEADQUARTERS: Zurich, Switzerland
ORGANIZATION TYPE: Nonprofit
GainForest's mission is to fight deforestation in the Amazon. The GainForest platform uses AI and blockchain-based contracts to generate novel incentives for communities that can impact Amazon's protection efforts.

Impact Observatory: IO Monitors

impactobservatory.com/10m-land-cover

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Private
AI-powered geospatial monitoring to understand risks and anticipate change at unprecedented speed and scale. This includes land use, land cover change, and ecosystem health, among others. (IO Monitor 3m Land Cover, 10m Land Cover, and IO Maps for Good).

iNaturalist

inaturalist.org/pages/computer_vision_demo

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Nonprofit
A crowd-sourcing of biodiversity science, iNaturalist is a tool that allows scientists and conservationists to support other scientists by logging observations from the ground. The tool uses AI to identify specific species from images, each of which is a verifiable observation. Data garnered from observations is also shared with data repositories like the Global Biodiversity Information Facility.

iWildCam: iWildCam Competition

github.com/visipedia/iwildcam_comp

HEADQUARTERS: Arlington, VA
ORGANIZATION TYPE: Research
The iWildCam competition is a challenge where participants develop machine learning models to identify wildlife from camera trap images, which are automatic cameras activated by motion or heat sensors in natural habitats. Hosted on platforms like Kaggle and GitHub, this competition helps improve automated image recognition to assist conservationists in monitoring animal populations and biodiversity.

Jocotoco Foundation

jocotoco.org.ec/wb#/EN/TheFoundation

HEADQUARTERS: Quito, Ecuador
ORGANIZATION TYPE: Nonprofit
Founded in 1998, the Jocotoco Foundation is an Ecuadorian NGO focused on protecting threatened species in Ecuador and conserving their habitats, largely through the establishment of wildlife reserves. Researchers from Jocotoco have recently leveraged AI to assist in species identification through audio data, tracking biodiversity in Ecuador's rainforests.

Kanop

kanop.io

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
Data analytics (SaaS) platform for forestry due diligence, compliance, and sustainable forestry management practices.

Forests and Land Management (continued)

Land Life Company

landlifecompany.com

HEADQUARTERS: Amsterdam, Netherlands
ORGANIZATION TYPE: Private
Land Life Company leverages AI, drones, and other technology to support the reforestation efforts of landowners as well as companies.

MORFO

morfo.rest/en

HEADQUARTERS: Rio de Janeiro, Brazil
ORGANIZATION TYPE: Private
MORFO has developed a solution for large-scale ecological restoration of forest ecosystems using forest engineering, computer vision, and drones. Focusing primarily on tropical and subtropical regions that were previously forested and have been deforested, becoming unproductive. The company provides analysis, seed selection, plantation using drones, and forest monitoring.

Naturalis Biodiversity Center: Bioacoustic AI

bioacousticai.eu/

HEADQUARTERS: Leiden, Netherlands
ORGANIZATION TYPE: Research
A research project that aims to develop AI algorithms to create a new generation of smart wildlife microphones with the objective of using acoustic monitoring to help protect wildlife.

NatureServe: The Map of Biodiversity Importance

www.natureserve.org/map-biodiversity-importance

HEADQUARTERS: Arlington, VA
ORGANIZATION TYPE: Nonprofit
NatureServe is a network hub for 60+ governmental and NGO programs in the U.S. and Canada that leverage science, AI, and data analytics to deliver insights that inform conservation action. In collaboration with The Nature Conservancy, Esri, and Microsoft, NatureServe used machine learning and cloud computing to create high-resolution individual species habitat maps for thousands of at-risk species in the conterminous US. These maps include detailed habitats of vertebrates, plants, aquatic invertebrates, and insects, providing a new synoptic view of biodiversity importance for imperiled species. When these maps are combined and overlaid with protected areas, it is easy to identify the most critical places in the country for conserving at-risk species.

NCX

ncx.com

HEADQUARTERS: Dallas, TX
ORGANIZATION TYPE: Private
NCX uses AI and satellites to generate precision forestry data and help landowners and managers make their operations more sustainable by connecting their data to dozens of programs that both encourage and reward sustainable change.

Ohio State University: ABC Global Climate Center

sites.google.com/view/abcglobalclimatecenter

HEADQUARTERS: Columbus, OH
ORGANIZATION TYPE: Research
The Artificial Intelligence and Biodiversity Change (ABC) Global Climate Center brings together ecologists and computer scientists from six universities in the United States and Canada to develop new AI-enabled, data-supported approaches for understanding the impacts of climate change on biodiversity. The Center will develop and implement a variety of AI-based methods and tools for integration and analysis of biodiversity data from remote sensing imagery from satellites and low-flying aircraft, ground-based visual and audio sensors, DNA sequences, and citizen science efforts, enabling global monitoring, analysis, and assessment of biodiversity changes.

Pachama

pachama.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Pachama uses satellite data and AI to improve carbon credits, including forest restoration and conservation.

Planet

planet.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Planet uses satellites to provide high-quality images to organizations that inform climate action. They also train AI and machine learning models on satellite imagery to build algorithms that can draw insights from those images, objects, and patterns that can then help identify interventions and create tools to solve climate and conservation problems worldwide.

Purdue University, FACAI: Forest Advanced Computing and Artificial Intelligence Lab

ag.purdue.edu/facai/

HEADQUARTERS: West Lafayette, IN
ORGANIZATION TYPE: Research
At Perdue University, the Forest Advance Computing and Artificial Intelligence Lab (FACAI) uses state-of-the-art AI and global resources to conduct globally consistent yet locally relevant research on forest ecosystems. FACAI also compiled the largest global in situ terrestrial biodiversity database (GFI-3D) and developed the first AI-based forest growth models (MATRIX). MATRIX aims to make forest growth models more affordable and accurate for developing countries, aiding in forest carbon accounting, forest management, and forest conservation and restoration.

Rainforest Connection: Arbimon

arbimon.org

HEADQUARTERS: Katy, TX
ORGANIZATION TYPE: Nonprofit
Arbimon is an open-source ecoacoustic analysis platform empowering scientists and conservationists with an efficient way to upload, store, and analyze mass amounts of acoustic data, enabling the ability to derive insights about the ecosystem at scale.

Terramonitor

terramonitor.com

HEADQUARTERS: Helsinki, Finland
ORGANIZATION TYPE: Private
Terramonitor uses AI, satellite images, machine learning, and remote sensing to monitor land change (such as vegetation cover and infrastructure assessments) to provide data-driven insights to customers, helping them make more informed decisions when it comes to environmental impact.

The Nature Conservancy (TNC): TNC

nature.org

HEADQUARTERS: Arlington, VA
ORGANIZATION TYPE: Nonprofit
TNC uses drones to generate massive amounts of complex visual data, which are then analyzed with AI-driven tools. These tools allow for the rapid identification of different animal species, supporting the tracking of populations and conservation efforts.

Timbeter

timbeter.com

HEADQUARTERS: Tallinn, Estonia
ORGANIZATION TYPE: Private
Timbeter leverages AI and machine learning to help industry and government stakeholders make forestry more sustainable and efficient.

University of California, Berkeley: Eric and Wendy Schmidt Center for Data Science & Environment (DSE)

dse.berkeley.edu/

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Research
Located at the University of California, Berkeley, the Eric and Wendy Schmidt Center for Data Science & Environment (DSE) has a variety of projects that leverage artificial intelligence and machine learning to solve ecology, conservation, and agricultural challenges. The project includes the co-design of Technology for Tribal Environmental Stewardship, Solving the Snow Problem with Remotely Sensed Data, and Ending Plastic Pollution Forever which created the Global Plastics AI Policy Tool (*https://global-plastics-tool.org*)

University of Minnesota Twin Cities: AI-Climate Institute

cse.umn.edu/aiclimate

HEADQUARTERS: Minneapolis, MN
ORGANIZATION TYPE: Research
Led by the University of Minnesota, researchers at the AI Institute for Climate-Land Interactions, Mitigation, Adaptation, Tradeoffs and Economy (AI-CLIMATE) want to leverage AI to create more climate-smart practices that will absorb and store carbon while simultaneously boosting the economy in the agriculture and forestry industries. AI-CLIMATE is one of the new National Artificial Intelligence Research Institutes, developed in partnership with the National Science Foundation (NSF) and the U.S. Department of Agriculture's (USDA) National Institute of Food and Agriculture (NIFA).

Forests and Land Management (continued)

University of Pittsburgh: Kitzes Lab

kitzeslab.org

HEADQUARTERS: Pittsburgh, PA
ORGANIZATION TYPE: Research
The lab is focused on researching biodiversity loss in landscapes affected by human activities. Its work primarily revolves around understanding species distributions, scarce and hard-to-detect species, using techniques from terrestrial bioacoustics. It develops and applies methods involving automated acoustic field recorders and machine learning models to address questions related to natural history, conservation, and ecology, with a focus on temperate breeding birds and anurans.

Wild Me: Codex / Wildbook

wildme.org/codex-and-wildbook.html

HEADQUARTERS: Portland, OR
ORGANIZATION TYPE: Nonprofit
Wild Me's Codex and Wildbook is an autonomous, cloud-based, open-source multi-user software that utilizes AI and machine learning to support the analysis of large volume crowd-sourced images to both interpret visual data and track wildlife data and enable collaborative wildlife studies. The program took part in NVIDIA's Inception Incubator Program.

WILDLABS

www.wildlabs.net

HEADQUARTERS: Cambridge, UK
ORGANIZATION TYPE: Network
WILDLABS is home to the global conservation technology community of 8,600 people in 120 countries discussing 1,500 topics like biologging, camera traps, and machine learning.

Wildlife Insights

wildlifeinsights.org

HEADQUARTERS: Arlington, VA
ORGANIZATION TYPE: Network
Wildlife Insights combines field expertise, sensors, and advanced analytics to generate valuable wildlife data. Users all over the world can upload images of wildlife—which Wildlife Insight's algorithm automatically identifies. It dramatically increases the speed of processing and analyzing images and camera trap data to get information to decision-makers in near- real-time.

Wildlife Protection Solutions: wpsWatch

wildlifeprotectionsolutions.org

HEADQUARTERS: Golden, CO
ORGANIZATION TYPE: Nonprofit
Wildlife Protection Solutions wpsWatch is a mobile and desktop app for researchers and conservationists, as well as land reserve managers and their security staff. It uses camera traps, sensors, and AI to automatically identify threats to wildlife (such as poaching and other illegal activity) and notify users.

Woodwell Climate Research Center: Permafrost Discovery Gateway

woodwellclimate.org/

ORGANIZATION TYPE: Nonprofit
HEADQUARTERS: Falmouth, MA
Online platform to visualize and analyze geospatial data in the Arctic landscape for trends and drivers of permafrost thaw datasets.

World Resources Institute: Global Forest Watch

globalforestwatch.org

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Nonprofit
An online platform that provides data and tools based on machine learning models for monitoring forests, allowing anyone to access near-real-time information about where and how forests are changing around the world. Their mobile app, Forest Watcher, takes that same data and makes it available via smartphone.

World Wildlife Fund: Wildlife Crime Technology Project

www.worldwildlife.org/projects/wildlife-crime-technology-project

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Nonprofit
Leveraging artificial intelligence through camera traps, drones, and IoT, the Wildlife Crime Technology Project focuses on addressing the challenges of spotting poachers at night and improving the connectivity and real-time sharing of information from digital sensors. The project is being implemented across the African continent.

Freshwater Management

Aquaconnect: Aquasat

aquaconnect.blue

HEADQUARTERS: Chennai, India
ORGANIZATION TYPE: Private
Aquasat uses AI and satellite remote sensing to bring transparency and efficiency into the aquaculture value chain. Geospatial data, powered by deep learning models, allows us to democratize pond boundaries, validate between fish & shrimp ponds, and predict the days of culture.

ASTERRA

asterra.io

HEADQUARTERS: Kfar Sava, Israel
ORGANIZATION TYPE: Private
ASTERRA's platform takes data from satellites and uses patented algorithms and artificial intelligence to detect leaks, assess pipes, and locate moisture near significant installations.

BioFishency

biofishency.com

HEADQUARTERS: Atlit, Israel
ORGANIZATION TYPE: Private
Biofishency uses AI, machine learning, and sensors to help make fish farming more sustainable and cost-effective.

DHI A/S: Global Wetland Watch

www.globalwetlandwatch.org

HEADQUARTERS: Hørsholm, Denmark
ORGANIZATION TYPE: Private
Using satellite imagery and big data analytics, the project will develop an AI-based algorithm to extract systematic and accurate information on wetland ecosystems to advance the world's understanding and management of wetlands.

Fracta

fracta.ai

HEADQUARTERS: Palo Alto, CA
ORGANIZATION TYPE: Private
Fracta uses machine learning to monitor drinking water distribution mains and identify risks. It helps both react and prevent events, helping companies reduce water waste and maintain/improve water quality.

Griffith University: Global Wetlands Project

globalwetlandsproject.org

HEADQUARTERS: Gold Coast, Australia
ORGANIZATION TYPE: Research
The Global Wetlands Project is an international research initiative that leverages AI to create multiple types of apps and tools to support ecology monitoring and conservation efforts across land as well as marine and freshwater ecosystems.

Freshwater Management (continued)

Indra: Reservoir Guard

indrallc.tech

HEADQUARTERS: Miami, FL
ORGANIZATION TYPE: Private
Indra's Reservoir Guard is a platform that uses AI to monitor reservoirs and help managers and municipalities make them more efficient and sustainable.

NASA: TERRAHydro

esto.nasa.gov/ai-powered-terrahydro-could-help-hydrologists-better-understand-the-water-cycle/

HEADQUARTERS: Greenbelt, MD
ORGANIZATION TYPE: Public
NASA's "Terrestrial Environmental Rapid-Replication and Assimilation Hydrometeorological" (TERRAHydro) software aims to revolutionize the creation of composite hydrological models using artificial intelligence. This open-source tool uses tensor-based modeling to help researchers more effectively integrate existing datasets and AI components into new models that describe dynamic aspects of the water cycle. TERRAHydro is poised to become a foundational software for Earth System Digital Twins, enhancing real-time model updates, predictions, and 'what-if' analyses using data from diverse airborne, spaceborne, and in-situ sensors.

NatureDots: AquaNurch

naturedots.com

HEADQUARTERS: New Delhi, India
ORGANIZATION TYPE: Private
NatureDots addresses loss in freshwater fishing and fish farming caused by water quality fluctuations. Its platform, AquaNurch, uses sensors as neural nodes in combination with AI models to assess water quality, identify water disturbances, and send insights to fish farmers on the ground.

Nexogensis

nexogensis.eu

HEADQUARTERS: Delft, Netherlands
ORGANIZATION TYPE: Network
Nexogenisis facilitates the next generation of effective and intelligent water-related policies utilizing artificial intelligence and reinforcement learning to assess the water-energy-food-ecosystem nexus. The project is funded by the European Union's Horizon 2020 program, which aims to support the development of policies that manage resources effectively.

Princeton University and University of Arizona: HydroGEN

hydrogen.princeton.edu

HEADQUARTERS: Princeton, NJ
ORGANIZATION TYPE: Research
The National Science Foundation (NSF) has awarded a $5 million grant to researchers from Princeton University and the University of Arizona to develop the HydroGEN (Hydrologic Scenario Generation) project, which will use machine learning and artificial intelligence to create simulated models of the nation's watershed systems. The project aims to integrate various data sources and modeling techniques to improve the prediction and management of water systems across the country. This initiative addresses critical challenges such as water scarcity, flooding, and infrastructure needs and is part of a broader effort to enhance the resilience and sustainability of U.S. water resources in the face of changing climate conditions and increasing demand.

RainGrid: Intelligent Rain Retention and Reuse (IR3)

raingrid.com

HEADQUARTERS: Toronto, Canada
ORGANIZATION TYPE: Private
RainGrid's mission is to help build more climate-resilient communities. Their IR3 system is a "community scale, property-based digital rain harvesting network" solution that uses AI and IoT technology to improve stormwater management. They claim that with IR3, stormwater runoff is virtually eliminated when used, and local watersheds are regenerated.

Smart Lagoon

smartlagoon.eu

HEADQUARTERS: Murcia, Spain
ORGANIZATION TYPE: Research
Funded by the EU's Horizon 2020 and led by the Fundación Universitaria San Antonio in Spain, Smart Lagoon's goal is to protect coastal lagoon ecosystems and boost the impact of environmental and conservation projects through data. They combine IoT infrastructure, AI, NLP, and social media sensing for this purpose. The project covers 135 square kilometers of coastal lagoon and has eight partners from the private sector as well as higher education. The project is set to end in December 2024.

TaKaDu

takadu.com

HEADQUARTERS: Yehud, Israel
ORGANIZATION TYPE: Private
TakaDu is a cloud-based SaaS platform that uses advanced statistical techniques and machine learning in water management (detecting damaged equipment and potential leaks earlier than would normally be possible, as well as monitoring water quality, flow, pressure, and consumer consumption, among other metrics), helping utilities save approximately one billion liters every year.

U.S. Geological Survey (USGS)

www.usgs.gov/data/stream-temperature-predictions-delaware-river-basin-using-pseudo-prospective-learning-and

HEADQUARTERS: Reston, VA
ORGANIZATION TYPE: Public
USGS used public datasets to create deep learning models to predict temperatures of stream water; those predictions are then used by reservoir managers to inform the timing of water releases. This effort helps keep water in the Delaware River Basin cooler overall, which protects aquatic species there, such as trout.

Xylem

xylem.com/en-us/

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Private
Xylem uses machine learning, remote sensing, and satellite images to interpret data on freshwater sources and help utilities better meet water quality standards, optimize operations, reduce water loss, and lower costs safely and sustainably.

Greenhouse Gas Emissions

Albo Climate

albosys.com

HEADQUARTERS: Tel Aviv, Israel
ORGANIZATION TYPE: Private
Albo Climate offers continuous monitoring of carbon sequestration by applying proprietary deep learning algorithms to satellite imagery data.

Carbon Mapper

carbonmapper.org

HEADQUARTERS: Pasadena, CA
ORGANIZATION TYPE: Nonprofit
A nonprofit organization that uses advanced remote-sensing technology to quantify and track potent methane and CO_2 emissions at facility scale, perform methane leak detection, and certify methane intensity for oil and gas supply chains.

CarbonCure

carboncure.com

HEADQUARTERS: Dartmouth, Canada
ORGANIZATION TYPE: Private
CarbonCure Technologies develops innovative concrete solutions aimed at reducing carbon emissions. Their AI-enabled system precisely controls the injection of carbon dioxide into concrete, where it mineralizes and permanently embeds, decreasing the concrete's carbon footprint without affecting its performance. This process not only contributes to the reduction of greenhouse gases but also enhances the sustainability of the building materials industry.

ClimateTRACE: Climate Trace

climatetrace.org

HEADQUARTERS: Oakland, CA
ORGANIZATION TYPE: Nonprofit
Leveraging technology from Kayrros, Climate TRACE is a nonprofit coalition that aims to empower climate action through radical transparency. Climate TRACE uses satellites, remote sensing technology, and AI to collect data from an extensive array of sources to provide an up-to-date snapshot of GHG emissions on a global scale. Their AI models are trained on those data to predict actual activity at the ground level accurately. They cross-check that information with individual emitting facilities, farms, forests, and other assets in their database to produce a detailed global emissions inventory.

Kayrros: Methane/Carbon Watch

kayrros.com

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
Kayrros is an environmental intelligence company that measures the effect of human activity on the environment at a global level. Using science, AI, and real-time satellite imagery, they aim to reduce GHG emissions through measurement and attribution, manage energy transitions, and protect populations, ecosystems, and assets—modeling climate risk, biomass, and biodiversity for voluntary carbon credits. Their products include Methane Watch, monitoring super emitters, and Carbon Watch, which provide information on carbon credits.

The European Space Agency: Tropomi

esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5P/Tropomi

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Public
The Tropomi instrument, which was launched on the Copernicus Sentinel-5P satellite, creates daily global maps of methane concentrations.

Perennial

perennial.earth/technology

HEADQUARTERS: Boulder, CO
ORGANIZATION TYPE: Private
Perennial is the leading measurement, reporting, and verification (MRV) platform for soil-based carbon removal. In partnership with Descartes Labs, Perennial developed the highest-ever resolution map of soil organic carbon for the continental USA. Its evaluations rely on land remote sensing technology, statistical quantification, an archive of in-situ soil samples of wide-ranging origin, and machine learning algorithms to map and predict the carbon content within soil over time.

Phycoworks

phycoworks.com

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Phycoworks' AI platform helps customers process large amounts of biological data on algae, identifying new, innovative, and more effective ways to produce algae—which is one of the most efficient, natural ways to recycle carbon from the atmosphere.

Industry

AICrete: AICreteOS

aicrete.com

HEADQUARTERS: Richmond, CA
ORGANIZATION TYPE: Private
AICreteOS is an operating system that uses AI, machine learning, and computer vision to help producers in the concrete industry optimize concrete mix designs and operations—lowering production costs, increasing profit margins, and reducing carbon footprints for users across the board. Moreover, it offers quality control, such as monitoring tickets, producing operation reports and insights, automating material testing, and assisting in managing mixes, materials, and tasks. With over thirty successful projects, it's proven effective at lowering costs and CO_2 production.

Atlas AI

atlasai.co

HEADQUARTERS: Palo Alto, CA
ORGANIZATION TYPE: Private
Atlas AI has developed AI-driven geospatial tools that help infrastructure actors in historically untapped, underserved markets select sites, manage logistics and energy usage, predict demand and supply, and optimize their networks, among other operations—assisting in making them more efficient, reducing waste and energy, and becoming more sustainable.

Augury

augury.com

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Private
Augury develops AI and IoT solutions for the industry, especially predictive maintenance, and supports operation optimization to help reduce emissions and waste across businesses.

Blue Yonder

blueyonder.com

HEADQUARTERS: Scottsdale, AZ
ORGANIZATION TYPE: Private
Blue Yonder uses AI to help businesses become more efficient across their supply chain, automating processes, integrating robotics into warehouse operations, and cutting down their carbon footprint.

Brancube: Braincube

braincube.com

HEADQUARTERS: Issoire, France
ORGANIZATION TYPE: Private
Braincube's AI- and Industrial IoT-powered software offers data analysis (as well as custom digital twins) to the manufacturing industry, helping them increase productivity, improve efficiency, meet goals, and become more sustainable overall.

Carbon Re: Delta Zero Cement

carbonre.com/delta-zero

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Carbon Re's product, Delta Zero Cement, applies AI and machine learning to the cement manufacturing process, helping manufacturers identify ways to become more energy-efficient, reduce production costs, and lower their carbon emissions.

Cemex

cemex.com

HEADQUARTERS: Monterrey, Mexico
ORGANIZATION TYPE: Private
Cemex uses "Model-Based Optimization" to generate models that predict the efficiency and performance of ball mills. Ball mills have been used in the end stages of cement production for over a century and account for the most electricity consumption of the entire process. Combining machine learning and high computing power, Cemex collects data on the speed at which material is added to the mill as well as that of the separator and the ventilator fans and makes alterations to the process that not only reduce the energy consumed but also produce a higher quality product,.—reducing the facility's carbon footprint in a critical industry, which alone is responsible for 8% of the world's total CO_2 emissions.

Industry (continued)

Charm: CHARM ECSEL JU Project

charm-ecsel.eu

HEADQUARTERS: Espoo, Finland
ORGANIZATION TYPE: Network
CHARM is a European collaboration focused on developing AI and Industrial IoT solutions for manufacturing operations across various domains (mining, paper mills, machining, solar panel manufacturing, nuclear power plant maintenance and decommissioning, and professional digital printing). They seek to optimize operations, making energy use more efficient, reducing waste, and reducing the impact of operations on the environment.

Citrine: From ALP

citrine.io

HEADQUARTERS: Redwood City, CA
ORGANIZATION TYPE: Private
Citrine uses AI to accelerate material science development—from consumer products and materials to chemicals and batteries—in ways that can be leveraged to make material creation more efficient and develop more sustainable consumer products.

CO_2 AI

www.co2ai.com

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
CO_2 AI, born out of the Boston Consulting Group, is helping large and complex organizations measure their impact, identify credible levers, and reduce at scale, leveraging the power of AI through decarbonizing supply chains, assessing carbon footprints, and measuring corporate emissions.

Concrete.ai: Concrete Copilot

concrete.ai

HEADQUARTERS: Los Angeles, CA
ORGANIZATION TYPE: Private
Concrete Copilot is a program Concrete.ai developed to help industry stakeholders optimize mix designs of concrete—processing vast amounts of data to produce solutions that not only reduce material costs and lower carbon footprints but also predict the performance of said material. In fact, after extensive testing across the U.S., Concrete.ai found that by using Concrete Copilot, producers saved an average of 5.04 USD per cubic yard of materials used, and reduced their carbon production by 30%.

Ecolab: ECOLAB3D

ecolab.com

HEADQUARTERS: Saint Paul, MN
ORGANIZATION TYPE: Private
ECOLAB3D is a cloud-based Industrial Internet of Things platform that helps industries become more sustainable by optimizing their water use in industrial processes (minimizing water waste, boosting water recycling and reuse, etc.). They currently operate across over 40 industries in over 170 countries.

Ericsson: Ericsson's Service Continuity AI

www.ericsson.com/en/network-services/support

HEADQUARTERS: Stockholm, Sweden
ORGANIZATION TYPE: Private
Taiwanese service provider Far EasTone deployed Ericsson's Service Continuity AI in 2023, which uses machine learning, data analysis, and prediction to manage the energy consumption of the network, cutting the network's daily energy consumption by 25% while maintaining network quality and equipment performance.

Eugenie.ai

eugenie.ai

HEADQUARTERS: Cupertino, CA
ORGANIZATION TYPE: Private
Eugenie is a SaaS-based emissions intelligence platform that enables asset-heavy manufacturers to track, trace, and reduce Scope I emissions through AI-powered digital twins.

Fero Labs

ferolabs.com

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Private
Fero Labs has AI-driven software to help manufacturers in the steel industry optimize production, increase profits, and improve the sustainability of their products by increasing steel recycling (they also work in cement and other areas of industry).

GeologicAI

geologicai.com

HEADQUARTERS: Calgary, Canada
ORGANIZATION TYPE: Private
GeologicAI is a firm that leverages AI to optimize the mining industry, reducing CO_2 emissions in the process.

Google DeepMind: GNoMe

deepmind.google/discover/blog/millions-of-new-materials-discovered-with-deep-learning/

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
The Graph Networks for Materials Exploration (GNoME) is Google's deep learning tool that dramatically increases the speed and efficiency of discovery by predicting the stability of new materials. In November 2023, GNoMe discovered 2.2 million new crystals, of which 380,000 were the most stable. The latest discoveries can be used to develop a range of technologies, including solar panels and next-generation batteries, to boost the efficiency of electric vehicles. GNoME's predictions are available to the research community, and they will contribute 380,000 stable materials to the Materials Project.

Intelecy

intelecy.com

HEADQUARTERS: Oslo, Norway
ORGANIZATION TYPE: Private
Intelecy's software platform is aimed toward sustainable industrial production. They use AI to assist industry actors in the actual creation of custom machine learning models focused on driving efficiency, improving the quality of produced products, and optimizing sustainable operations. So far, they have been deployed in the following industries: food and beverage; mining, metals and minerals; power and renewable energy; and water and wastewater.

Materials Project

next-gen.materialsproject.org/ml

HEADQUARTERS: Berkeley, CA
ORGANIZATION TYPE: Network
The Materials Project's mission is to use machine learning to reduce the time and cost involved in discovering and synthesizing new materials. Their web-based suite of apps can be used by scientists and industry to help create cheaper, more efficient, and more sustainable novel materials.

METRON: Energy Management and Optimization System (EMOS)

metron.energy

HEADQUARTERS: Paris, France
ORGANIZATION TYPE: Private
METRON's EMOS helps stakeholders in industry and manufacturing manage and optimize their energy consumption by leveraging machine learning algorithms and digital twins to contextualize data and support decision-making.

MongoDB: MongoDB Atlas

mongodb.com/atlas

HEADQUARTERS: Dublin, Ireland
ORGANIZATION TYPE: Private
MongoDB is a tech company that specializes in databases. Their MongoDB Atlas is an AI-enabled product that can assist industry manufacturing and automotive sectors in monitoring stock, inventory management, predictive maintenance for equipment, and optimization of equipment performance and, therefore, energy use (thus helping them plan around and cut down their carbon footprint).

Normative

normative.io

HEADQUARTERS: Stockholm, Sweden
ORGANIZATION TYPE: Private
Normative's carbon accounting platform helps businesses monitor their carbon footprint and uses AI to identify carbon insights to inform interventions that help reduce it.

Penn State University: Materials Genome Initiative (MGI)

censai.psu.edu

HEADQUARTERS: State College, PA
ORGANIZATION TYPE: Research
Located at Penn State, there are various initiatives stemming from the Center for Artificial Intelligence Foundations and Scientific Applications CENSAI. MGI, for example, is aimed at using AI, algorithms, and machine learning to generate novel materials, which have great potential for the creation of more circular, sustainable materials.

refiberd

refiberd.com

HEADQUARTERS: Cupertino, CA
ORGANIZATION TYPE: Private
Understanding that less than 1% of textile waste is recycled into new clothing and 186 billion pounds of it is disposed of annually, refiberd uses AI to create sorting technology for fashion industry manufacturers that is capable of salvaging up to 70% of textile waste, which can then be recycled into other textiles.

Rivelin Robotics

rivelinrobotics.com

HEADQUARTERS: Sheffield, UK
ORGANIZATION TYPE: Private
Rivelin Robotics develops robotic- and AI-powered tools to help metal additive manufacturers become more efficient, reduce waste, reduce energy use, and optimize operations.

Industry (continued)

Schneider Electric: EcoStruxure Platform

se.com/us/en/work/campaign/innovation/platform.jsp

HEADQUARTERS: Rueil-Malmaison, France
ORGANIZATION TYPE: Private
The EcoStruxure Platform uses IoT technology, embedded connectivity, and AI to help business owners, managers, and industry professionals monitor operations across their enterprise and optimize those activities—which in turn helps them reduce the climate impact of those operations.

Scoutbee

scoutbee.com

HEADQUARTERS: Berlin, Germany
ORGANIZATION TYPE: Private
Scoutbee's platforms can assist industry supply chains using AI-powered data analytics to give a holistic, transparent view of their supply chains. The platform can help managers optimize their operations and make supply chains more sustainable.

Seeq

seeq.com

HEADQUARTERS: Seattle, WA
ORGANIZATION TYPE: Private
Seeq uses AI and Industrial IoT to help companies optimize process manufacturing in industries like food and beverage, oil and gas, and electric utilities. Benefits such as predictive maintenance, real-time monitoring, and energy management help manufacturers cut down their carbon footprint.

Solidia

solidiatech.com

HEADQUARTERS: San Antonio, TX
ORGANIZATION TYPE: Private
Solidia, in collaboration with Uncountable, developed an AI-powered data analysis platform that can accelerate the process of trialing concrete formulations that would typically require years of experimentation by digitizing it. With accelerated experimentation, the technology can help identify newer, less-carbon-intensive cement chemistries.

Streem.ai

streem.ai

HEADQUARTERS: Berlin, Germany
ORGANIZATION TYPE: Private
Streem.ai's software allows industry actors to monitor operations, identify anomalies, and make operations more efficient and more sustainable.

U.S. Steel: MineMind

ussteel.com

HEADQUARTERS: Pittsburgh, PA
ORGANIZATION TYPE: Private
In August 2023, U.S. Steel announced it was partnering with Google Cloud to produce AI-powered software that is aimed to help the steel industry improve operations, energy use, automation, supply chain, logistics, and sustainability.

Valiot: FactoryOS/ ValueChainOS

valiot.io

HEADQUARTERS: Austin, TX
ORGANIZATION TYPE: Private
Valiot's platforms, FactoryOS and ValueChainOS, use AI to help plant managers monitor operations, identify bottlenecks, optimize activities, and reduce waste carbon footprint.

Watershed

watershed.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Watershed helps businesses reduce their carbon footprint across supply chains by monitoring water use and waste, energy use, and GHG emissions and garnering insights for customers using AI.

Wizata

wizata.com

HEADQUARTERS: Capellen, Luxembourg
ORGANIZATION TYPE: Private
Wizata's AI-powered platform helps industrial manufacturers streamline and optimize their operations. This can assist manufacturers in identifying actionable insights to reduce their operation's energy usage and carbon footprint.

Yokogawa Energy: Factorial Kernel Dynamic Policy Programming

www.yokogawa.com/special/artificial-intelligence/

HEADQUARTERS: Tokyo, Japan
ORGANIZATION TYPE: Private
FKDPP is an AI-driven learning algorithm developed in partnership with the Nara Institute of Science and Technology (NAIST) in 2018. It has many potential uses, including pharmaceutical, energy, and material production. It uses reinforcement learning technology to improve and optimize plant operations and automate aspects of plant activity that have traditionally necessitated manual control. In 2023, Japan's Industrial Technology Awards awarded the FKDPP algorithm the Prime Minister's Prize—the highest-level award.

Ocean Management

Allen Institute for Artificial Intelligence (AI2): Skylight

allenai.org

HEADQUARTERS: Seattle, WA
ORGANIZATION TYPE: Research
AI2's Skylight tool helps to tackle unregulated fishing practices through real-time monitoring and tracking of marine vessels using synthetic aperture radar satellite imagery and computer vision.

Aquabyte Inc.: Aquabyte

aquabyte.ai

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Aquabyte, which began with a single pen in Norway, uses AI and machine learning to monitor fish health, weight, growth rate, and abnormalities, as well as their aquatic environment, to help fish farmers optimize their harvests, which reduces waste and makes their farms more sustainable. They also state an effort to help the world meet a growing need for protein.

AquaEasy

HEADQUARTERS: Molde, Norway

aquaeasy.life

HEADQUARTERS: Singapore
ORGANIZATION TYPE: Private
AquaEasy uses AI, sensors, and IoT technology to help shrimp farmers make their farming operations more sustainable by monitoring and analyzing shrimp behaviors and health, automating feeding, improving resource management, and reducing feed waste.

Arizona State University (ASU): Allen Coral Atlas

allencoralatlas.org

HEADQUARTERS: Tempe, AZ
ORGANIZATION TYPE: Research
Managed by ASU in partnership with other academic institutions and NGOs, the Allen Coral Atlas uses satellite imagery and machine learning to automate coral reef monitoring, generating near-real-time maps. The data garnered is used by policymakers and marine conservationists to help make informed decisions on ocean conservation, protection, and intervention. It is one of the projects officially endorsed by the United Nations Decade of Ocean Science for Sustainable Development.

Coastal Zone Management Authority and Institute: AI for the Belize National Marine Habitat Map

geobon.org/wp-content/uploads/2021/11/GEO-Week-side-event_Belize-CZMAI.pdf

HEADQUARTERS: Belize City, Belize
ORGANIZATION TYPE: Public
In 2021, Coastal Zone Management Authority used Microsoft Azure and satellite data—such as the Sentinel-2 and PlanetScope—and machine learning to create a marine habitat map of the coast of Belize. With it, they were able to update a Habitat Risk Assessment model and produce new maps to help inform conservation activities, policies, opportunities, and costs in the area.

Createview

createview.ai

HEADQUARTERS: Molde, Norway
ORGANIZATION TYPE: Private
Createview uses sensors to provide AI-driven data insights in real-time for more sustainable and profitable fish production and to optimize animal welfare.

Ocean Management (continued)

Global Fishing Watch

globalfishingwatch.org

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Nonprofit
Combines vessel reporting data from the automatic identification system (required of vessels by the International Maritime Organization and other management bodies) with vessel monitoring systems (managed by smaller authorities) to track human activity at sea, monitor commercial fishing vessels and transportation vessels, protect ocean habitats, and to improve ocean management.

Liquid Robotics: Wave Glider

liquid-robotics.com

HEADQUARTERS: Herndon, VA
ORGANIZATION TYPE: Private
The Wave Glider was developed by Liquid Robotics (a Boeing company) to autonomously navigate the ocean and collect data. It uses AI to identify and monitor marine life. Wave Gliders can be used by many different types of organizations to gather data for their businesses, including organizations working in environmental monitoring, marine habitat conservation, and fisheries management.

Manolin

manolinaqua.com

HEADQUARTERS: Bergin, Norway
ORGANIZATION TYPE: Private
Using AI, machine learning, and data analytics to provide real-time information to salmon farmers and suppliers to support them in making their farms more sustainable and their fish healthier, boosting production, and reducing risks.

Mercator Ocean International: Digital Twin Ocean

digitaltwinocean.mercator-ocean.eu

HEADQUARTERS: Toulouse, France
ORGANIZATION TYPE: Nonprofit
A high-resolution, multi-dimensional representation of the earth's oceans with nearly real-time accuracy by integrating a wide range of data sources, including sensors and satellites. They aim to provide an interactive digital twin of the ocean to strengthen ocean governance, restore marine habitats and biodiversity, and improve disaster risk management.

Ocean Infinity

oceaninfinity.com

HEADQUARTERS: Austin, TX
ORGANIZATION TYPE: Private
Ocean Infinity is a company involved in marine vessel and shipping robotics. They have a mission to protect the planet "by transforming operations at sea" with technology. Part of that effort involves using AI and machine learning to increase their operations payload offshore in low bandwidth environments and optimize operations.

Ocean Vision AI: Ocean Vision AI Portal/ FathomNet / Fathom Verse

www.oceanvisionai.org

HEADQUARTERS: Moss Landing, CA
ORGANIZATION TYPE: Research
Ocean Vision AI streamlines access to artificial intelligence and machine learning tools to accelerate the analysis of ocean visual data. Ocean Vision AI consists of three portals: (1) Portal: Online, collaborative tool for end-to-end AI-assisted processing of ocean imagery, (2) FathomNet: Open-source database for machine learning models and expertly labeled ocean imagery for understanding our ocean and its inhabitants, (3) Fathom Verse: Mobile game that teaches casual gamers about ocean life while improving machine-learning models and expanding annotated datasets. Ocean Vision AI is part of the Monterey Bay Aquarium Research Institute.

OceanMind

oceanmind.global

HEADQUARTERS: Didcot, UK
ORGANIZATION TYPE: Nonprofit
OceanMind's goal is to stop illegal and unreported fishing. They use satellites and AI to assist authorities in monitoring overfishing practices, enforcing penalties, and thereby encouraging the fishing industry to operate more sustainably and responsibly.

Oceans5

oceans5.org

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Network
Oceans5 works to reduce illegal and unreported fishing and overfishing, set limits on offshore oil and gas, and demarcate protected marine areas through many different initiatives around the world, many of which use machine learning, big data processing, and visualization and analysis tools. These tools allow them to assemble analysis reports, training programs, and monitoring tools that can be passed along to governments and other partners, who then use that data to make better, data-informed decisions to protect the ocean.

OceanX

oceanx.org

HEADQUARTERS: New York, NY
ORGANIZATION TYPE: Nonprofit
OceanX partnered with Group 42, an AI and cloud computing company based in Abu Dhabi, UAE, to deploy drone and remote sensing technologies to monitor marine ecosystems off the coast of Indonesia to support the Ministry for Maritime Affairs and Investment to protect and manage ocean resources and conserve aquatic species and their habitats.

ReelDataAI: ReelAppetite / ReelBiomass / ReelStress / ReelHealth

reeldata.ai

HEADQUARTERS: Halifax, Canada
ORGANIZATION TYPE: Private
ReelDataAI's platforms provide AI-driven data insights to land-based fish farmers, helping them make their farms more profitable and sustainable while limiting waste and maximizing fish health.

Saildrone

saildrone.com

HEADQUARTERS: Alameda, CA
ORGANIZATION TYPE: Private
Saildrone is an autonomous ocean vehicle that navigates the ocean via sail, collecting data using solar- and AI-powered systems such as water temperature, water salinity, fish life, and marine mammals. This data is used to assist and inform conservation efforts.

SeaDeep

seadeep.io

HEADQUARTERS: Boston, MA
ORGANIZATION TYPE: Private
AI-powered computer vision sensing platform for marine infrastructure that helps monitor and protect the marine environment.

SINAY: Metocean Analytics, Developer Platform

sinay.ai

HEADQUARTERS: Caen, France
ORGANIZATION TYPE: Private
Sinay's AI-driven, big-data maritime solutions, such as Metocean Analytics and the Developer Platform, offer users ways to monitor and assess their maritime operations (such as container tracking for shipping) and related weather information. Data collected and analyzed can help them make more informed decisions that make their operations more efficient, reduce fuel usage, and cut back on waste and loss.

The Ocean Cleanup

theoceancleanup.com

HEADQUARTERS: Rotterdam, Netherlands
ORGANIZATION TYPE: Nonprofit
The Ocean Cleanup, which develops technology to extract plastic pollution from the oceans, uses Microsoft Azure Machine Learning and other Azure tools to support its efforts in cleaning up plastic and debris from the ocean. Their goal is to remove 90% of plastic from the ocean by 2040.

The Woods Hole Oceanographic Institution: CUREE

warp.whoi.edu/curee/

HEADQUARTERS: Woods Hole, MA
ORGANIZATION TYPE: Research
The Woods Hole Oceanographic Institution Autonomous Robotics and Perception Laboratory (WARPLab) and MIT are developing an autonomous underwater vehicle--CUREE (Curious Underwater Robot for Ecosystem Exploration)--for studying coral reefs and their ecosystems. Enabled by NVIDIA technology, CUREE gathers visual, audio, and other environmental data alongside divers to help understand the human impact on reefs and the sea life around them.

Ocean Management (continued)

World Wildlife Fund: ManglarIA

www.worldwildlife.org/projects/manglaria-using-artificial-intelligence-to-save-mangroves-in-a-changing-climate

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Nonprofit
WWF and its partners will deploy various sensors—such as weather stations, camera traps, and drones—in Mexico's R√≠a Lagartos along the coast of the Yucatan Peninsula and Marismas Nacionales Biosphere Reserves in Naryarit along the Pacific Coast. These sensors and other technologies will provide data on mangrove health, including air and sea surface temperatures, seawater salinity, freshwater flows, and the presence of animals. AI will look for patterns in this data to help answer questions such as how carbon stocks change over time, how quickly mangroves can recover from hurricanes, and which mangroves species are most resilient to environmental change. This information will be used to adapt mangrove conservation strategies to help ensure the long-term viability of mangroves as a nature-based solution.

X (a Division of Google): Tidal

x.company/projects/tidal

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Private
Google's Tidal project, developed by X (formerly known as Google X), aims to protect ocean ecosystems and contribute to sustainable seafood production. Tidal's approach involves the use of an underwater camera system and machine perception tools. These technologies are designed to provide enhanced visibility and understanding of underwater environments, particularly in the context of fish farming. By monitoring fish behavior, health, and the surrounding environmental conditions (like temperature and salinity), Tidal aims to assist fish farmers in making more informed and environmentally friendly decisions.

XpertSea

xpertsea.com

HEADQUARTERS: Québec, Canada
ORGANIZATION TYPE: Private
Dedicated to the responsible generation of protein for growing populations, XpertSea's mission is to make global aquaculture better and more sustainable by empowering farmers to make their farms more resilient and transparent. They offer AI-driven shrimp harvest optimization to maximize profitability and boost the overall health and transparency of shrimp farms.

Power

Algebra Intelligence: TaQTaK

algebraintelligence.com

HEADQUARTERS: Amman, Jordan
ORGANIZATION TYPE: Private
Algebra Intelligence integrates artificial intelligence solutions into the Energy Sector with the aim of ushering in smart technology in sustainability development.TaQTaK, the startup's platform, tracks, monitors, and observes energy production from generation systems as well as power consumption by consumers to collect data. The platform's AI algorithm generates insights that allow the implementation of predictive maintenance and the forecasting of energy demand. These insights also aid in the feasibility studies for the development of new renewable energy products. The startup's solution enables grid operators and local energy prosumers to optimize energy production, maximize financial returns, and increase machine life.

Avokado Energy: Avokado AI/ AVoS/ AVOX

avokado.energy

HEADQUARTERS: Athens, Greece
ORGANIZATION TYPE: Private
Avokado AI uses machine learning to offer utilities energy monitoring and supply chain event prediction. AvoS is a system that combines AI with battery energy storage systems to make them more efficient and sustainable. AVOX is a platform that uses AI to provide useful data insights to cities and supply chains that can help them transition to decarbonize their networks.

Brightnight: Box Canyon

brightnightpower.com

HEADQUARTERS: West Palm Beach, FL
ORGANIZATION TYPE: Private
BrightNight is a U.S. company working to decarbonize power by developing customized, renewable power solutions for utilities, commercial buildings, industrial buildings, and private landowners. Its Box Canyon Solar Project--underway in collaboration with Cordelio Power and Southwest Public Power Agency--used BrightNight's proprietary AI platform to design and optimize a solar farm near Florence, Arizona, to maximize its performance at the lowest possible cost. The first project of its kind in the state, Box Canyon is expected to produce enough electricity for 77,000 homes and businesses and generate $47 million for the county.

Drishya: VoltOS

www.drishya.ai/voltos

HEADQUARTERS: Calgary, Canada
ORGANIZATION TYPE: Private
VoltOS, the startup's AI platform, uses accurate IoT data and smart AI algorithms to enable automated operations of distributed renewable energy sources and trading of power. The platform simplifies the deployment, operation, and improvement of microgrids by predicting usage patterns and automating workflows. This allows the widespread roll-out of distributed renewable energy resources. The startup's technology integrates with existing infrastructure with minimal disruption in normal operations.

E.on

www.eon.com/en/new-energy/digitization/artificial-intelligence.html

HEADQUARTERS: Essen, Germany
ORGANIZATION TYPE: Private
E.on uses AI to maximize the energy yield in wind farms, synchronize the turbines, and align them optimally with the wind. Using AI and meta-forecasts, the company calculates precisely how much wind will be at a particular wind farm so that it can react accordingly in advance—both in the event of a shortage of wind energy and in the event of an expected surplus. The company also uses AI for predictive maintenance to identify when medium voltage cables in the electrical grid need to be replaced.

eSmart Systems: Grid Vision

gridvision.com

HEADQUARTERS: Halden, Norway
ORGANIZATION TYPE: Private
Grid Vision is an AI-powered software tool that offers utilities data on their assets and virtual, automated transmission line inspections to help make grids more resilient and efficient, thereby helping to optimize the power grid.

General Electric: GE Vernova

ge.com

HEADQUARTERS: Cambridge, MA
ORGANIZATION TYPE: Private
GE Vernova focuses its research on accelerating the energy transition through innovative developments in decarbonization, renewables, and electrification. Utilizing advanced research methods, including AI and robotics, the organization drives the creation of sustainable energy solutions, aiming for enhanced efficiency and a zero-carbon future in energy-intensive industries.

Power (continued)

Google DeepMind: Accelerating fusion science through learned plasma control

deepmind.google/discover/blog/accelerating-fusion-science-through-learned-plasma-control/

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
The DeepMind project, in collaboration with the Swizz Plasma Centre, utilizes artificial intelligence to advance nuclear fusion research by mastering plasma control in tokamak-style reactors. This complex process involves creating and sustaining a plasma that is hotter than the sun's core, which can only be contained using rapidly adjusted magnetic fields. DeepMind's approach integrates deep reinforcement learning to autonomously control magnetic coils, enabling the plasma to be shaped and maintained in desired configurations. This not only enhances the understanding of fusion processes, but also demonstrates a significant application of AI in facilitating breakthroughs in clean and limitless energy production.

Google DeepMind

deepmind.google/discover/blog/machine-learning-can-boost-the-value-of-wind-energy/

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Private
Google Deepmind applied machine learning algorithms to wind farms to assess weather and turbine data, predicting energy production up to 36 hours in advance. The AI model then uses that data to recommend energy delivery commitments a day in advance, raising the wind farms' energy value by approximately 20%. The drive behind the effort is to strengthen the business case for wind power and increase the uptake of clean energy on power grids at scale.

Gridware

gridware.io

HEADQUARTERS: Walnut Creek, CA
ORGANIZATION TYPE: Private
Gridware is a US-based startup that uses remote telemetry and edge AI to detect faults in and around electrical assets that can ignite wildfires. Gridware raises alerts that enable the scheduling of timely repairs and rapidly respond to transmission line incidences before damage can occur.

Hepta Airborne

heptaairborne.com

HEADQUARTERS: Tallinn, Estonia
ORGANIZATION TYPE: Private
Hepta Airborne is software that uses IR and LIDAR images from drones, satellites, and helicopters, and AI to identify defects in power lines and report those defects, allowing utilities to more effectively maintain their power lines and speed up grid analysis, thereby optimizing performance.

Husk Power Systems: Husk

huskpowersystems.com

HEADQUARTERS: Fort Collins, CO
ORGANIZATION TYPE: Private
Husk uses AI, IoT, and smart meters to upscale and remotely manage mini-grid solar systems in Africa and Asia. Predictive AI is used to forecast supply and demand and then deploys AI-powered algorithms to deliver electricity to its customers at the lowest cost at any given time. The company provides renewable energy, power generation, and transmission lines to offer affordable, maintainable energy solutions to historically energy-poor communities.

Microsoft and Pacific Northwest National Laboratory: Azure Quantum Elements

cloudblogs.microsoft.com/quantum/2024/01/09/unlocking-a-new-era-for-scientific-discovery-with-ai-how-microsofts-ai-screened-over-32-million-candidates-to-find-a-better-battery/

HEADQUARTERS: Redmond, WA
ORGANIZATION TYPE: Private
Azure Quantum Elements was recently used by researchers at Pacific Northwest National Laboratory to create a new type of battery. It analyzed over 32,000,000 potential compounds and predicted stable materials from them (about 500,000). In the process, the model not only identified more than ten years' worth of collective battery knowledge but also identified eighteen new possibilities. The researchers then deployed virtual machines onto that data, synthesizing and experimenting with reliable, solid electrolytes. From their findings, they built a new, functional electrolyte material battery prototype notable for its potential as a sustainable energy-storage solution. Their research demonstrates the power of AI to create new, more sustainable, more efficient battery materials.

National Grid Electricity System Operator (ESO): National Grid ESO

nationalgrideso.com

HEADQUARTERS: Warwick, UK
ORGANIZATION TYPE: Public
National Grid ESO uses AI and machine learning to make their solar energy forecasting abilities much more accurate and efficient in an effort toward more renewable energy and net zero carbon emissions.

Open Climate Fix

openclimatefix.org

HEADQUARTERS: London, UK
ORGANIZATION TYPE: Nonprofit
Open Climate Fix uses AI to improve the efficiency and effectiveness of the energy sector. They focus on creating open-source models that predict solar photovoltaic electricity generation, enabling better integration of solar power into the grid. By forecasting solar energy output more accurately, utilities can reduce reliance on carbon-intensive power sources.

ORE Catapult: Multi-Platform Inspection, Maintenance and Repair in Extreme Environments (MIMRee)

ore.catapult.org.uk/stories/mimree/

HEADQUARTERS: Glasgow, UK
ORGANIZATION TYPE: Research
The MIMRee project provided proof of concept for robotic teams repairing offshore wind farms. It was funded by Innovate UK and enabled by eight cross-sector collaborators led by ORE Catapult. MIMRee used AI and robotics to automate the repair of offshore wind turbines. Optimizing wind turbine maintenance enables increased performance and better energy outputs, making wind farms more viable.

Stanford University: DeepSolar Project

deepsolar.web.app

HEADQUARTERS: Stanford, CA
ORGANIZATION TYPE: Research
DeepSolar is a deep learning framework that analyzes satellite imagery to identify the GPS locations and sizes of solar photovoltaic (PV) panels. Leveraging its high accuracy and scalability, DeepSolar constructed a comprehensive high-fidelity solar deployment database for the contiguous U.S.

Stem: Athena

stem.com

HEADQUARTERS: San Francisco, CA
ORGANIZATION TYPE: Private
Stem's Athena platform leverages AI to optimize the clean energy value chain—grid power, generator usage, EV charging, battery energy storage, and other distributed resources (like solar panels).

Toyota Research Institute

tri.global

HEADQUARTERS: Los Altos, CA
ORGANIZATION TYPE: Private
The Toyota Research Institute (in partnership with Northwestern University) established a nanomaterial data factory that uses AI to assist the experimental process of exploring material data and potential combinations for novel energy storage solutions.

United States Department of Energy: Office of Critical and Emerging Technologies

www.energy.gov/cet/office-critical-and-emerging-technologies

HEADQUARTERS: Washington, DC
ORGANIZATION TYPE: Public
The U.S. DOE established the Office of Critical and Emerging Technologies in December 2023 in response to President Biden's Executive Order on AI. The office is tasked with investigating and amplifying the impact of AI technologies across many areas of national interest, as well as developing partnerships to accomplish this. One national interest the office is focused on is AI solutions to the climate crisis.

Power (continued)

Uplight: Autogrid

auto-grid.com

HEADQUARTERS: Redwood City, CA
ORGANIZATION TYPE: Private
Autogrid (recently acquired by Uplight) is a cleantech company that offers AI-driven distributed energy resource management that helps forecast and optimize energy consumption for microgrids, EV grids, and virtual power plants. AutoGrid leverages AI to transform data into actionable intelligence for electricity providers, enabling them to automate grid operations, predict energy demand, and integrate renewable resources efficiently.

Uplight

uplight.com

HEADQUARTERS: Boulder, CO
ORGANIZATION TYPE: Private
Uplight uses AI models to analyze vast amounts of energy consumption data and draw actionable insights for customers (utility companies or their customers), allowing them to reduce energy consumption and costs and making their business more sustainable.

WattTime

watttime.org

HEADQUARTERS: Oakland, CA
ORGANIZATION TYPE: Nonprofit
WattTime is an environmental tech nonprofit that empowers all people, companies, policymakers, and countries to slash emissions and choose cleaner energy. Founded by UC Berkeley researchers, WattTime develops data-driven tools and policies that increase environmental and social good, especially through load shifting, renewables sitting, and supply chain decarbonization.

Technological Carbon Removal

Brilliant Planet

brilliantplanet.com

HEADQUARTERS: Harperden, UK
ORGANIZATION TYPE: Private
Brilliant Planet removes CO_2 from the atmosphere permanently using algae supported by remote sensing via satellites, machine vision, and data processing.

Heriot Watt University: ECO-AI

ai4netzero.github.io/eco-ai/

HEADQUARTERS: Edinburgh, UK
ORGANIZATION TYPE: Research
Heriot-Watt University's ECO-AI is a UKRI-funded project to address critical barriers to large-scale Carbon Capture and Storage (CCS) implementation, including a) high energy demands of the capture process, b) high cost for predicting and monitoring, and c) uncertainties in financing CCS projects and lack of understanding of the impact of regulatory and market interventions. The project aims to address the barriers by developing: AI materials discovery pipeline for energy-efficient CO_2 capture, AI-solvers for modeling CO_2 flow in geological storage formations, Modelling CO_2 target progress coupled with innovation trajectories for each industrial sector.

Stanford University: CCSNet

ccsnet.ai

HEADQUARTERS: Stanford, CA
ORGANIZATION TYPE: Research
CCSNet is a deep-learning modeling suite for CO_2 storage (digital twins for carbon capture and storage). CCSNet provides CO_2 storage predictions for 2D and 3D saline reservoirs with a wide range of reservoir conditions, injection design, rock properties, and permeability maps. This work was also carried out with the California Institute of Technology, Purdue University, and NVIDIA and supported by the Stanford Center for Carbon Storage and ExxonMobil through the Strategic Energy Alliance at Stanford University.

U.S. Department of Energy's (DOE) Argonne National Laboratory: Argonne National Laboratory

www.energy.gov/ea/argonne-national-laboratory

HEADQUARTERS: Lemont, IL
ORGANIZATION TYPE: Research
The Argonne National Laboratory is using AI to identify new materials for carbon capture through generative AI to dream up previously unknown building block candidates, machine learning, and high-throughput screening of candidate materials. They are working on metal-organic frameworks or MOFs, a porous material that can selectively adsorb carbon dioxide.

Xyonix

xyonix.com

HEADQUARTERS: Seattle, WA
ORGANIZATION TYPE: Private
In addition to the many AI-driven tools Xyonix has developed, it has crafted an entire category of custom AI and machine learning models solely focused on carbon sequestration within the industry. They incorporate a variety of approaches, including satellite image processing, molecule prediction technology, and emissions forecasting. Together, these tools offer a flexible, customizable approach to myriad stakeholders within industry and manufacturing.

Transport

ADLINK: AVA-5500

adlinktech.com

HEADQUARTERS: Taoyuan, Taiwan
ORGANIZATION TYPE: Private
ADLINK's AVA-5500 is an intelligent platform that can inspect trains and railway equipment, identify faulty equipment, notify maintenance crews, and analyze video streams with parallel computing and deep learning.

Altexsoft

www.altexsoft.com/artificial-intelligence-ai-solutions/

HEADQUARTERS: Foster City, CA
ORGANIZATION TYPE: Private
Altexsoft is a technology and consulting company that creates tailored software and machine learning solutions for the aviation and transportation industries, helping them with route optimization, shipment management, and fuel efficiency, among other aspects of their operations.

BSNF

bnsf.com

HEADQUARTERS: Fort Worth, TX
ORGANIZATION TYPE: Private
BSNF uses machine vision and AI to monitor the condition of trains and railways to predict maintenance, identify defaults, and optimize train transportation for increased profits and decreased energy consumption.

Chemix: MIX Platform

chemix.ai

HEADQUARTERS: Sunnyvale, CA
ORGANIZATION TYPE: Private
Chemix, a California tech startup, uses its MIX,Ñ¢ Platform to apply AI and machine learning to EV battery design. Battery design has always been challenging: producing highly complex objects made of nearly infinite available materials is a demanding effort with typically long and slow testing times. With AI, however, Chemix can accelerate battery development and performance through new material discovery and predictive modeling. It helps identify new, better-performing, lower-carbon battery materials and chemistry and quickens and digitizes the battery-testing process.

CSX

csx.com

HEADQUARTERS: Jacksonville, FL
ORGANIZATION TYPE: Private
CSX uses sensors, machine learning, and industry IoT systems to monitor the company's locomotives and freight cars. It monitors car movements continuously and assesses bearings, wheels, lateral forces, and axles passing through stationary monitoring sites.

Descartes: Descartes Route Planner AI Advisor

descartes.com

HEADQUARTERS: Waterloo, Canada
ORGANIZATION TYPE: Private
Descartes Route Planner AI Advisor uses machine learning to process real-time data on weather, road networks, traffic patterns, driver capability, truck type, geography, type of asset, geography, and delivery location to generate highly accurate arrival time estimations, reduce fuel consumption, and lower emissions from transportation. They claim to help their customers cut 693,000 metric tons of CO_2 each year.

ElaadNL

elaad.nl

HEADQUARTERS: Gelderland, Netherlands
ORGANIZATION TYPE: Private
ElaadeN researches and tests smart and sustainable charging for electric vehicles, supporting EV infrastructure planning and design.

Google Research: Green Light

sites.research.google/greenlight/

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Private
Green Light, a Google Research initiative, optimizes traffic lights to reduce vehicle emissions. It is currently underway across a dozen cities in North America, South America, Europe, and Asia. It leverages AI in conjunction with Google Maps data to analyze and predict traffic behaviors, understand intersections, measure traffic trends, develop recommendations for the city, and analyze impact—all delivered through a user-friendly recommendation interface.

Google Research, American Airlines: Project Contrails

sites.research.google/contrails/

HEADQUARTERS: Mountain View, CA
ORGANIZATION TYPE: Private
Google Research teamed up with American Airlines and Breakthrough Energy to study the development of contrails. By combining massive quantities of weather data, satellite data, and flight data, AI is used to create state-of-the-art predictions of when and where contrails are likely to form. Pilots and dispatchers can then use this information to adjust the altitudes of their flights.

KONUX: KONUX Switch / KONUX Traffic

konux.com

HEADQUARTERS: Munich, Germany
ORGANIZATION TYPE: Private
KONUX Switch is an AI- and IoT-driven predictive maintenance platform for railway switches—responsible for 20-30% of railway delay minutes—which can continuously monitor the health of switches and inform managers when switches require repair and what kind of repairs are required. KONUX Traffic uses algorithms based on neural networks to monitor train movement data, identify delays, and anticipate the effect of those delays on the rest of the railway network, thereby helping managers optimize timetables. Together, these tools make railways greener by optimizing time spent on the rails and reducing delays across the entire network.

Norfolk Southern

www.norfolksouthern.com

HEADQUARTERS: Atlanta, GA
ORGANIZATION TYPE: Private
Norfolk Southern develops AI-powered solutions that help make their rail networks more efficient and sustainable by optimizing operations, automating railcar and railway inspections, predicting maintenance, improving safety, and preventing delays.

Otaski Energy Solutions (OtaskiES): OtaskiES

otaskies.com

HEADQUARTERS: Gateshead, UK
ORGANIZATION TYPE: Private
OtaskiES is an energy management company that focuses on decarbonizing EV infrastructure and improving the energy efficiency of EVs, as well as AI and machine learning, to optimize the charging of EVs and improve driving distance timing/capability between charges.

Parallel Systems

moveparallel.com

HEADQUARTERS: Los Angeles, CA
ORGANIZATION TYPE: Private
Parallel Systems, a startup founded by SpaceX engineers, builds modular electric freight cars (much cleaner than traditional railcars) with fully automated systems that use machine learning to help optimize routes, energy consumption, and scheduling. Their goal is to make railways cheaper, safer, and more profitable and eventually get them to net zero emissions.

Plugger.ai: Human Detection, Vehicle Detection

plugger.ai

HEADQUARTERS: Wilmington, DE
ORGANIZATION TYPE: Private
Plugger.ai's AI-driven human and vehicle detection software has many applications, including retail analytics, search and rescue, healthcare, and security; its climate applications, however, involve traffic management and generating insights to help decision-makers make data-informed decisions on traffic and parking infrastructure.

Progress Rail: Talos

www.progressrail.com

HEADQUARTERS: Albertville, AL
ORGANIZATION TYPE: Private
Talos is a platform created by Progress Rail that leverages AI and machine learning to analyze train runs and engineer behavior to optimize train routes and operation, making performance more efficient and reducing fuel consumption and time spent on the rails.

Rail Vision: Main Line/ Shunting Yard

railvision.io

HEADQUARTERS: Ra'anana, Israel
ORGANIZATION TYPE: Private
Rail Vision's technologies use AI, vision sensors, and deep learning to detect obstacles on railway tracks, monitor weather and light conditions, and help optimize train transportation—which can help the industry become more sustainable. In February 2024, Rail Vision joined NVIDIA Metropolis to enhance its ability to innovate in rail transportation.

Thales

thalesgroup.com

HEADQUARTERS: La Défense, France
ORGANIZATION TYPE: Private
Thales develops AI-powered tools aimed toward automating trains and railways. They have AI tools to detect obstacles, monitor occupancy and location, and help make train transportation more efficient (and, ultimately, more sustainable).

Transport (continued)

TrinityRail: Trinsight

trinityrail.com

HEADQUARTERS: Dallas, TX
ORGANIZATION TYPE: Private
TrinityRail's railway management platform, Trinsight, leverages AI and big data to create actionable insights supporting railway networks, helping make rail transportation more efficient and sustainable.

TuSimple

tusimple.com

HEADQUARTERS: San Diego, CA
ORGANIZATION TYPE: Private
TuSimple used deep learning algorithms to develop software to make autonomous trucks for the shipping and transportation industry. A University of California San Diego study on TuSimple's autonomous trucks determined they were 10% more fuel efficient than human-driven trucks. In 2023, the company announced it would be closing its U.S. business and moving to China.

Uptake: Uptake Fleet

uptake.com

HEADQUARTERS: Chicago, IL
ORGANIZATION TYPE: Private
Uptake Fleet is AI-enabled software that helps companies manage their truck fleets and predict maintenance needs; it delivers work order analytics, system insights through sensors, detects anomalies and identifies high-risk trucks to prioritize repairs, as well as visualizes assets and diagnostics. And, by optimizing truck transportation, Uptake increases companies' fuel efficiency and reduces the carbon footprint of their shipping operations.

Vialytics

vialytics.com

HEADQUARTERS: Short Hills, NJ
ORGANIZATION TYPE: Private
Vialytics is an intelligent road management platform that uses AI to automatically record road infrastructure conditions and plan maintenance and repair operations tasks. The centralized nature of the data and insights allows municipalities to save money, time, fuel, and energy in road maintenance.