Tackling Climate Change with Machine Learning

Climate Change AI Virtual Summer School 2026

Maria João Sousa, David Rolnick, Priya L. Donti

Climate Change AI

Lecture outline

Why	**Climate change and climate action framing**
What	AI and machine learning (ML) framing
What	Technological roles of AI for climate action
How	Considerations for development and deployment
Which	Machine learning approaches for climate problems
How	Best practices spotlight: approaches, resources & tools

Climate change requires rapid action

Impacts are felt globally

Disproportionally affects
most vulnerable populations



Limiting **global warming to 1.5°C**:

- Requires **net-zero CO_2 emissions and deep cuts to other GHG emissions** by 2050 (IPCC 2018)

Emissions are still increasing each year

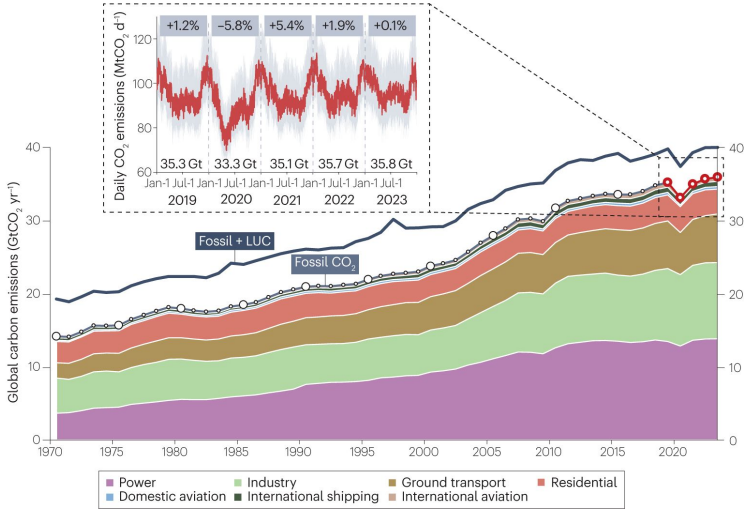


Image source: Liu et al (2023)

💬 Type your answer in the Zoom chat

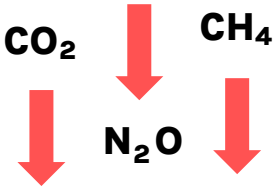
What is one example approach for addressing climate change?

Feel free to choose an example that is especially relevant to your country or local context.

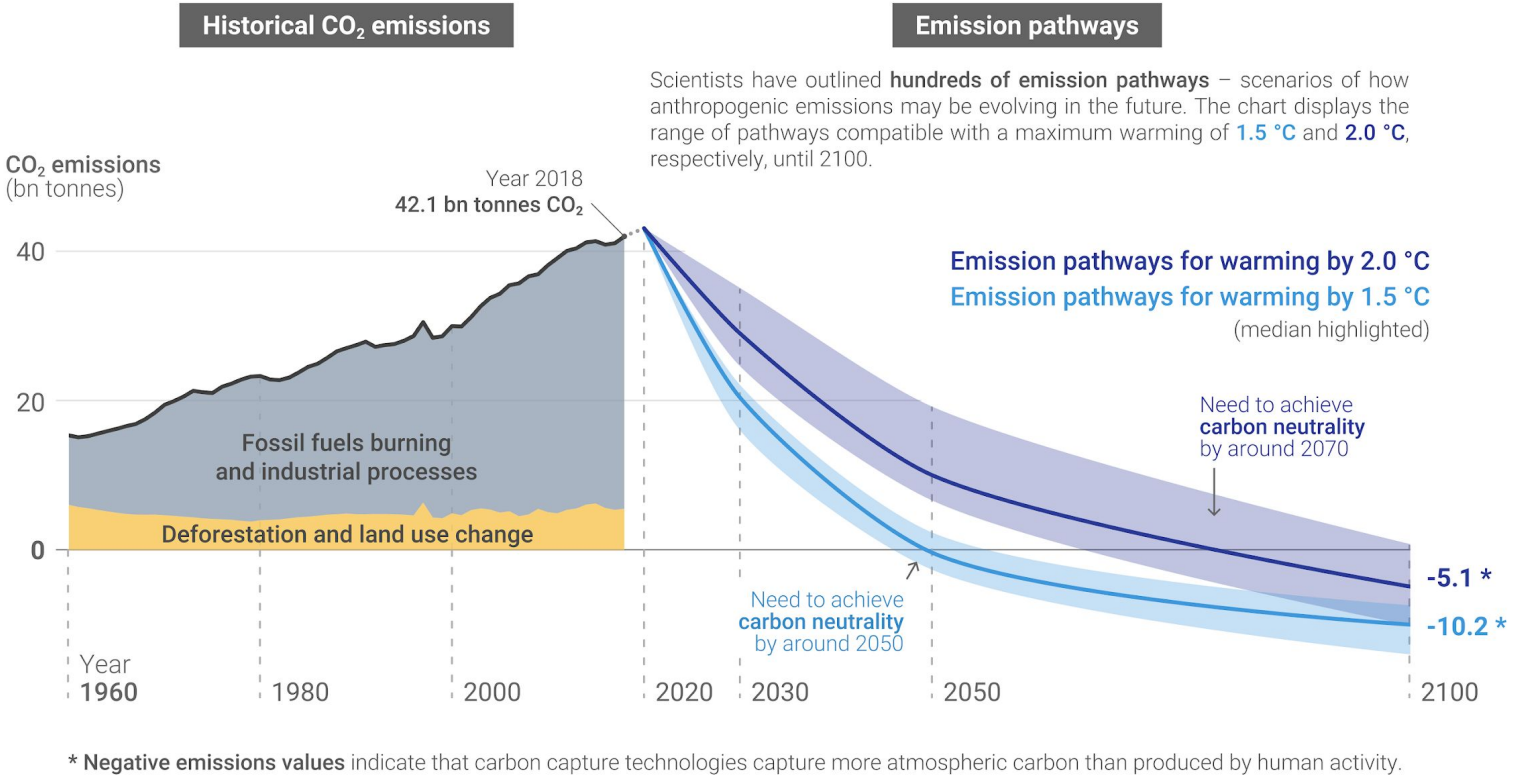
What it means to tackle climate change

Mitigation Actions that **reduce the rate** of climate change

To reduce or prevent **greenhouse gas emissions**



Path towards limiting global warming to 1.5°C?



* **Negative emissions values** indicate that carbon capture technologies capture more atmospheric carbon than produced by human activity.

Source: factsonclimate.org/emission-pathways-paris

Climate change mitigation sectors

Mitigation: Reducing/preventing GHG emissions

Sectors

- Energy supply
- Transportation
- Buildings
- Industry
- Agriculture
- Forestry
- Other land use
- CO_2 removal

Energy-related emissions

Land use (AFOLU) emissions

Negative emissions

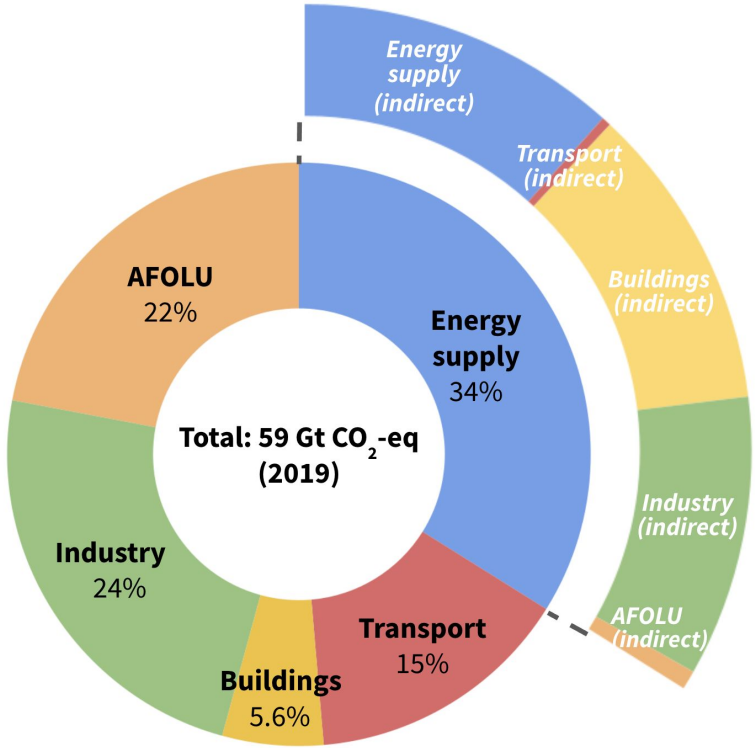
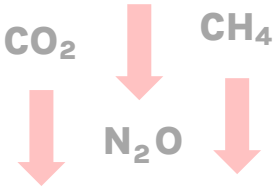


Figure data based on IPCC AR6 WG3 Report (2022). Percentages shown do not add to exactly 100% due to rounding to two significant figures.

What it means to tackle climate change

Mitigation Actions that **reduce the rate** of climate change

To reduce or prevent **greenhouse gas emissions**



Adaptation Actions that **respond** to a changing climate

To **prepare for** and **adjust** to both the **current effects** of climate change and the **predicted impacts** in the future



Science Actions that **improve** understanding of climate change

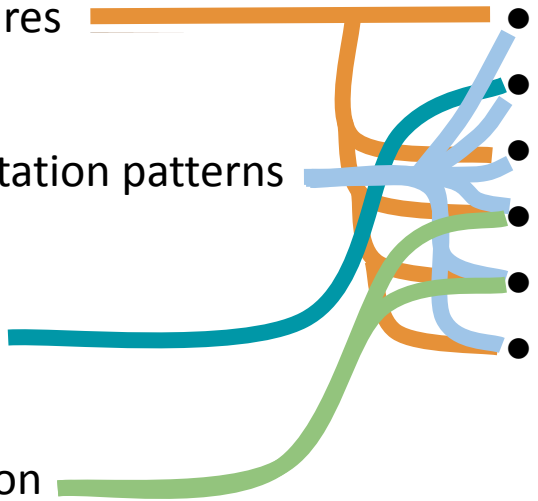
Climate change is **not an on/off switch**, but reaching **tipping points** may have irreversible consequences



Climate impacts and downstream effects

Climate impacts

- Rising temperatures
- Changing precipitation patterns
- Rising sea levels
- Ocean acidification



Downstream effects

- Droughts and heatwaves
- More intense storms and flooding
- More frequent wildfires
- Loss of ecosystem services
- Biodiversity loss
- Spread of disease vectors and pests

Figure adapted from Kris Sankaran

Climate change adaptation

Adaptation: Responding to the effects of a changing climate

Climate change adaptation

Adaptation: Responding to the effects of a changing climate

1. Measuring and predicting risks
   - **Risk**: Impact x probability

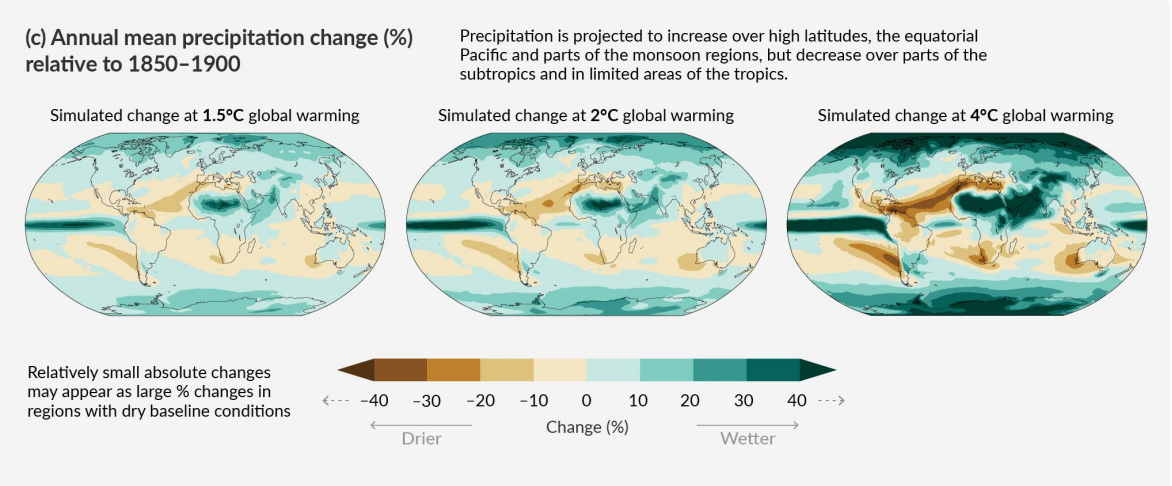


Figure source: IPCC AR6 Summary for Policymakers (2021)

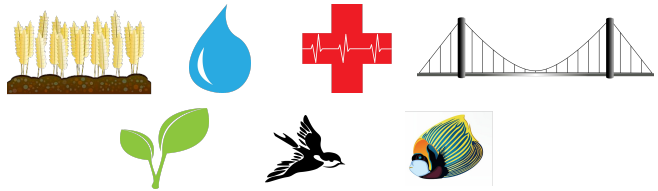
Climate change adaptation

Adaptation: Responding to the effects of a changing climate

1. Measuring and predicting risks
   - **Risk**: Impact x probability

2. Strengthening adaptive capacity
   - **Robustness:** Withstand a range of outcomes with no/minimal impact
   - **Resilience:** Recover quickly after impact

Human & ecological systems



Connections with UN SDGs

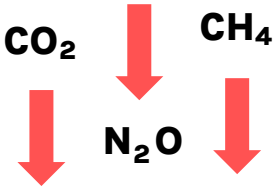


Figure source (bottom): United Nations

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What it means to ensure socially just climate futures

Climate justice Actions promoting an **equity-centered approach** to climate action

Beyond environmental impacts, **social, ethical** and **political** issues are also at play, requiring placing **equity** and **human rights** at the center of climate action

Co-benefits Actions aligned with **human development and economic prosperity**

Consider **explicit linkages** between climate action and other **UN Sustainable Development Goals (SDGs)**



Image source: Leal Filho et al. (2023)



Benjamin Cook

Research Scientist, NASA Goddard Institute for Space Studies and Columbia University

Foundation Lecture: Introduction to Climate Change

Friday, July 24 (14:00-16:00 UTC)



Clara Iglesias

Climate Interactive

Tutorial: Simulating Climate Futures in En-ROADS

Asynchronous

Lecture outline

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What is AI?

Artificial intelligence (AI): Any algorithm that allows a machine to perform a complex task (e.g., tasks associated with human intelligence)

Rule-based systems:
Techniques that automatically reason over an explicit set of rules

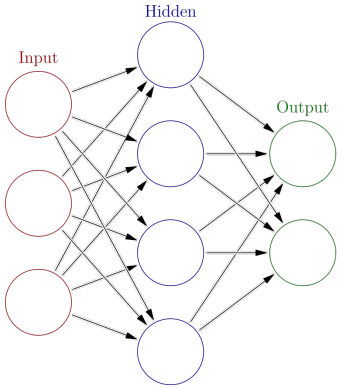


Machine learning (ML):
Techniques that automatically extract patterns from data

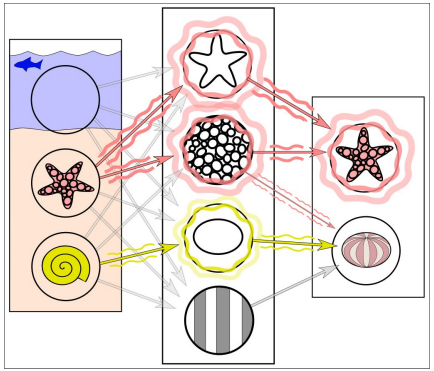


What is an ML Model?

The **model** consists of parameters and a structure that together transform inputs into outputs



The “learning” part means these parameters get adjusted through **training** to produce a “learned model” that can achieve a task



💬 Type your answer in the Zoom chat

What's one example of an machine learning model/approach?

Ways to classify machine learning algorithms

1. What kind of data?

- images (computer vision)
- text (natural language processing)
- sequences (time series analysis)
- …. many more possibilities / subtypes for data
- multiple data types together (multimodal learning)

2. What kind of problem?

- classification
- prediction
- clustering
- optimization
- control
- generation / simulation
- …

3. What kind of model?

- neural networks = deep learning
- Bayesian methods
- decision trees
- support vector machines
- …

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Example:

Residual Network (ResNet)

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Example:

Diffusion model

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- **Decision trees**
- Support vector machines
- …

Example:

Random forest



Tẹ́júmádé Àfọ̀njá

PhD Candidate,
CISPA Helmholtz Center |
Co-founder, TRI AI

Foundation Lecture: Introduction to AI

Thursday, July 23 (14:00-16:00 UTC)



Tarini Bhatnagar

NVIDIA

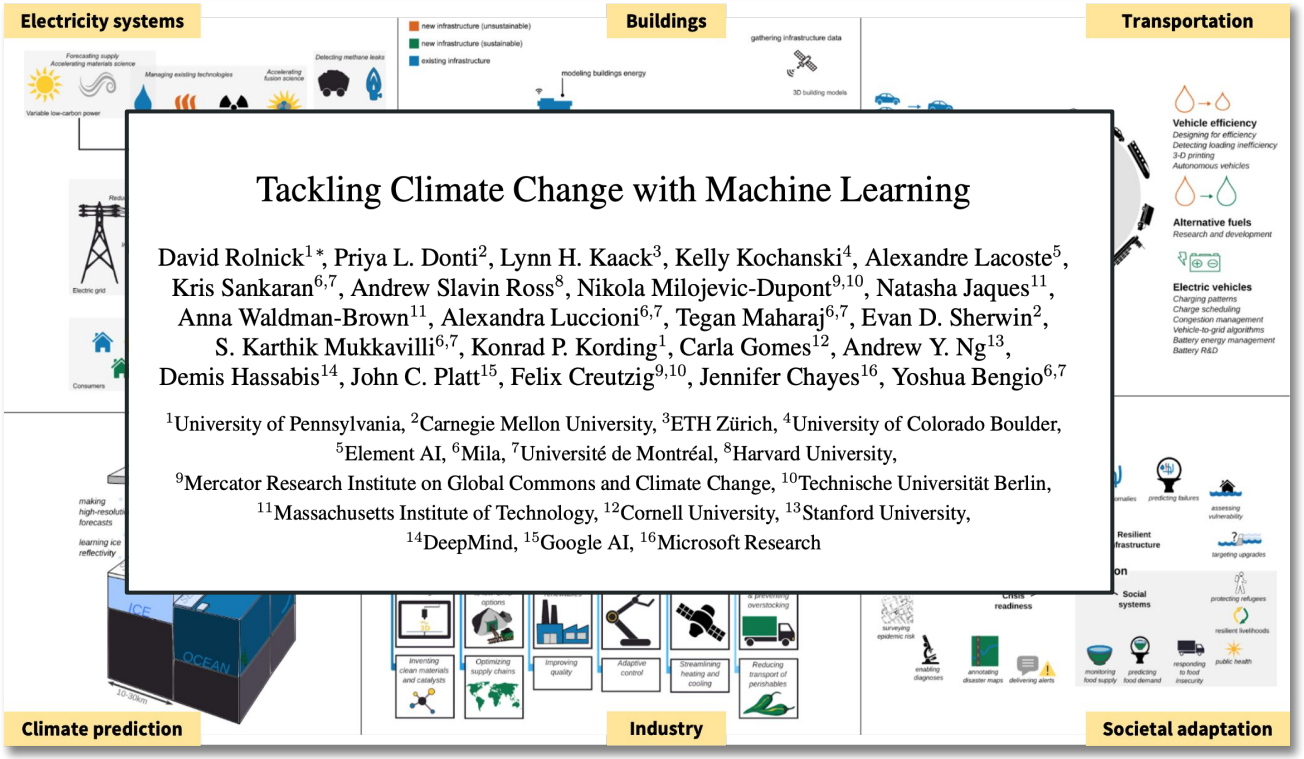
Tutorial: Introduction to AI - Predicting Tsunami Alerts from Earthquake Observations

Asynchronous, with walkthrough video

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AI technology *can enable strategies* ***to accelerate climate action*** *when applied responsibly in partnership with relevant stakeholders.*



Climate Change AI Report
Tackling Climate Change with Machine Learning
(2019)

Energy, Materials, & Built Environment



AI for Power & Energy Systems

Jose Córdova-García

European School of Political and Social Sciences



AI for Buildings

Nipun Batra

Indian Institute Of Technology Gandhinagar



AI for Cities & Urban Planning

Binyu Lei

University of Birmingham

AI for Optimal Power Flow

Enming Liang (City University of Hong Kong), Jorge Montalvo, Utkarsha Agwan, Panos Moutis (City College of New York)





AI for Transportation

Cathy Wu

Massachusetts Institute of Technology



AI for Accelerated Materials Science

Francisco J. Martin-Martinez

King's College London

CityLearn: Reinforcement Learning Control for Grid-Interactive Efficient Buildings and Communities

Kingsley Nweye, Allen Wu, Hyun Park, Yara Almilaify (University of Texas at Austin), Ava Mohammadi, Zoltan Nagy (Eindhoven University of Technology)



Predicting Mobility Demand from Urban Features

Developed by Konstantin Klemmer, Shafat Rahman, Felix Wagner, Florian Nachtigall (TU Berlin, MCC Berlin); revised by Gabriela Yaulli Herrera (Cornell Tech)



Earth & Climate Systems



AI for Climate Science

Claire Monteleoni

University of Colorado Boulder, Inria, Climate Informatics





AI for Weather

Rendani Mbuvha (University of the Witwatersrand, AfriClimate AI) and Shruti Nath (University of Oxford, AfriClimate AI)



AI for Oceans & Marine Systems

Maike Sonnewald

University of California Davis

Planning for Floods & Droughts: Intro to AI-Driven Hydrological Modeling

Kshitij Tayal (Oak Ridge National Labs), Arvind Renganathan (University of Minnesota), Siyan Liu (Oak Ridge National Labs), Dan Lu (Oak Ridge National Labs), Puja Das (MIT)



Monitoring Coastal Water Quality and Marine Ecosystem Change Using Remote Sensing and Machine Learning

Tedi Yankov (University of Oxford)





AI for Water Resources and Hydrology

Nagesh Kumar

Indian Institute of Science



AI for Carbon Accounting

Daniel Cusworth

Carbon Mapper

Statistical Downscaling of Climate Projections with Deep Learning

Jose González-Aba (Instituto de Física de Cantabria)



PiggyCast - Improving Weather Prediction Accuracy through a Stacking-Based Ensemble AI Approach

Josiah Kimani (AIMS South Africa), Oliver Angélil (Ishango.ai), Chris Toumping (Ishango.ai), Steffen Knoblauch (Heidelberg University)



Estimating Coal Power Plant Operation from Satellite Images with CV

André Ferreira (TransitionZero), Isabelle Tingzon (RISE Research Institutes of Sweden), El Khalil Cherif (Institute For Systems and Robotics)



Land, Food, & Nature



Combining AI and Indigenous Knowledge for Climate Action

Sonajharia Minz

Jawaharlal Nehru University



AI for Agriculture and Food Security

Aliny Reis

Corvian



AI for Forestry

Silvana Amaral Kampel

INPE



AI for Biodiversity & Ecosystems

Benjamin Kellenberger

EPFL

Combining AI and Indigenous Knowledge for Climate Action: A Bird Bioacoustic Monitoring Pipeline — The Lkotkote Case Study

Developed by Douglas Mbura (Lkotkote)



Agricultural Monitoring with Fields of the World (FTW)

Developed by Hannah Kerner (Arizona State University), Caleb Robinson (Microsoft AI for Good Lab), Isaac Corley (Wherobots), Matthias Mohr (Taylor Geospatial Engine), Gedeon Muhawenayo (Arizona State University), Ivan Zvonkov (University of Maryland), Tristan Grupp (World Resources Institute), Nathan Jacobs (Washington University in St Louis)
Revised by Akram Zaytar (Microsoft AI for Good Lab)



Detecting Deforestation from Satellite Image Time Series

Developed by Eduardo Ulises Moya-Sanchez (IIEG Jalisco)



Agile Modeling for Bioacoustic Monitoring

Developed by Jenny Hamer, Rob Laber, and Tom Denton (Google DeepMind, Google)



Society, Policy & Economics



AI for Climate Finance

Malte Toetzke

TU Munich, Max Planck Institute for Innovation and Competition



AI for Public Policy

Carlos Rodriguez-Pardo

Politecnico di Milano, CMCC Foundation



AI for Social Sciences

Mary Sanford

University of Bath, CMCC Foundation

Sea Water Flood Risk Assessment in Egypt using Deep Learning, Sentinel-1 & 2, and Copernicus DEM

Developed by Casper Fibaek and Andreas Luyts (ESA Φ-lab); revised by Nirdesh Kumar Sharma (EarthSense Labs)





AI for Public Health

Joyce Nakatumba-Nabende

Makerere University, Data Science Africa



AI for Risk Assessment, Disaster Management & Relief

Mersedeh TariVerdi

The World Bank

NLP Models for Climate Policy Analysis

Daniel Spokoyny (Carnegie Mellon University), Max Callaghan (Potsdam Institute for Climate Impact Research, MCC-Berlin), Tobias Schimanski (University of Zurich)



Hands-On Outbreak Analytics: Dengue Forecasting with RAG and LLM Evaluation

Avinash Laddha (data.org)



AI for Climate Finance: Estimating Hurricane Wind Value-at-Risk from an AI Weather Ensemble

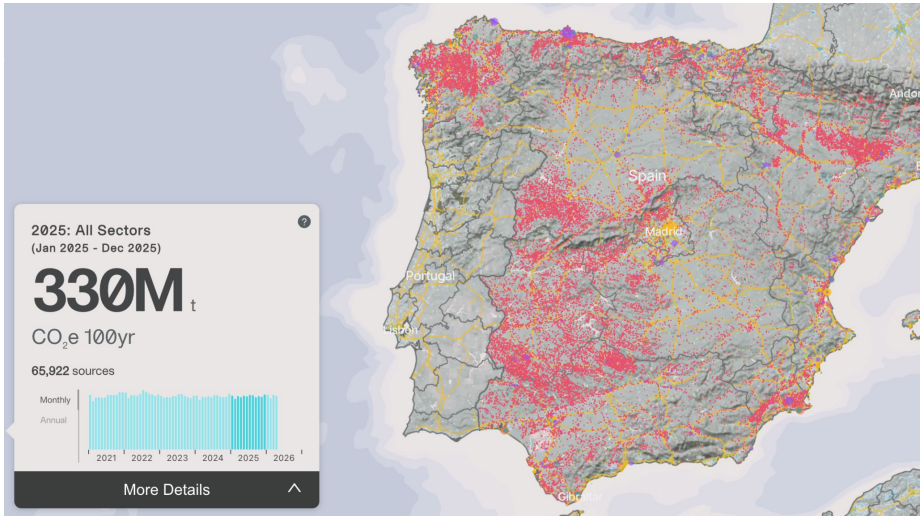
Tristan Ballard (Zeus AI)



Opportunities in AI-for-climate applications

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Gathering information
flooding, deforestation, infrastructure, crops, biodiversity



Source: Climate TRACE

Opportunities in AI-for-climate applications

Gathering information
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Forecasting
renewable energy, transportation demand, extreme events

Forecast 4 Africa
by AfriClimate AI



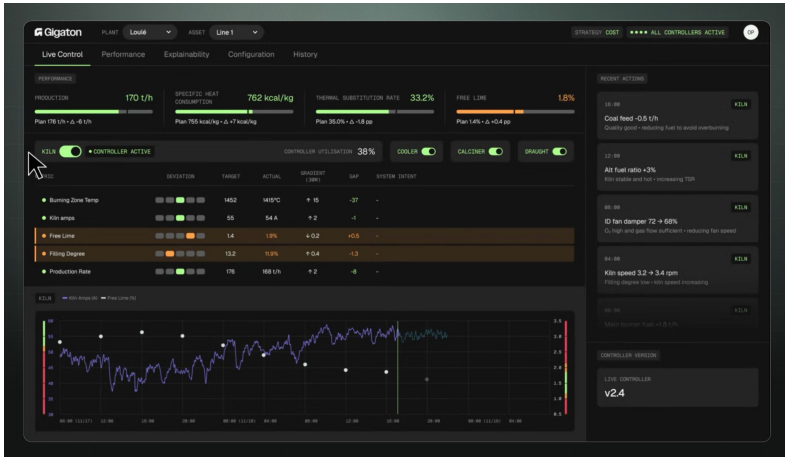
Source: African Farming

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Optimizing complex systems
power and energy, heating and cooling, freight, food waste



Source: Gigaton

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methane leaks, resilient infrastructure



Source: East Japan Railway Company

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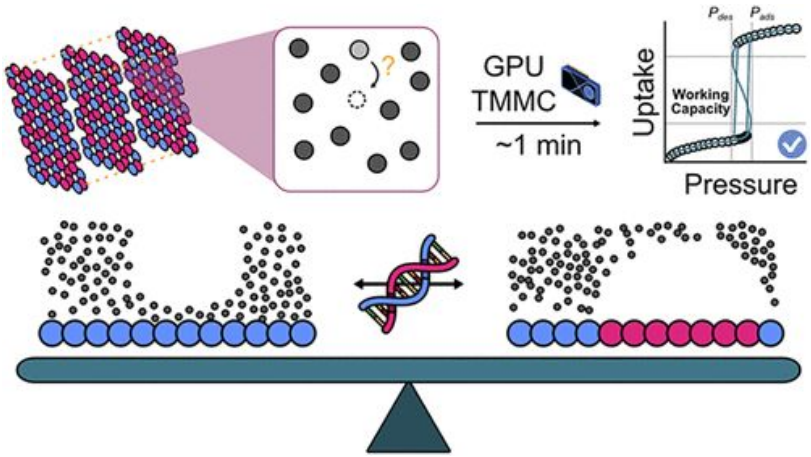
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Source: Prelesnik et al. 2026

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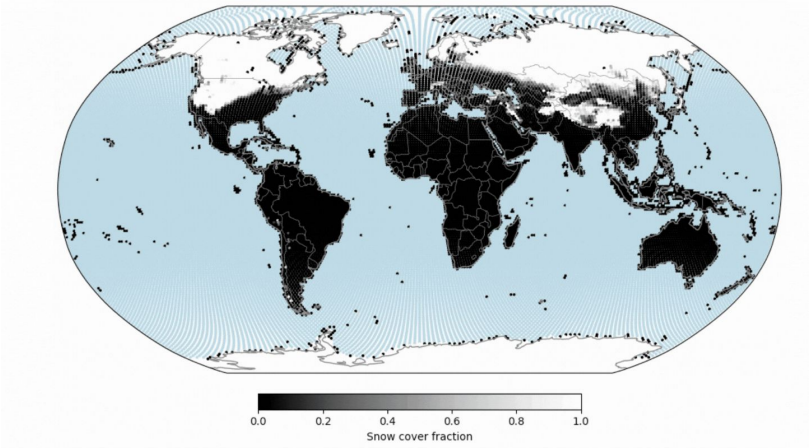
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climate, energy, city planning



Source: ECMWF / Destination Earth

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Data management
data matching, collation, fusion, augmentation

Platform	Format	Version	User Types	Use Cases
PUDL Data Viewer	Parquet, CSV	`nightly`	Data Explorer, Spreadsheet Analyst, Jupyter Notebook User	Explore PUDL data interactively in a web browser, including hourly timeseries data. Select data to download as CSVs for local analysis in spreadsheets. Download full tables as Parquet files to play with programmatically.
Kaggle	SQLite, Parquet	`nightly`	Data Scientist, Data Analyst, Jupyter Notebook User	Work with PUDL data products in Jupyter Notebooks via the web with minimal setup. Explore curated and contributed analyses and visualizations using PUDL data. notebooks. Create and share your own interactive notebooks using PUDL data.
Cloud Storage	SQLite, Parquet	`nightly`, `stable`	Data Scientist, Analytics Engineer, Data Engineer, Cloud Developer	Performant remote queries of clearly versioned PUDL Parquet outputs from cloud computing platforms or GitHub Actions. Fast bulk download of SQLite or Parquet outputs for local use. Parquet based data warehouse for large-scale data analysis in the cloud. Integrates well with Pandas, DuckDB, and other dataframe libraries.
Zenodo Archives	SQLite, Parquet	`stable`	Researcher, Publisher, Archivist	Access a specific, immutable version of the PUDL data by DOI for citation in academic publications or other applications where long-term reproducibility is needed. Web-based bulk download of data for local analysis.

Source: Catalyst Cooperative / Public Utility Data Liberation Project

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What are we aiming to illustrate here?

Diversity of

- Relevant sectors / problems
- Locations / geographical contexts
- Types of AI
- Kinds of organizations involved

There isn’t one (or even 100) “best” applications of AI for climate

Valuable projects are often quite specific

Often far from the AI (and climate) projects in the news

Ways that the AI-for-climate space has advanced

Innovations in ML methods (e.g., diffusion models) relevant to certain applications (e.g., climate science)

Maturation of **application-driven areas of ML** (e.g. physics-informed ML)

Many projects have **advanced beyond proof of concept** (e.g. geospatial tools)

Uptick in **interdisciplinary subcommunities with AI expertise** (e.g. energy, ecology)

Ways that the discourse has changed in last few years

Climate change now perceived as **flagship area of "AI for Good"** alongside health

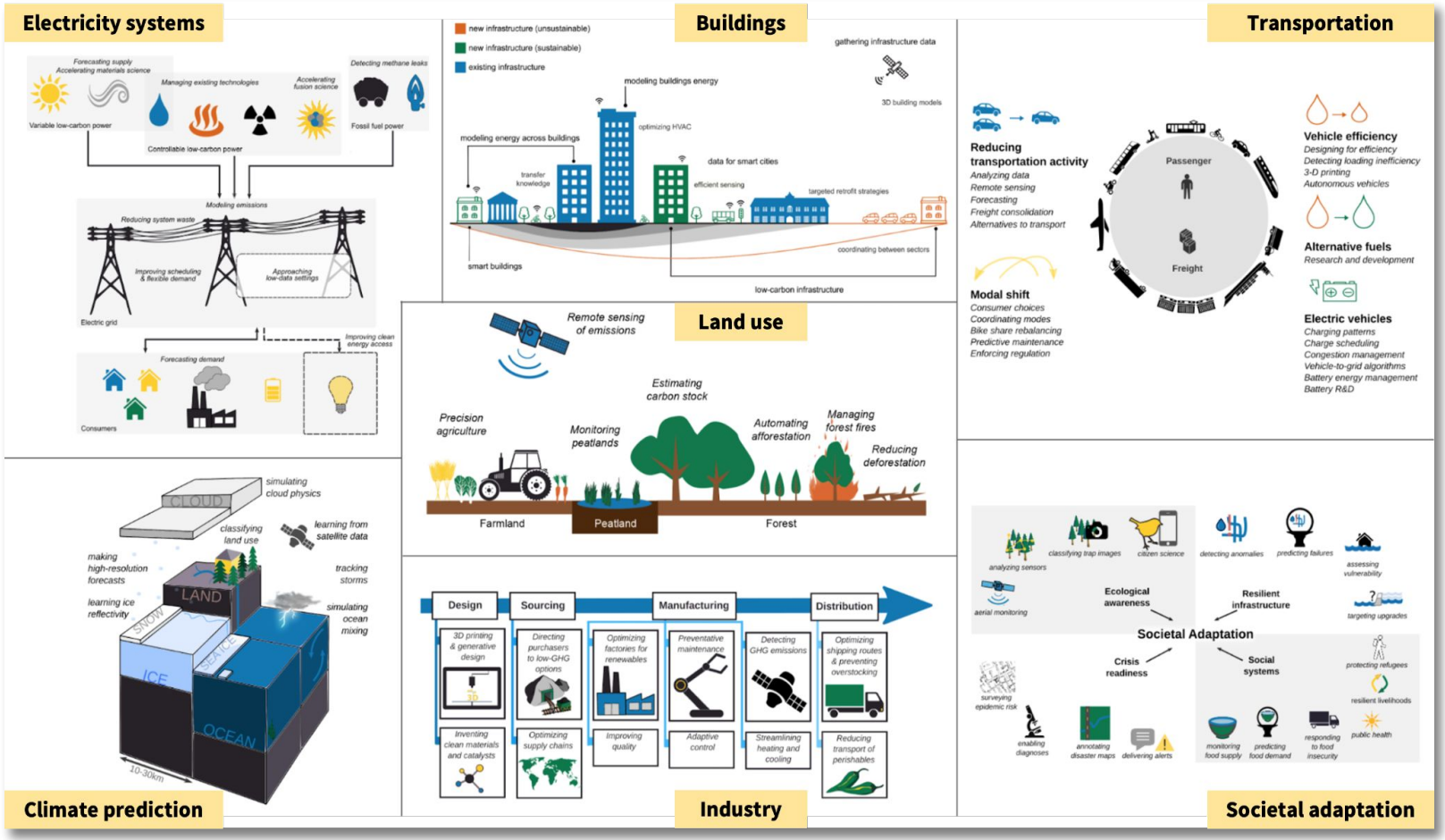
High visibility of AI - increased interest (for better and for worse)

Public attention on **large generative models (e.g. ChatGPT)**, conflation with other AI

Vast growth in **energy use** and data centers due to **large generative models**

Above trends have led to **perception that AI innovation is about centralization**

"Democratization" of AI often used to refer to more users, instead of more "shapers"


Electricity systems
Forecasting supply
Accelerating materials science
Managing existing technologies
Accelerating fusion science
Detecting methane leaks
Variable low-carbon power
Controllable low-carbon power
Fossil fuel power
Modeling emissions
Reducing system waste
Improving scheduling & flexible demand
Approaching low-data settings
Electric grid
Improving clean energy access
Forecasting demand
Consumers
Buildings
new infrastructure (unsustainable)
new infrastructure (sustainable)
existing infrastructure
gathering infrastructure data
3D building models
modeling buildings energy
optimizing HVAC
modeling energy across buildings
transfer knowledge
data for smart cities
efficient sensing
targeted retrofit strategies
smart buildings
coordinating between sectors
low-carbon infrastructure
Transportation
Reducing transportation activity
Analyzing data
Remote sensing
Forecasting
Freight consolidation
Alternatives to transport
Passenger
Freight
Modal shift
Consumer choices
Coordinating modes
Bike share rebalancing
Predictive maintenance
Enforcing regulation
Vehicle efficiency
Designing for efficiency
Detecting loading inefficiency
3-D printing
Autonomous vehicles
Alternative fuels
Research and development
Electric vehicles
Charging patterns
Charge scheduling
Congestion management
Vehicle-to-grid algorithms
Battery energy management
Battery R&D
Land use
Remote sensing of emissions
Estimating carbon stock
Precision agriculture
Monitoring peatlands
Automating afforestation
Managing forest fires
Reducing deforestation
Farmland
Peatland
Forest
Climate prediction
simulating cloud physics
CLOUD
classifying land use
learning from satellite data
making high-resolution forecasts
tracking storms
learning ice reflectivity
LAND
SNOW
ICE
simulating ocean mixing
OCEAN
10-30km
Industry
Design
Sourcing
Manufacturing
Distribution
3D printing & generative design
Directing purchasers to low-GHG options
Optimizing factories for renewables
Preventative maintenance
Detecting GHG emissions
Optimizing shipping routes & preventing overstocking
Inventing clean materials and catalysts
Optimizing supply chains
Improving quality
Adaptive control
Streamlining heating and cooling
Reducing transport of perishables
Societal adaptation
analyzing sensors
classifying trap images
citizen science
detecting anomalies
predicting failures
assessing vulnerability
aerial monitoring
Ecological awareness
Resilient infrastructure
targeting upgrades
Societal Adaptation
Crisis readiness
Social systems
protecting refugees
resilient livelihoods
surveying epidemic risk
enabling diagnoses
annotating disaster maps
delivering alerts
monitoring food supply
predicting food demand
responding to food insecurity
public health

💬 Type your answer in the Zoom chat

What is one organization you're aware of that is exploring or creating AI-for climate solutions?

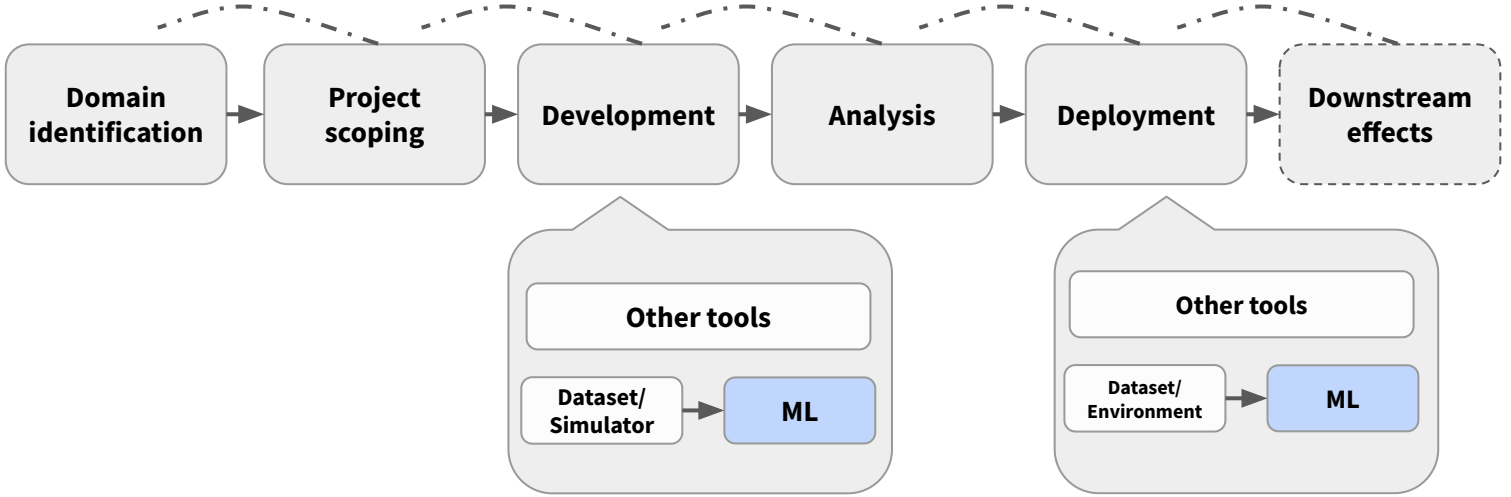
Feel free to mention in a couple words what problem they are trying to address.

Lecture outline

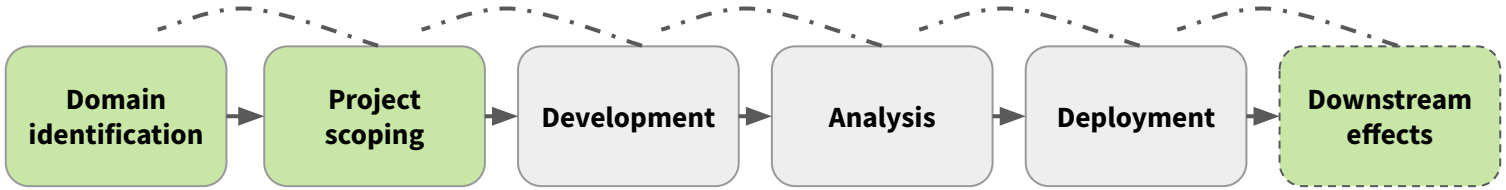
5-minute break

Why	Climate change and climate action framing
What	AI and machine learning (ML) framing
What	Technological roles of AI for climate action
How	Considerations for development and deployment
Which	Machine learning approaches for climate problems
How	Best practices spotlight: approaches, resources & tools

ML-for-climate: Pathway to impact



ML-for-climate: Pathway to impact

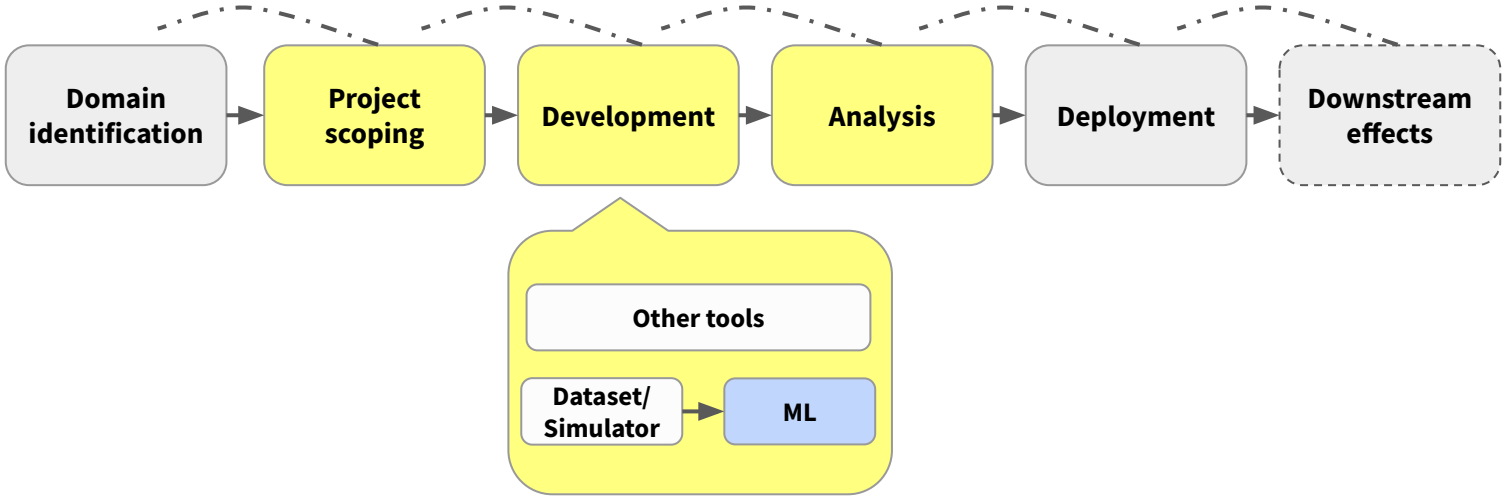


Who are the **relevant stakeholders** who are involved in or affected by the application?

What is the **scope** of impact?

What is the **time horizon** of impact?

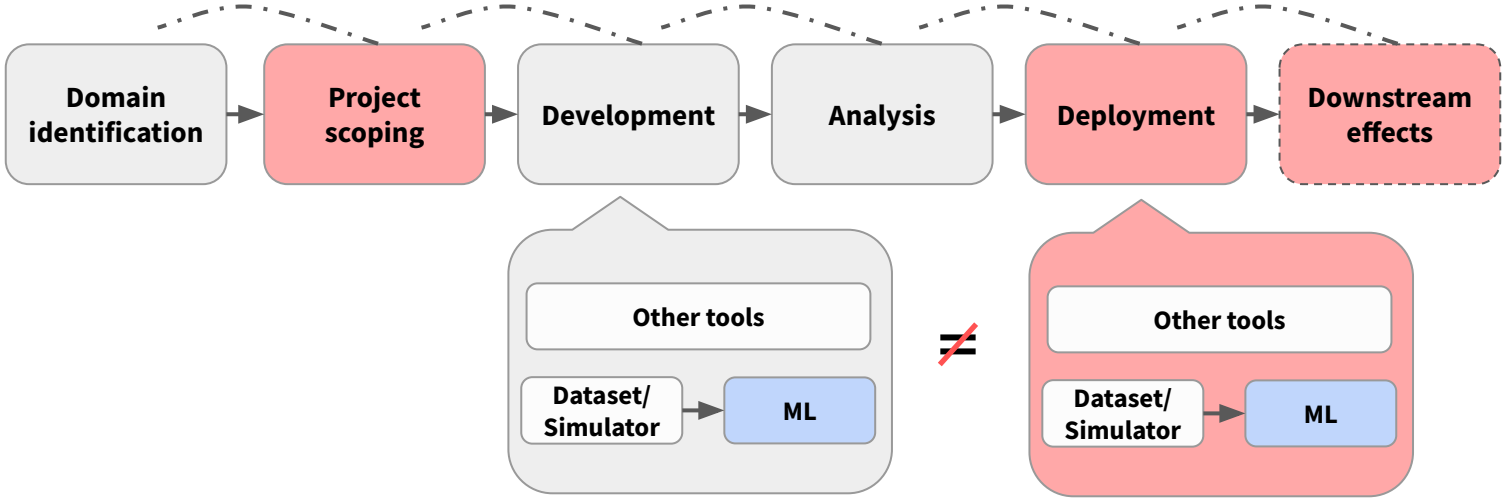
ML-for-climate: Pathway to impact



Is AI/ML **suitable and needed** to address the problem?

What is the **likelihood** that a solution can be found?

ML-for-climate: Pathway to impact



Can a solution feasibly be deployed?

What are the **potential side effects** of deploying the candidate solution?

New applications require new specialized infrastructure

Data: Collection, annotation, collation, inference, and/or licensing

- Note: “Data” can mean different things to different communities

Simulators: Needed for innovations in physical domains

- E.g., power systems, transport, buildings, heavy industry

Evaluation metrics: Need agreement and iteration from ML researchers, domain researchers, deployers, and other affected stakeholders

Resources and venues

- CCAI Dataset Wishlist (https://www.climatechange.ai/dev/datagaps)
- Lacuna Fund funding for climate datasets
- NeurIPS Datasets and Benchmarks track

Who is involved in developing ML is critical

High-impact ML applications **are not always flashy**

Domain **knowledge and experience** is essential for deployable technologies

Interdisciplinary collaboration

- Scoping the right problems
- Incorporating relevant domain information
- Shaping pathways to impact

Equity considerations

- Empowering diverse stakeholders
- Selecting and prioritizing problems
- Ensuring data is representative

*Developing AI with **responsible**, **impact-driven** and **equity-centered** approaches*

Avoiding techno-solutionism

- *AI is not a silver bullet*
- *Where it's applicable, only one part of the strategy*

Mitigating biases in data and models

- *E.g., Buildings data: Housing discrimination, uneven availability across geographies*
- *E.g., Weather models: Calibration may be optimized for particular regions*

Improving trustworthiness and accountability

- *Safety and robustness: Critical in, e.g., power systems and industrial operations*
- *Interpretability and auditability: Critical in, e.g., policymaking contexts*

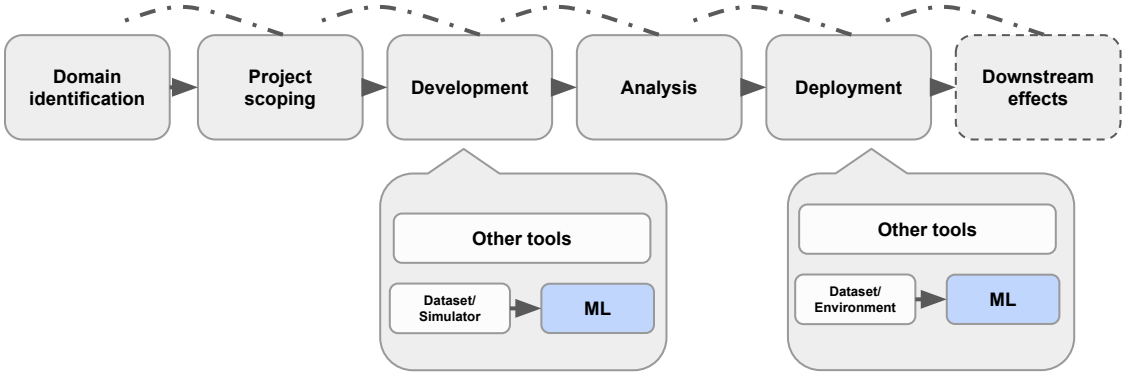
Centering equity and climate justice

- *Centering diverse stakeholders: E.g., industrial agriculture vs. smallholder farmers*
- *Avoiding centralization of power: Democratized access to capacity and compute*
- *Avoiding digital colonialism: E.g., smart meters, analysis of remote sensing data*

Impactful AI-for-climate needs a sociotechnical approach

Consider the full pathway to impact, including

- Data, simulators, metrics
- Responsible AI & climate considerations
- Stakeholder engagement

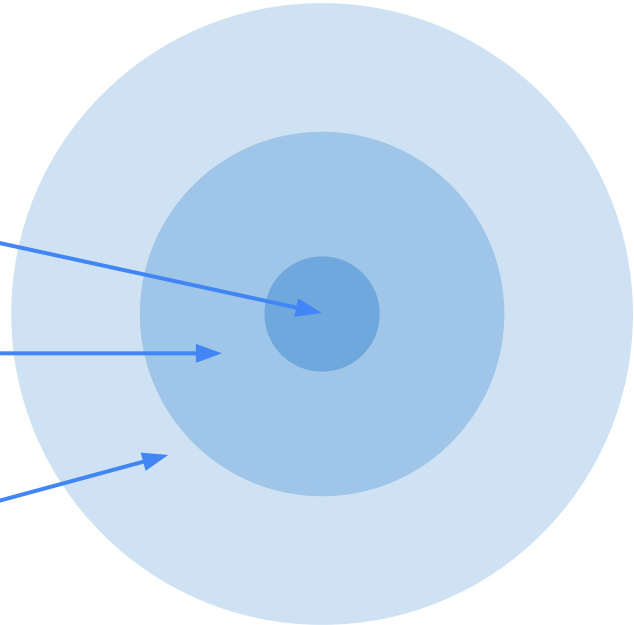


Responsible & ethical AI requires a holistic perspective

Project-level considerations
(how to actualize a project)

Choice of projects (where AI is used, who actually gets to benefit from AI projects)

Systemic & geopolitical impacts of AI trajectories (choices around investments, extraction & supply chains, capacity-building, etc.)



Multifaceted relationship *between AI and climate*

AI applications
for climate action

Impacts from AI
computation and hardware

AI applications
with **uncertain** or
systemic impacts

AI applications that
increase emissions



Responsible & Ethical AI

Virginia Dignum
Umeå University



Intro to AI Policy & Regulation

Costa Samaras
Carnegie Mellon University



Shaping Your AI-for-Climate Project in Practice

Dina Machuve
DevData Analytics, Data Science Africa



Intro to Climate Policy & Regulation

Vaibhav Chugh
Council on Energy, Environment and Water (CEEW)



Sustainability Impacts of AI

Nikola Milojević-Dupont
Climate Change AI

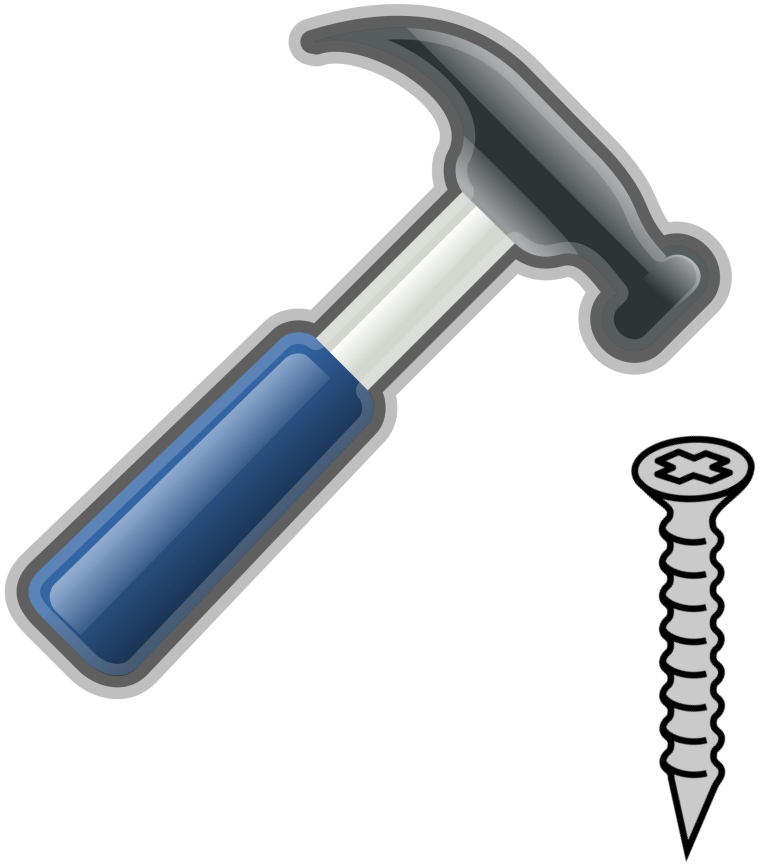
Reducing your Climate Impact when Training ML Models

Melanie Hanna (Quanata), Andres Felipe Perez Murcia (Uni. of Manitoba)



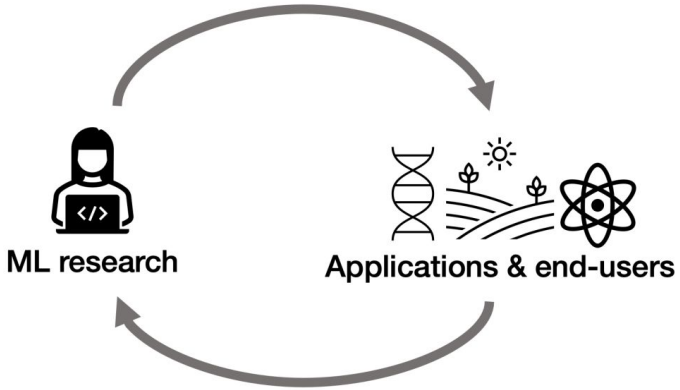
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Flathead
Phillips
Torx
Robertson
Hex
Pozidriv
Tri-Wing

Climate challenges can drive climate technology innovation

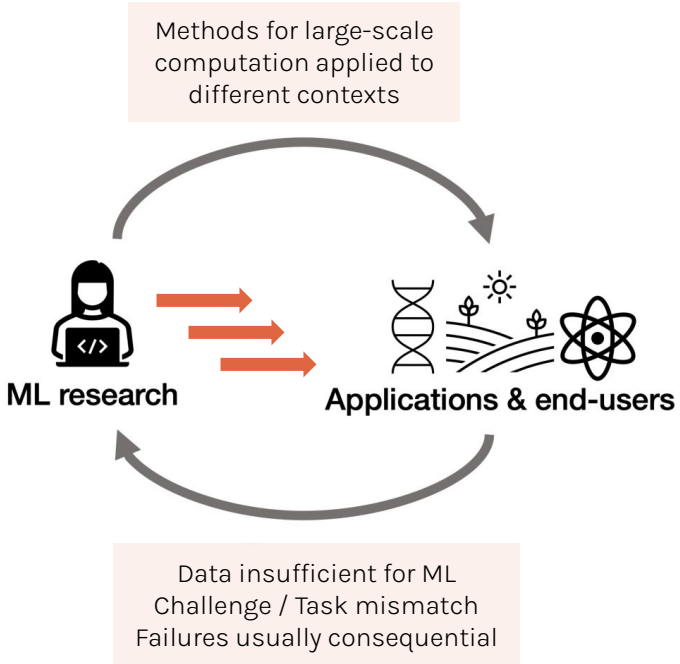


See: David Rolnick, Alan Aspuru-Guzik, Sara Beery, Bistra Dilkina, Priya L. Donti, Marzyeh Ghassemi, Hannah Kerner et al. "Position: Application-Driven Innovation in Machine Learning." *International Conference on Learning Representations* (2024).

Standard **ML methods** prone to fail in **“non standard” settings**

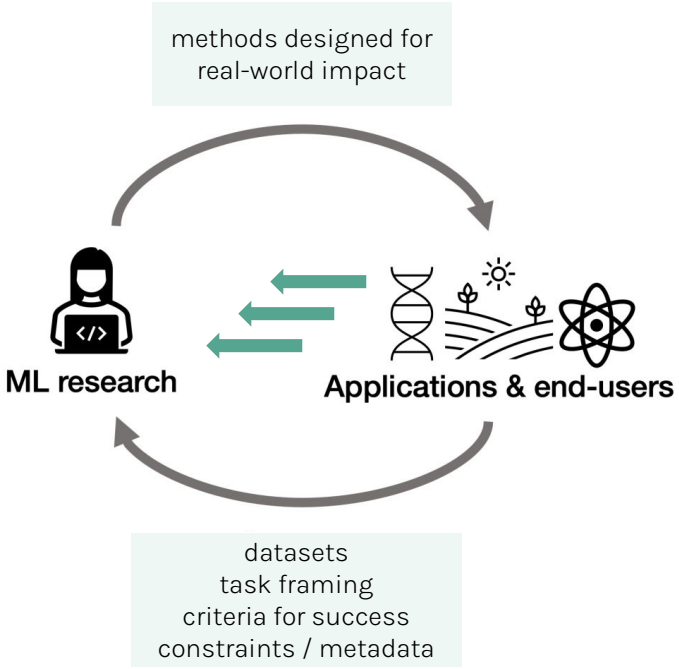
Top-down approach

Frontier AI **methods applied to** climate change problems



See: David Rolnick, Alan Aspuru-Guzik, Sara Beery, Bistra Dilkina, Priya L. Donti, Marzyeh Ghassemi, Hannah Kerner et al. "Position: Application-Driven Innovation in Machine Learning." *International Conference on Learning Representations* (2024).

Climate challenges must drive climate technology innovation



Bottom-up approach

Climate **applications shape** AI-for-climate innovation

Example requirements for ML methods:

- **Power grid optimization:** Satisfy engineering constraints
- **Weather forecasting:** Handle scarce data, depending on the region
- **Drone-based wildfire detection:** Run efficiently on low-power devices

See: David Rolnick, Alan Aspuru-Guzik, Sara Beery, Bistra Dilkina, Priya L. Donti, Marzyeh Ghassemi, Hannah Kerner et al. "Position: Application-Driven Innovation in Machine Learning." *International Conference on Learning Representations* (2024).

Diverse settings require diverse approaches

Dominant ML paradigm (e.g.)

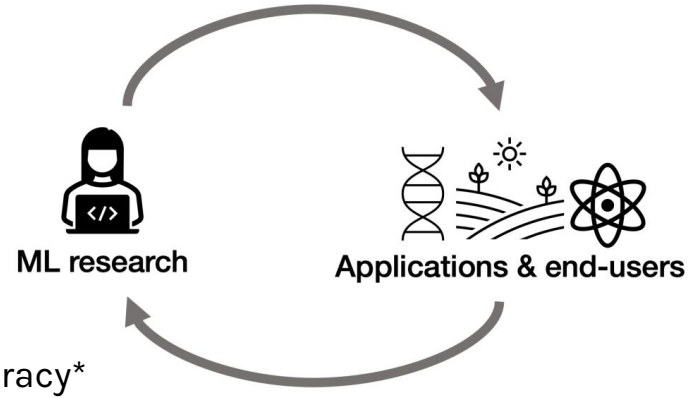
Big data

Big compute

Computation is not a limit

Data is all you need

Performance = average accuracy*



AI-for-climate domains (e.g.)

Less data; data hard to move

Less compute; edge devices; reducing energy/emissions

Useful knowledge in task/domain

Diverse set of metrics
(e.g., group-weighted accuracy, safety, robustness, privacy, interpretability, explainability, uncertainty quantification, ...)

See also: Birhane, Abeba, et al. "The values encoded in machine learning research." *ACM Conference on Fairness, Accountability, and Transparency*. 2022.

💬 Type your answer in the Zoom chat

Think about a climate application in your local context.

What is one “non-standard” requirement an AI/ML system would need to meet to actually be useful for your application?

Consider aspects such as data, performance metrics, constraints, and alignment with existing knowledge.

Opportunities in AI-for-climate applications

Gathering information
flooding, deforestation, infrastructure, crops, biodiversity

Forecasting
renewable energy, transportation demand, extreme events

Optimizing complex systems
power and energy, heating and cooling, freight, food waste

Predictive maintenance
methane leaks, resilient infrastructure

Accelerating scientific experimentation
batteries, electrofuels, catalysts, carbon capture

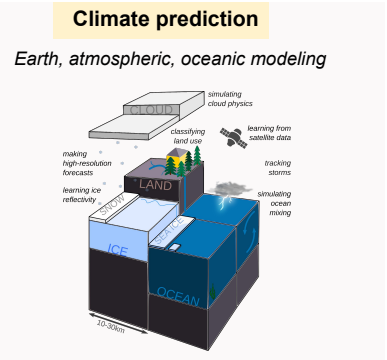
Approximating time-intensive simulations
climate, energy, city planning

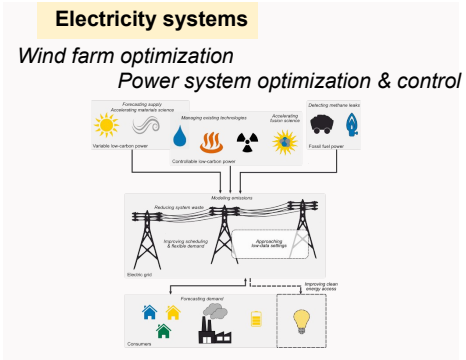
Data management
data matching, collation, fusion, augmentation

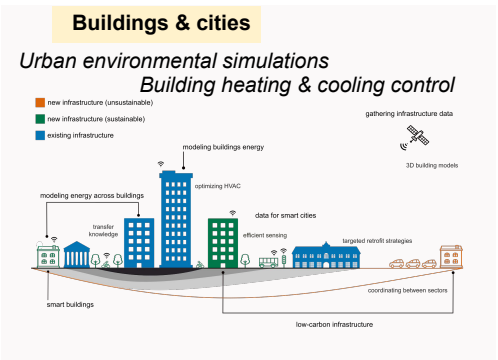
Methodological frontiers with climate relevance

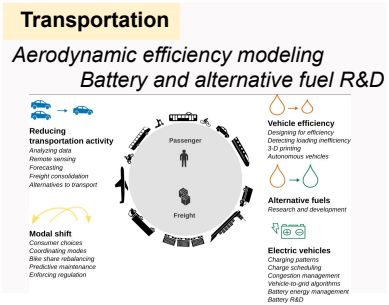
Physics-informed ML

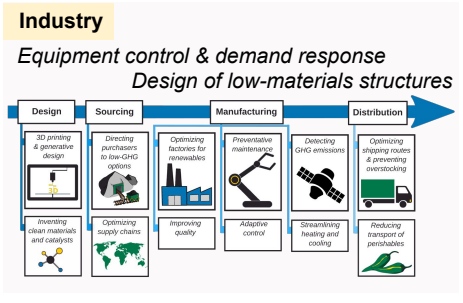
Safe and robust ML

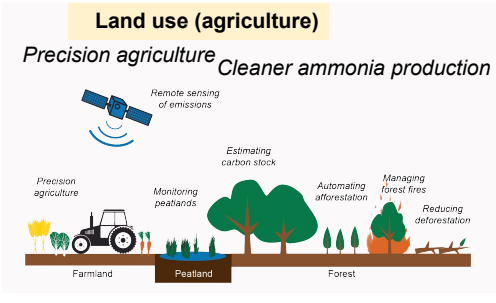












See also: Priya L. Donti, David Rolnick, Lynn H. Kaack, “Climate Change and ML: Opportunities, Challenges, and Considerations,” *ICML 2022 tutorial.*

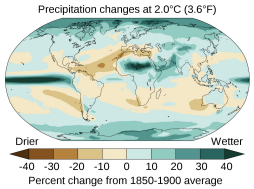
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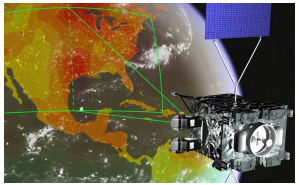
Safe and robust ML

Interpretable ML

Uncertainty quantification



Scientific understanding and predictions of climate change



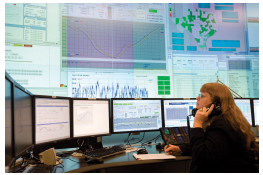
Monitoring, reporting, and verification of emissions and climate change effects



Early warning and emergency response



Policy-making on international, national, and local levels



Planning and operation of critical infrastructure



Innovation and technology assessment

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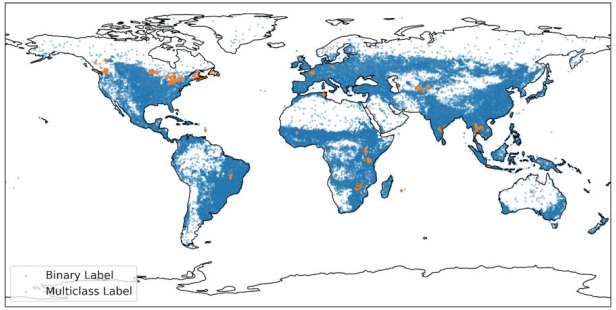
Physics-informed ML

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Interpretable ML

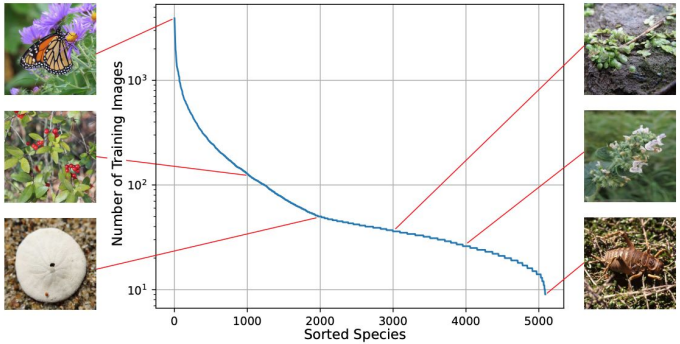
Uncertainty quantification

Generalization
(spatio-temporal, concept drift, limited data)



G. Tseng, et al., "CropHarvest: A global dataset for crop-type classification," NeurIPS 2021 Datasets and Benchmarks Track.

G. Van Horn et al., "The iNaturalist species classification and detection dataset," CVPR 2018.



See also: Priya L. Donti, David Rolnick, Lynn H. Kaack, “Climate Change and ML: Opportunities, Challenges, and Considerations,” *ICML 2022 tutorial.*

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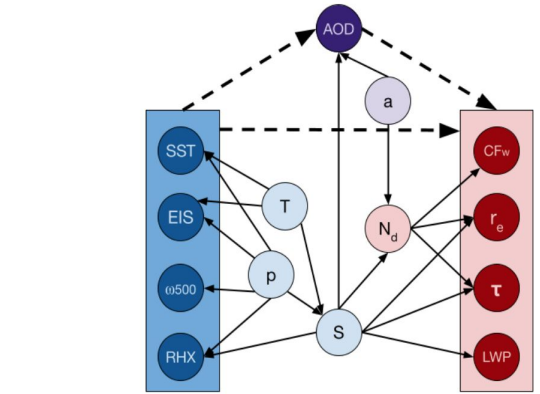
Safe and robust ML

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Causality



AOD	Aerosol optical depth	T	Temperature	CFw	Warm Cloud Fraction
SST	Sea surface temperature	p	Pressure	r_e	Effective radius
EIS	Effective inversion strength	S	Supersaturation	τ	Optical thickness
W500	500 hPa vertical velocity	N_d	Droplet Number Concentration	LWP	Liq. Water Path
RHX	X hPa relative humidity	a	Aerosol		

A. Jesson et al., "Using non-linear causal models to study aerosol-cloud interactions in the southeast Pacific," *Tackling Climate Change with Machine Learning workshop at NeurIPS 2021.*

See also: Priya L. Donti, David Rolnick, Lynn H. Kaack, “Climate Change and ML: Opportunities, Challenges, and Considerations,” *ICML 2022 tutorial.*

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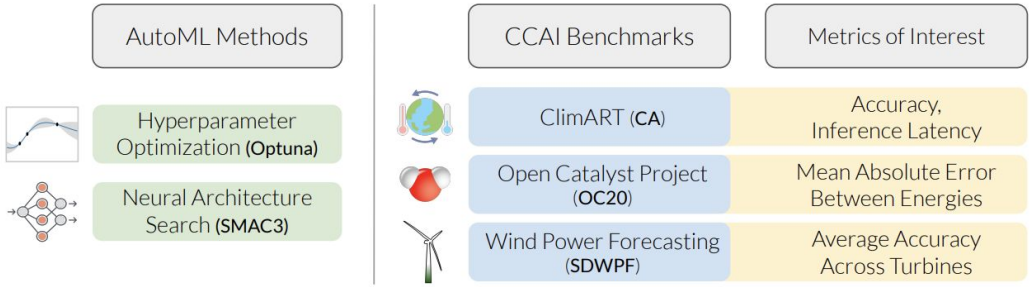
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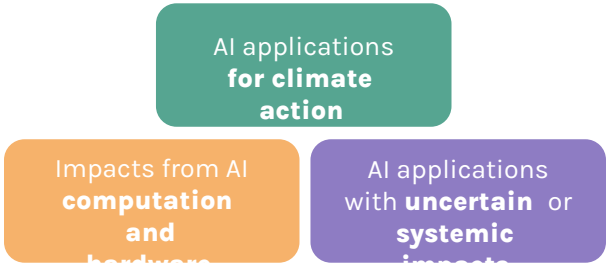
Causality

Energy efficient ML & TinyML

AutoML



Tu, Renbo, et al. "AutoML for climate change: A call to action." *Tackling Climate Change with Machine Learning workshop at NeurIPS 2022.*

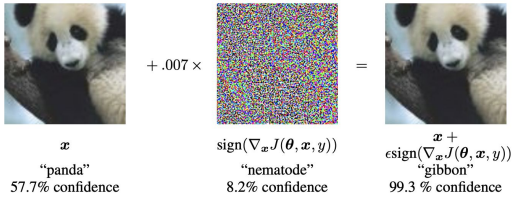


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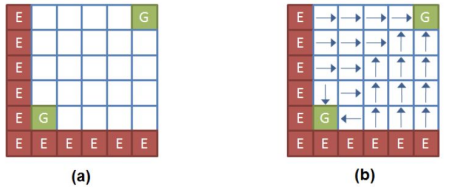
Shared challenges still differ across contexts

Example: Different notions of safety and robustness

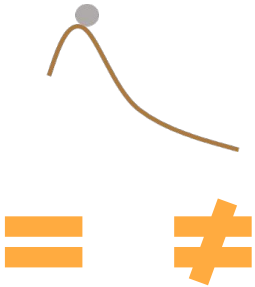
Adversarial robustness [ML]: Robustness to perturbations of inputs



Safe reinforcement learning [ML]: Avoid error states or catastrophic scenarios



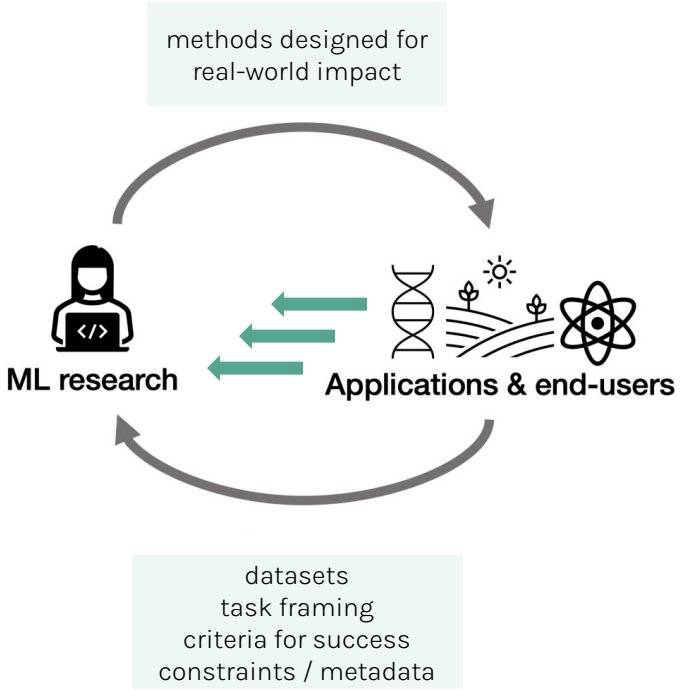
Robust control [e.g., power systems, buildings]: Bring system to an equilibrium (e.g., Lyapunov stability)



Physical feasibility [e.g., power systems, climate science]: Ensure satisfaction of physical equations

Adversarial robustness figure source: Goodfellow, I. J., Shlens, J., & Szegedy, C. (2015). Explaining and harnessing adversarial examples. *ICLR*.
Safe RL figure source: Garcıa, J., & Fernández, F. (2015). A comprehensive survey on safe reinforcement learning. *JMLR*, *16*(1), 1437-1480.

Takeaway: AI innovation must be shaped by the needs of climate problems



See: David Rolnick, Alan Aspuru-Guzik, Sara Beery, Bistra Dilkina, Priya L. Donti, Marzyeh Ghassemi, Hannah Kerner et al. "Position: Application-Driven Innovation in Machine Learning." *International Conference on Learning Representations* (2024).

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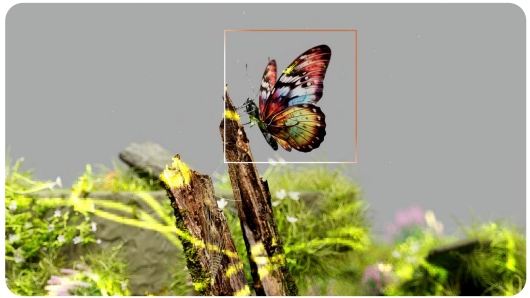
Representing AI holistically: benefits, harms and impacts



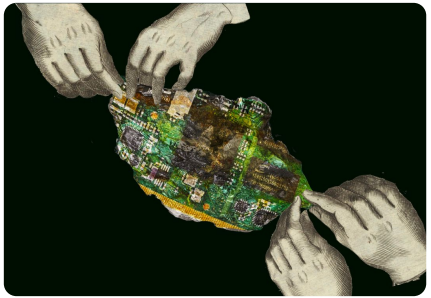
Source: Getty Images



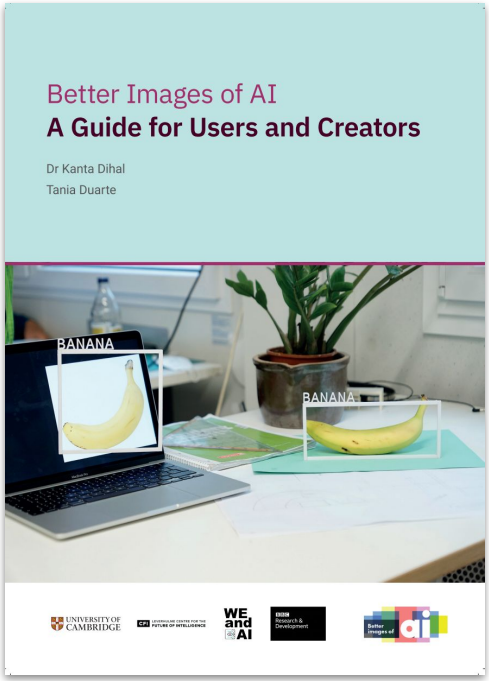
Source: Shutterstock.com



Source: [Diaz & Google DeepMind , AI for Biodiversity]

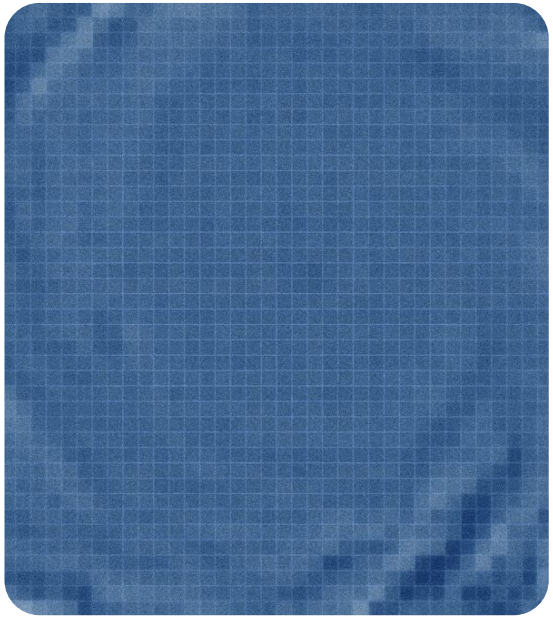


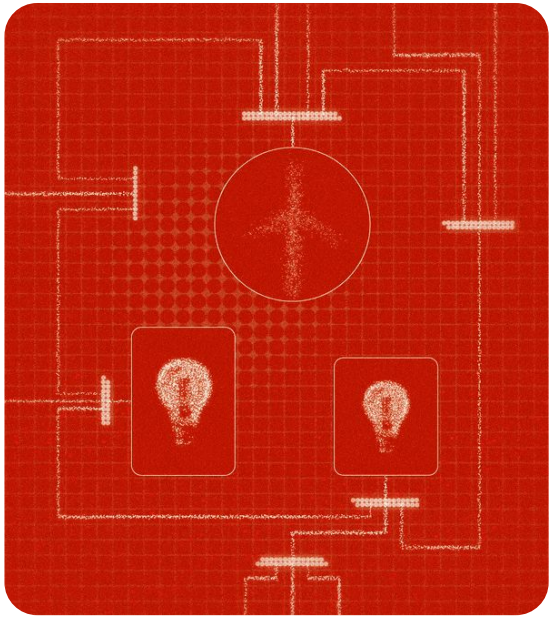
Source: [Hanna Barakat, Rare Metals 2]

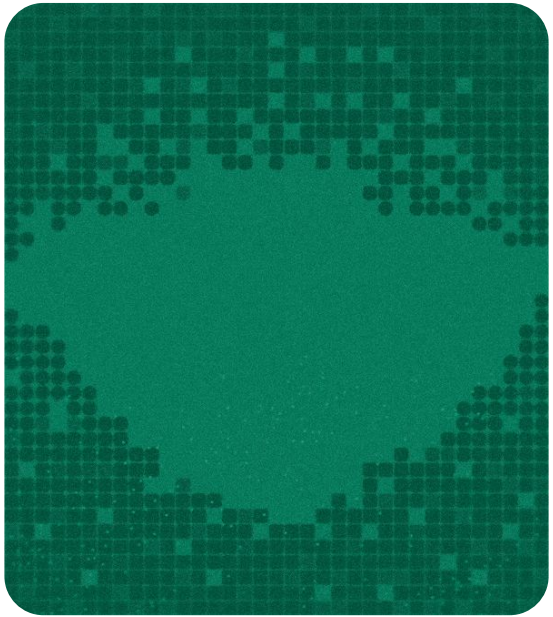


Source: [Better Images of AI]

Understand what types of climate data are relevant for concrete AI-for-climate applications

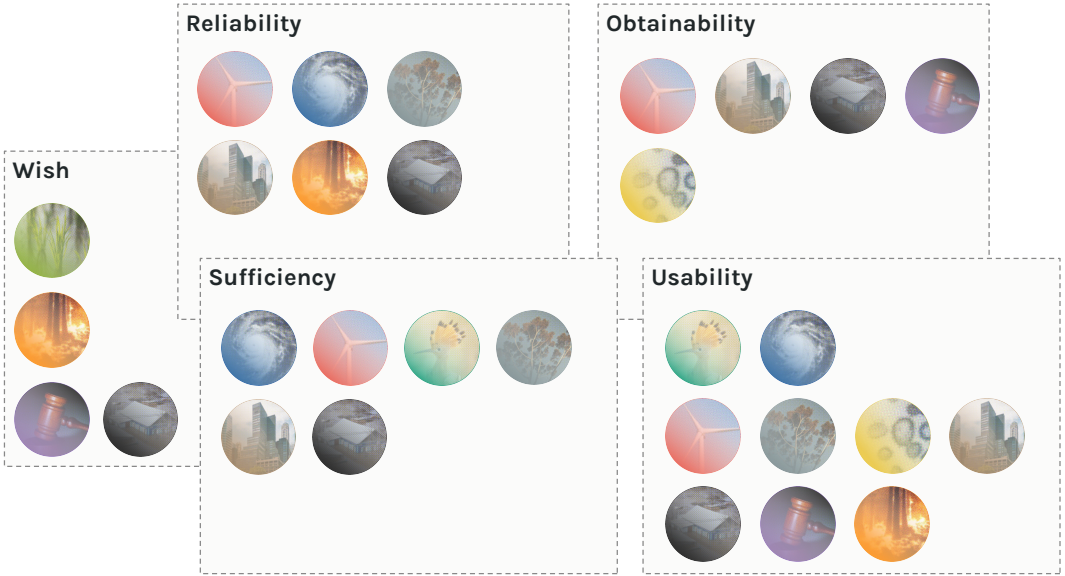






Source: Climate Change AI

Assessing what data to use and its limitations



Wish
Dataset does not exist

Reliability
Data quality or integrity needs improvement

Obtainability
Data is not easily obtainable
(e.g., is not findable or accessible)

Sufficiency
Data is insufficient, requiring additional data collection and/or simulation

Usability
Data is not readily usable
(by people and/or machines)

Miscellaneous
Additional challenges, including challenges that arise from the use of multiple datasets

Source: Climate Change AI Data Gaps

Fostering open development and reproducibility

Datasheets for datasets

Dataset documentation framework that allows dataset creators to reflect on important **data lifecycle questions**.

Motivation	Composition
Collection Process	Preprocessing, Cleaning, labelling
Uses	Distribution	Maintenance

- Guide **dataset creators** and **consumers** to evaluate datasets in a structured manner
- Improve **transparency** and **accountability**
- Help selection process in **future usage**
- Enable greater **reproducibility** and comparison of results

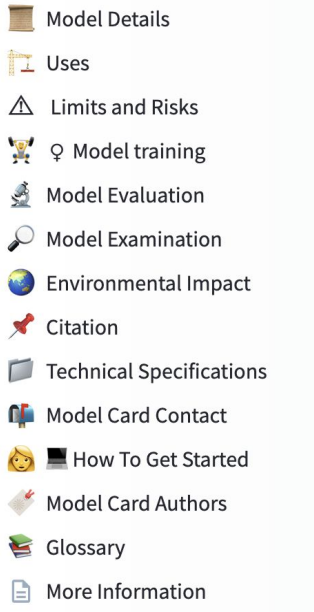
Source: Gebru *et al.* (2021), Datasheets for Datasets

Model cards

Model cards are a standardized way of providing information about models, including the way they were trained and evaluated.

Often include

- Intended uses (and out-of-scope uses)
- Evaluation metrics
- Training data (including processing techniques)
- Ethical considerations



Source: HuggingFace Model Cards Writing Tool

Source: Mitchell *et al.* (2018) Model Cards for Model Reporting

Evaluating carbon footprint estimation

Off-line estimation of carbon footprint based on your setup

The Green Algorithms calculator, allows you to estimate the carbon footprint **before model training and inference** based on your hardware and carbon intensity of electricity usage in the location where the computation will take place.

Allows you to compare setups ahead of experimentation or spending resources on hardware and/or compute.

On-line estimation of carbon footprint

Tools such as ML CO2 Impact, CodeCarbon, Carbontracker, or tools specifically from cloud providers allow you to estimate the carbon footprint **during training and inference runs** by considering the hardware, runtime, and cloud provider **on which the experiments were executed**.

Enables you to report the carbon footprint of you ML models

Characteristic of each strategy	Online calculator	Embedded package	Server-side tool
Compatible with any hardware	Yes	No, a dedicated tool needs to be built for each	Yes, provided hardware usage can be monitored
Compatible with any programming language	Yes		Yes
Compatible with any task or research field	Yes		Yes
Computing metrics are collected automatically	No	Yes	Yes
Does not interfere with existing code	Yes	No	Yes
Estimates can be obtained beforehand	Yes	No	No
Estimates can be obtained in real time	No	Yes	Yes
Estimates can be obtained retrospectively	Yes	Only if the tracker was active at the time	Yes
Scalable with large numbers of jobs	No	Yes	Yes
Scalable over long periods of time	No	Only if the tracker is used every time	Yes

Source: Lannelongue and Inouye (2023), Carbon footprint estimation for computational research

Entry points and paths forward



Computational Sustainability Network (from 2008)

Climate Informatics (from 2011)

Regional AI initiatives, e.g. Data Science Africa, the Deep Learning Indaba, KHIPU, and Affinity Groups



Climate Change AI (from 2019)

Work on Climate (from 2020)

Digital Futures Lab initiative
AI + Climate Futures Asia (from 2023)





GeoAI-Africa (from 2024)

AfriClimate AI (from 2024)



Climate AI Nordics (from 2024)

ESCS Community (from 2025)
Environmentally Sustainable Computational Science

💬 Type your answer in the Zoom chat

Think about how you would like to engage in the AI-for-climate space.

What are the kinds of resources that will help you move forward?

Consider the domain you are working on, the communities of practice you want to engage with (within or outside you main domain), the types of content you want to read (research, policy, educational), tools that you will need to practice?

Lecture recap

Why	Climate change and climate action framing
What	AI and machine learning (ML) framing
What	Technological roles of AI for climate action
How	Considerations for development and deployment
Which	Machine learning approaches for climate problems
How	Best practices spotlight: approaches, resources & tools

CCAI Virtual Summer School 2026 Materials & Access

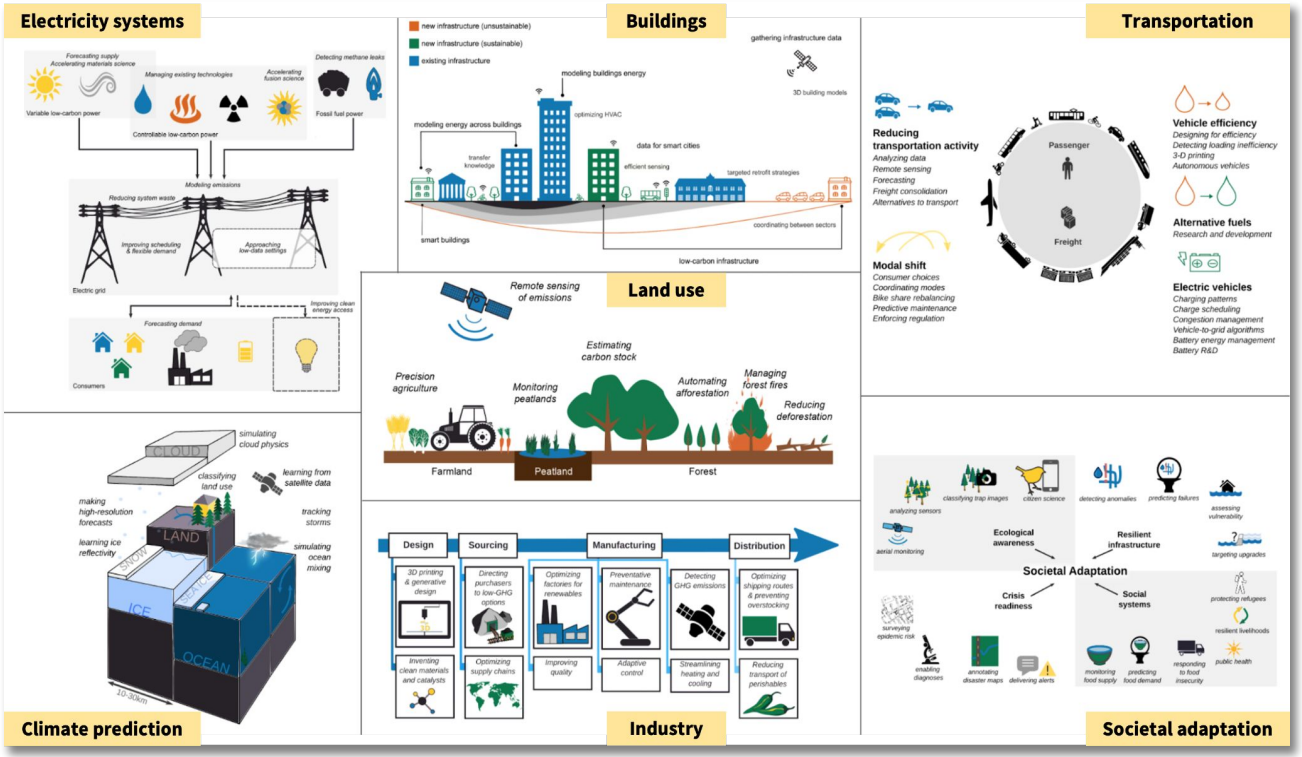
Slides, readings, quiz questions, and the lecture recording will be posted in the **LearnWorlds** platform

🌐 You can use the **Community Platform** to ask further questions about this lecture and all other content, as well as to engage with other participants

Feedback forms for each lecture & tutorial will be available in LearnWorlds. We'll also show a quick feedback form in Zoom that you can fill out before you leave the Zoom webinar.

We hope you have an enriching, engaging, and fruitful Climate Change AI Virtual Summer School 2026!

Questions?


Electricity systems
Buildings
Transportation
Land use
Climate prediction
Industry
Societal adaptation
Reducing transportation activity
Modal shift
Vehicle efficiency
Alternative fuels
Electric vehicles
Passenger
Freight
Societal Adaptation
Design
Sourcing
Manufacturing
Distribution
Farmland
Peatland
Forest
CLOUD
LAND
OCEAN
ICE