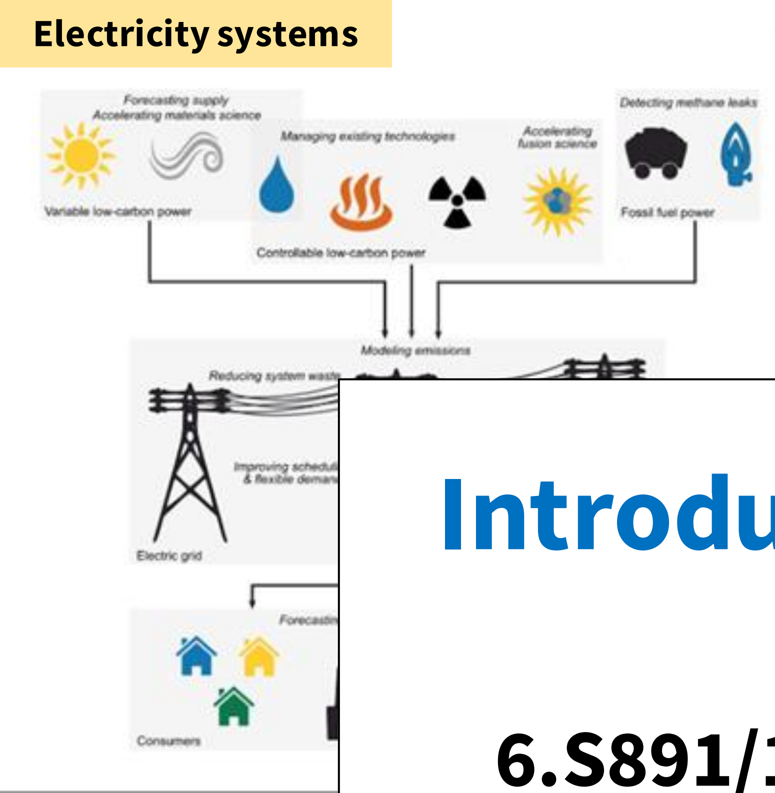
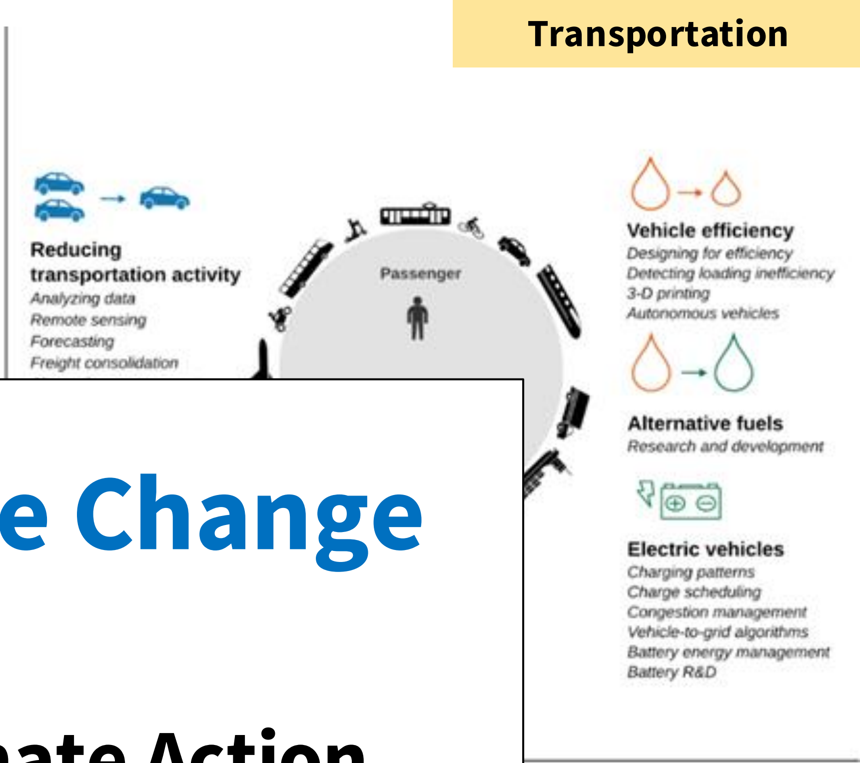
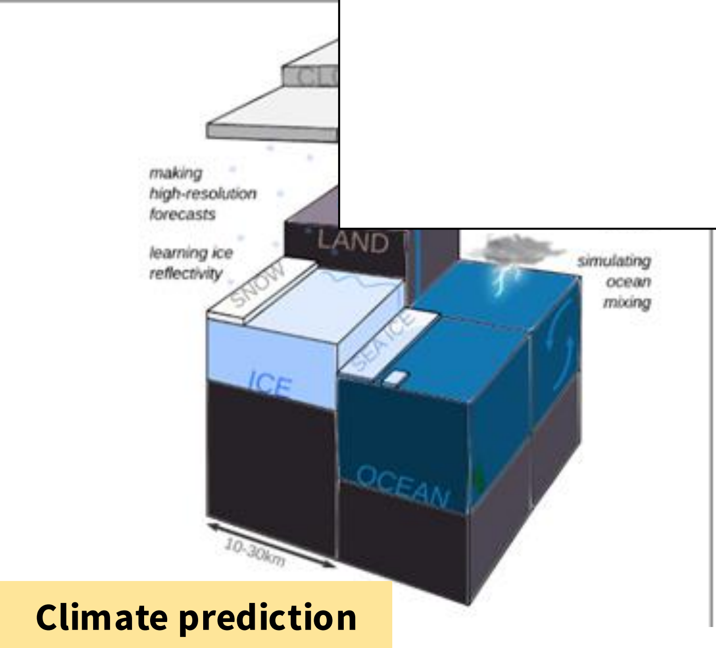


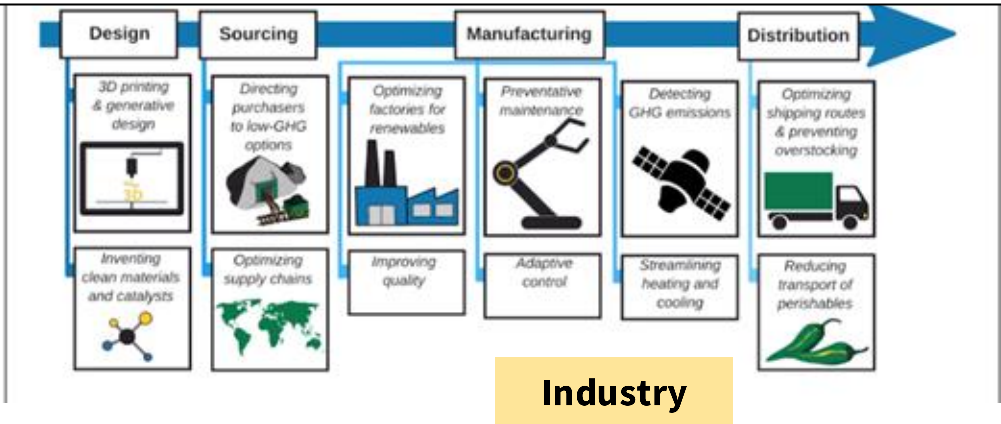


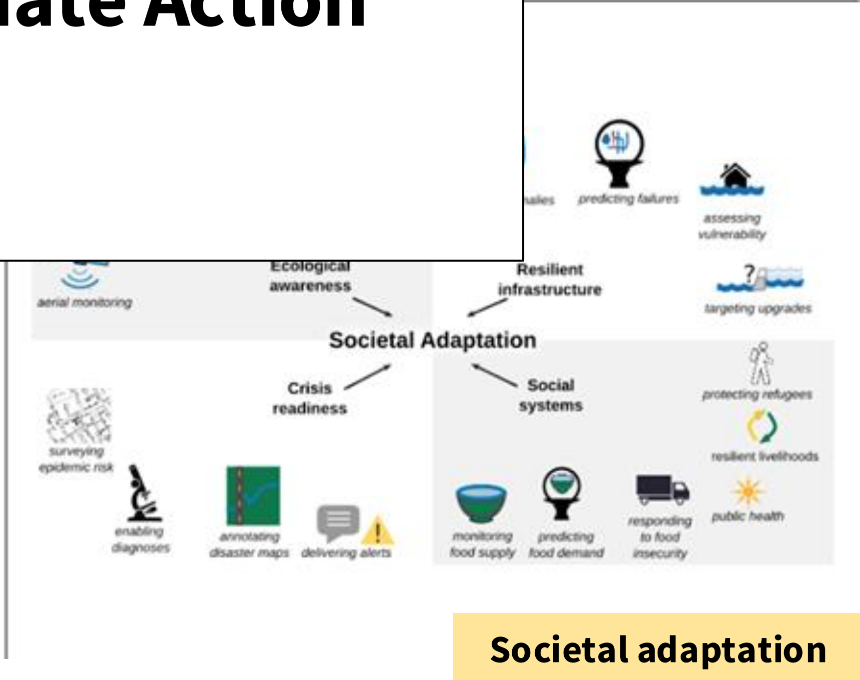
Introduction to AI & Climate Change

6.S891/12.S992/6.S893: AI for Climate Action

Spring 2026







The state of climate change

Earth has already warmed over 1°C, compared to pre-industrial period

Due to excess greenhouse gas (GHG) emissions from human activities

- E.g., carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O)

- Has induced major changes in climate
  - Climate = "average weather"
  - Extreme heatwaves, precipitation, droughts, hurricanes, etc.

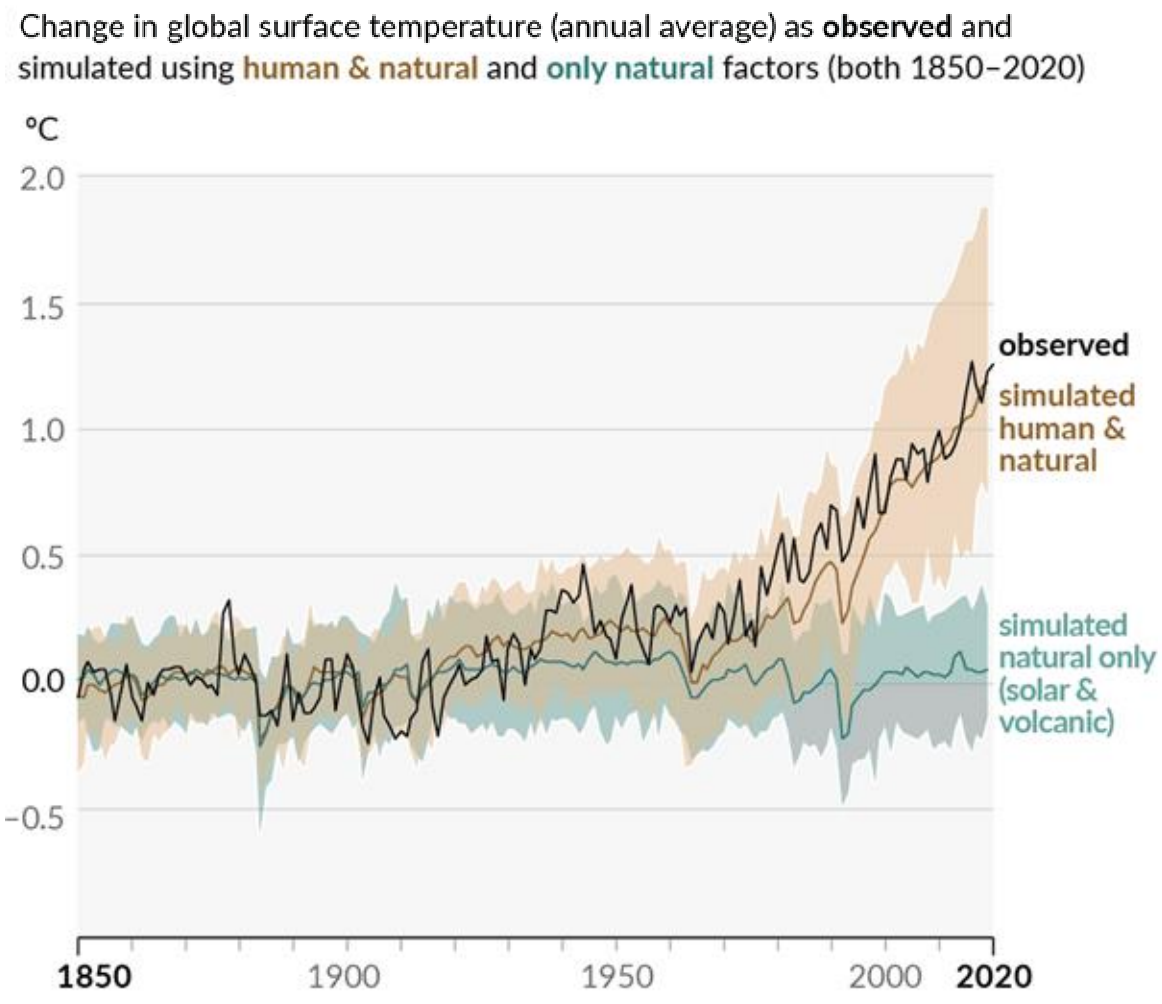


Figure source: IPCC AR6 WG1 Report (2021)

Approaches to addressing climate change

Axes of action

- **Climate science:** Understanding and predicting climate change
- **Mitigation:** Reducing or preventing greenhouse gas emissions

Rapid action is needed to limit warming

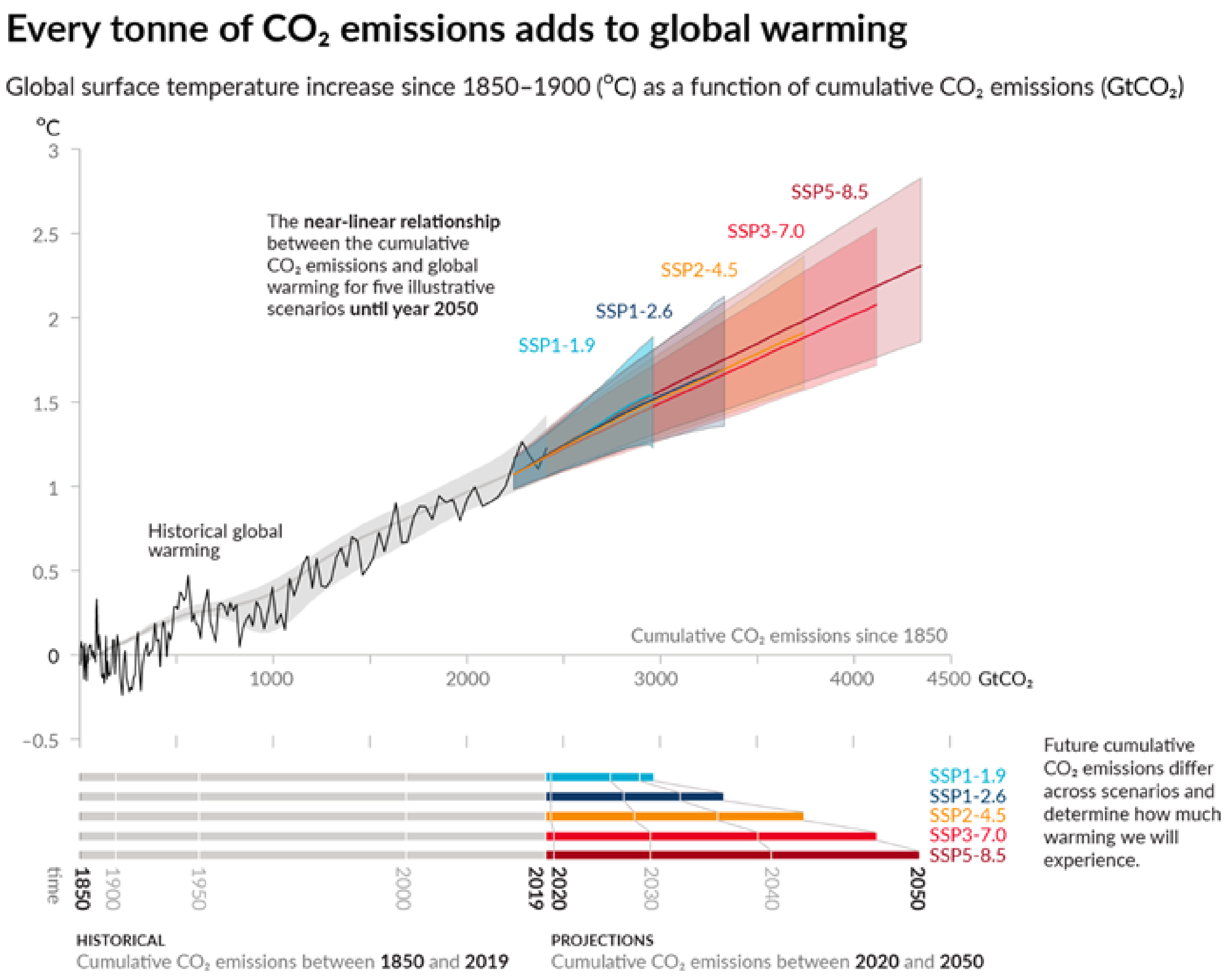


Figure source: IPCC AR6 WG1 Report (2021)

Speed and scale of systemic changes affects total warming

Net-zero by 2050 (**SSP1-1.9**) limits warming to ~1.5°C

Climate change is **not an on/off switch** - every unit of GHG emissions reduction matters

Approaches to addressing climate change

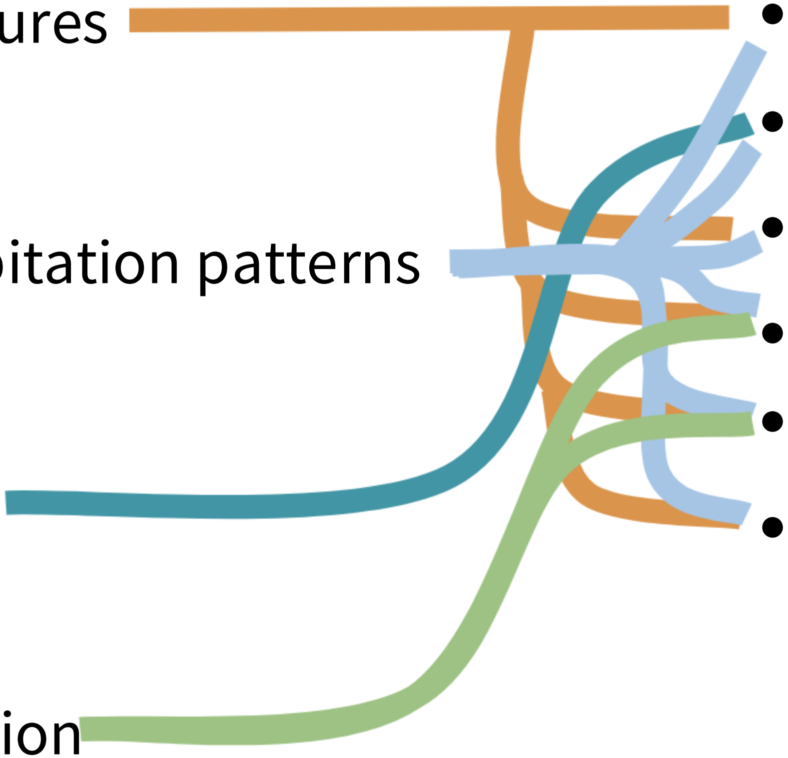
Axes of action

- **Climate science:** Understanding and predicting climate change
- **Mitigation:** Reducing or preventing greenhouse gas emissions
- **Adaptation:** Responding to the effects of a changing climate

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 & flooding
- More frequent wildfires
- Loss of ecosystem services
- Biodiversity loss
- Spread of disease vectors & 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

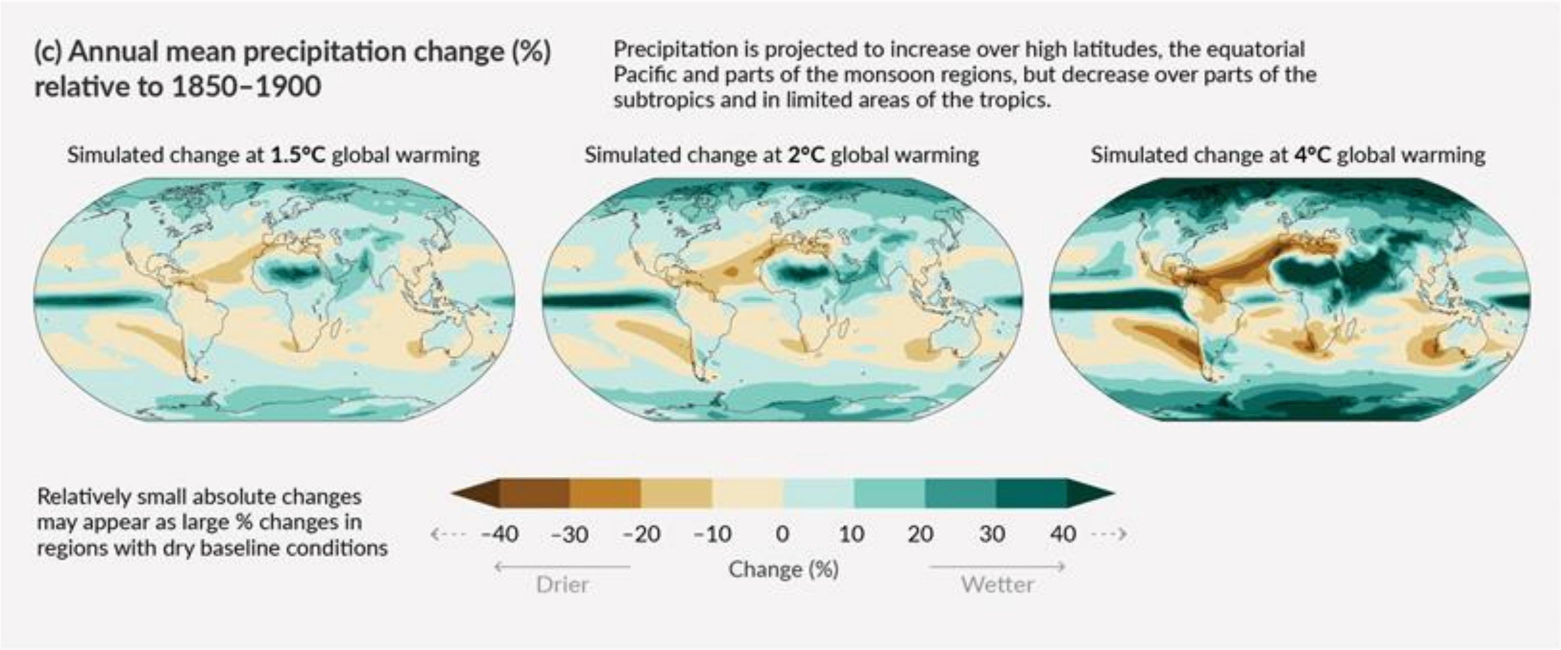


Figure source: IPCC AR6 Summary for Policymakers (2021)

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:** Withstanding a range of outcomes with no/minimal impact
   - **Resilience:** Recovering quickly after impact

Human & ecological systems

Connections with UN SDGs

Figure source (bottom): United Nations

Approaches to addressing climate change

Axes of action

- **Climate science:** Understanding and predicting climate change
- **Mitigation:** Reducing or preventing greenhouse gas emissions
- **Adaptation:** Responding to the effects of a changing climate

Important frameworks

- **Co-benefits:** Explicitly considering linkages between climate action and other UN Sustainable Development Goals (SDGs)
- **Climate justice:** An equity-centered approach to climate change


6.S891 / 12.S992 / 6.S893
AI FOR CLIMATE ACTION
MW 2:00-3:30PM (SPRING 2026)
SARA BEERY / ABIGAIL BODNER / PRIYA DONTI
Learn about applications of AI and machine learning to climate change mitigation, adaptation, and monitoring.

Course Schedule

Week / Date	Format	Topic	Instructor
Week 1 - Merged Lessons			
Mon 02/02	Merged	Lecture: Logistics; Intro to AI and Climate Change	Donti
Wed 02/04	Merged	Lecture: Application-driven Innovation in ML	Beery
Week 2 - Merged Lessons			
Mon 02/09	Merged	Lecture: Mitigation of Climate Change (IPCC WG3)	Donti
Wed 02/11	Merged	Lecture: Impacts, Adaptation, & Vulnerability (IPCC WG2)	Beery
Week 3 - Merged Lessons			
Tue 02/17 (MIT Mon.)	Merged	Lecture: The Physical Science Basis (IPCC WG1)	Bodner
Wed 02/18	Merged	Lecture: Foundation Models for Climate	Bodner

Course Schedule, Ctd.

Weeks 4-12: "Forked" sections focusing on a specific subarea of AI for climate action

- Lectures on key topics
- Presentation and discussion of relevant papers

‼️ Students should register for the subject number associated with the "fork" in which they would like to participate:

- **6.S891:** Biodiversity and environment - Prof. Sara Beery
- **12.S992:** Climate models - Prof. Abigail Bodner
- **6.S893:** Power and energy systems - Prof. Priya Donti

Course Schedule, Ctd.

Week / Date	Format	Topic	Instructor
Week 13 - Merged Lessons			
Mon 04/27	Merged	Lecture: Benchmarks & Evaluation	Beery
Wed 04/29	Merged	Lecture: Data-centric Research	Bodner
Week 14 - Merged Lessons			
Mon 05/04	Merged	Lecture: Incorporating Domain Knowledge	Donti
Wed 05/06	Merged	Guest Lecture: TBD	
Week 15 - Merged Lessons			
Mon 05/11	Merged	Moderated Panel: “Now what?” Opportunities to work on climate-related issues beyond the classroom	(Moderator: Sara)

Homework and Assessments

📱 **In-Class Quizzes** (10%)**:** Beginning of class, starting next lecture

📜 **Paper Readings:** ~3-5 papers assigned weekly during forked weeks

🤔 **Paper Reflections** (10%)**:** 1 page total, due each Tuesday during forked weeks

🧑‍🏫 **Paper Presentations** (30%)**:** In groups; approx. 2-4 times each, during forked weeks

🤝 **Group Project** (50%)**:** Propose AI-based research for a climate application

You will get out of this class what you put in!

Course Staff

Instructor Sara Beery
beery at mit dot edu

Instructor Abigail Bodner
abodner at mit dot edu

Instructor Priya Donti
donti at mit dot edu

TA Julia Chae
chaenayo at mit dot edu

TA Xin Kai Lee
xinkai at mit dot edu

TA Pragnya Govindu
pgovindu at mit dot edu

Course Website

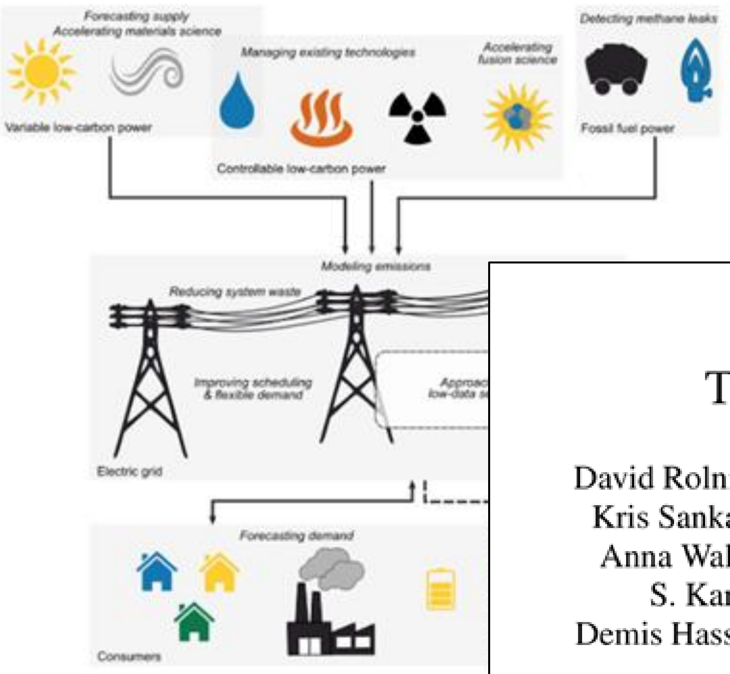
ai4climateaction.github.io

Check the website for

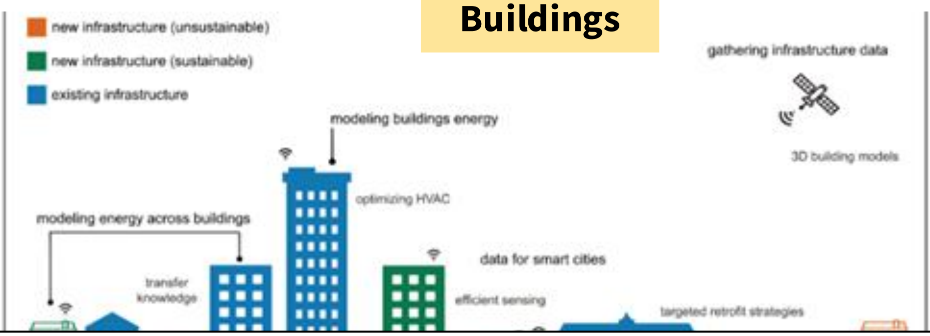
- Detailed course schedule (including readings)
- Calendar of office hours
- Canvas and Piazza links (different for each fork)
- Assignment rubrics
- Course policies (late assignments, AI assistants, collaboration)

This is a new course, so your feedback and understanding are especially welcome!

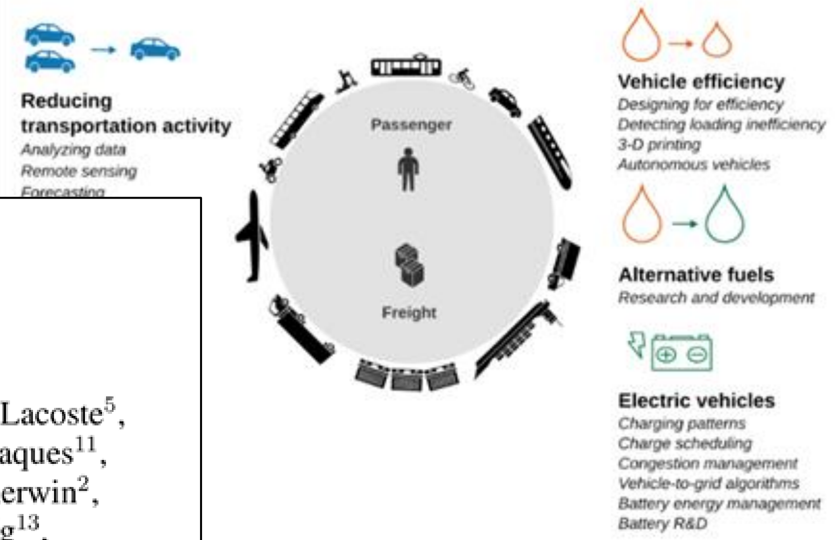
Electricity systems



Buildings



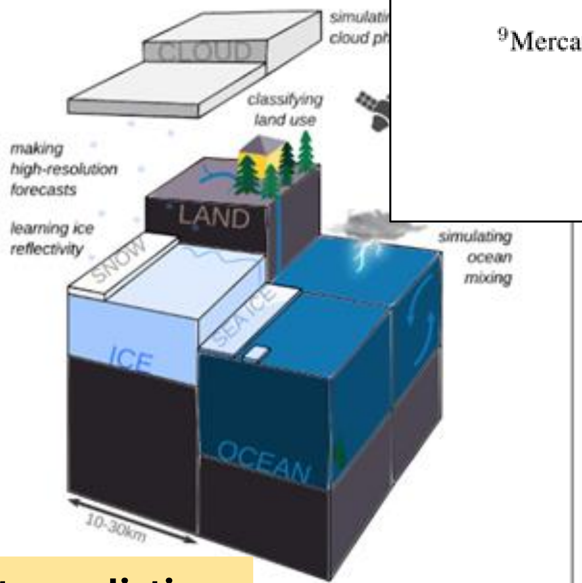
Transportation



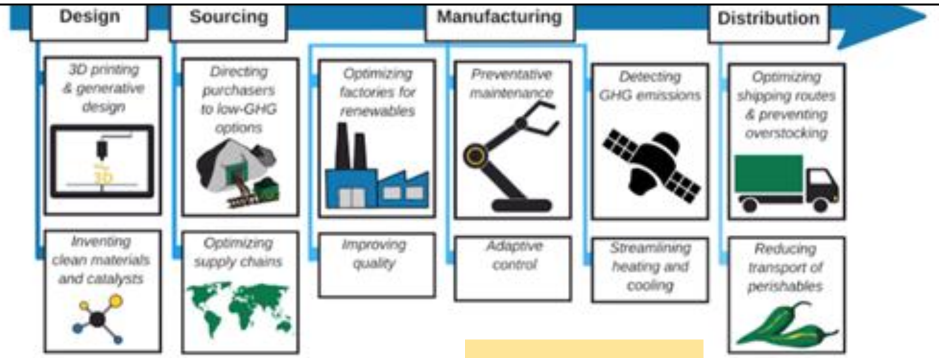
Tackling Climate Change with Machine Learning

David Rolnick[1*], Priya L. Donti[2], Lynn H. Kaack[3], Kelly Kochanski[4], Alexandre Lacoste[5], Kris Sankaran[6,7], Andrew Slavin Ross[8], Nikola Milojevic-Dupont[9,10], Natasha Jaques[11], Anna Waldman-Brown[11], Alexandra Luccioni[6,7], Tegan Maharaj[6,7], Evan D. Sherwin[2], S. Karthik Mukkavilli[6,7], Konrad P. Kording[1], Carla Gomes[12], Andrew Y. Ng[13], Demis Hassabis[14], John C. Platt[15], Felix Creutzig[9,10], Jennifer Chayes[16], Yoshua Bengio[6,7]

[1]University of Pennsylvania, [2]Carnegie Mellon University, [3]ETH Zürich, [4]University of Colorado Boulder, [5]Element AI, [6]Mila, [7]Université de Montréal, [8]Harvard University, [9]Mercator Research Institute on Global Commons and Climate Change, [10]Technische Universität Berlin, [11]Massachusetts Institute of Technology, [12]Cornell University, [13]Stanford University, [14]DeepMind, [15]Google AI, [16]Microsoft Research

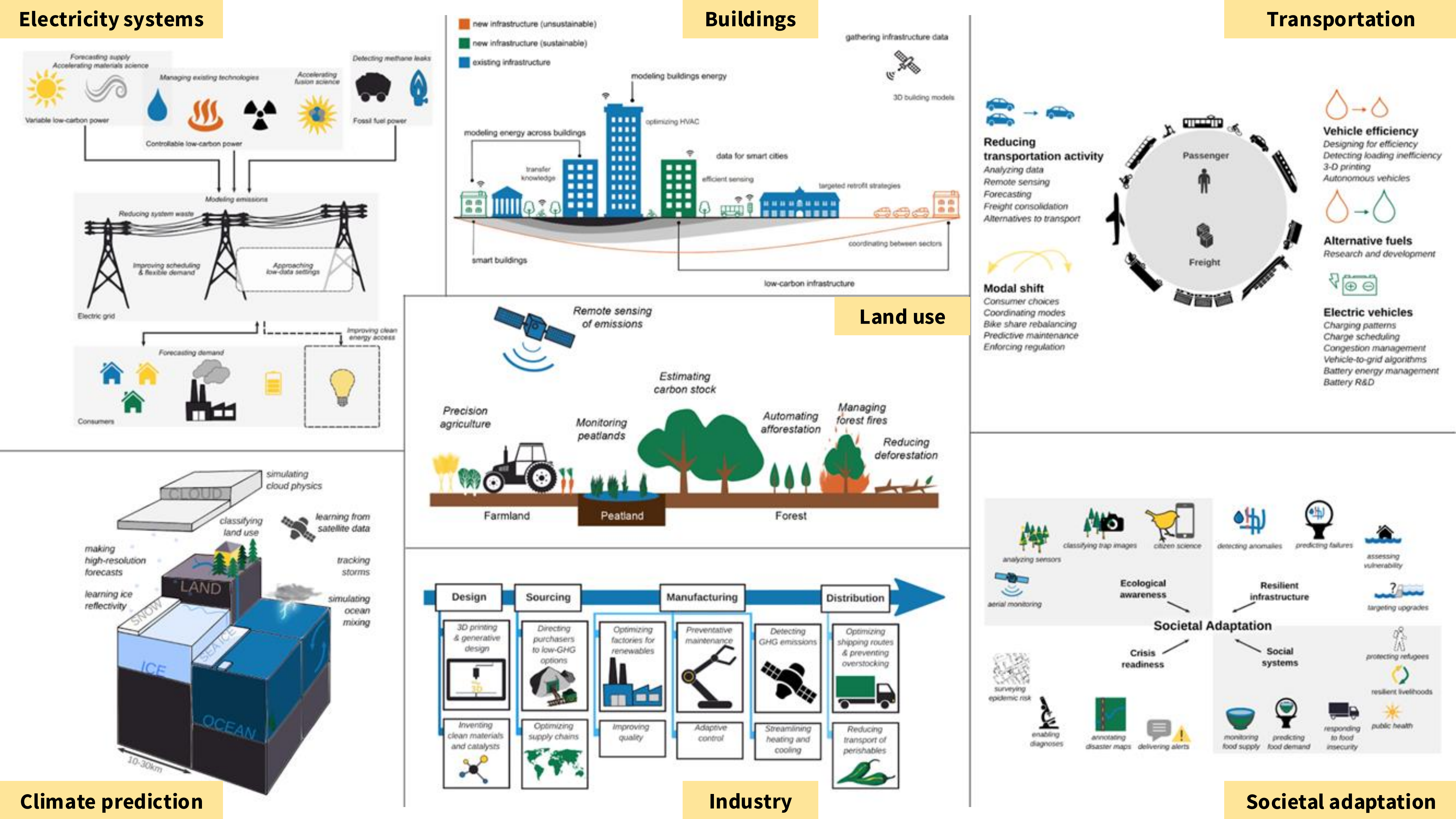


Climate prediction



Industry

Societal adaptation



Electricity systems
Forecasting supply
Accelerating materials science
Variable low-carbon power
Managing existing technologies
Accelerating fusion science
Controllable low-carbon power
Detecting methane leaks
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
coordinating between sectors
smart buildings
low-carbon infrastructure
Transportation
Reducing transportation activity
Analyzing data
Remote sensing
Forecasting
Freight consolidation
Alternatives to transport
Modal shift
Consumer choices
Coordinating modes
Bike share rebalancing
Predictive maintenance
Enforcing regulation
Passenger
Freight
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
simulating ocean mixing
LAND
SNOW
SEA ICE
ICE
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
surveying epidemic risk
protecting refugees
resilient livelihoods
enabling diagnoses
annotating disaster maps
delivering alerts
monitoring food supply
predicting food demand
responding to food insecurity
public health

AI for climate action: Recurring themes

Distilling raw data (emissions, deforestation, buildings, crops, species, policy)

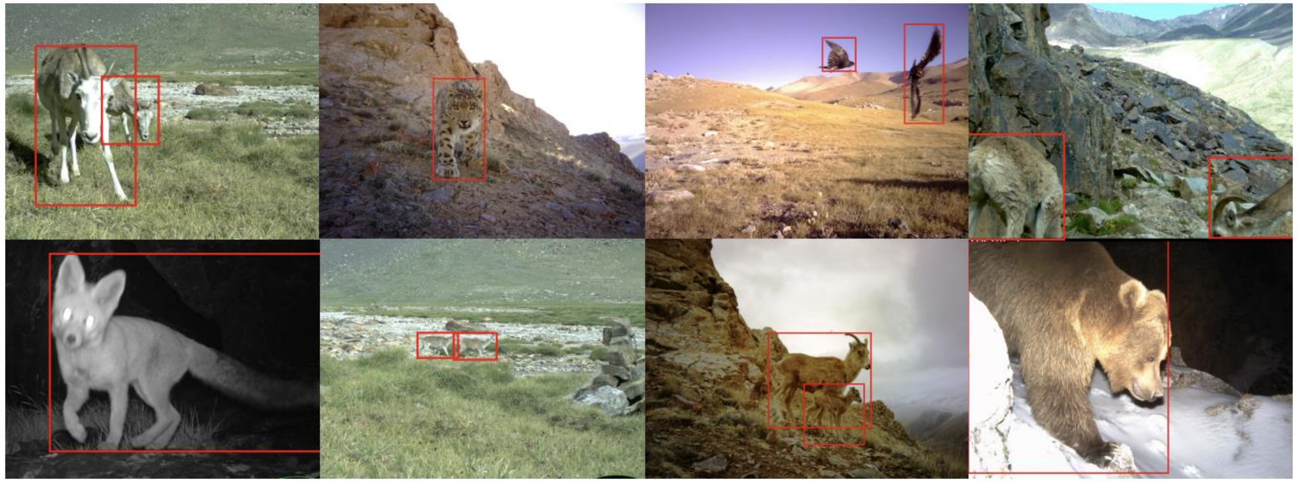
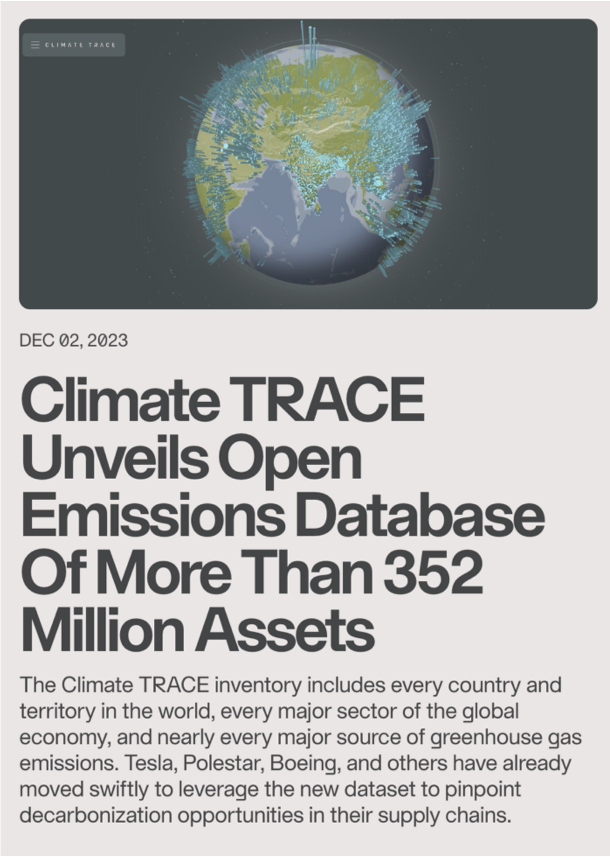


Image source: Beery, Morris, Yang (2019)



DEC 02, 2023

Climate TRACE Unveils Open Emissions Database Of More Than 352 Million Assets

The Climate TRACE inventory includes every country and territory in the world, every major sector of the global economy, and nearly every major source of greenhouse gas emissions. Tesla, Polestar, Boeing, and others have already moved swiftly to leverage the new dataset to pinpoint decarbonization opportunities in their supply chains.

Image source: Climate TRACE

AI for climate action: Recurring themes

Distilling raw data (emissions, deforestation, buildings, crops, species, policy)

Improving predictions (renewables, transportation demand, extreme events)

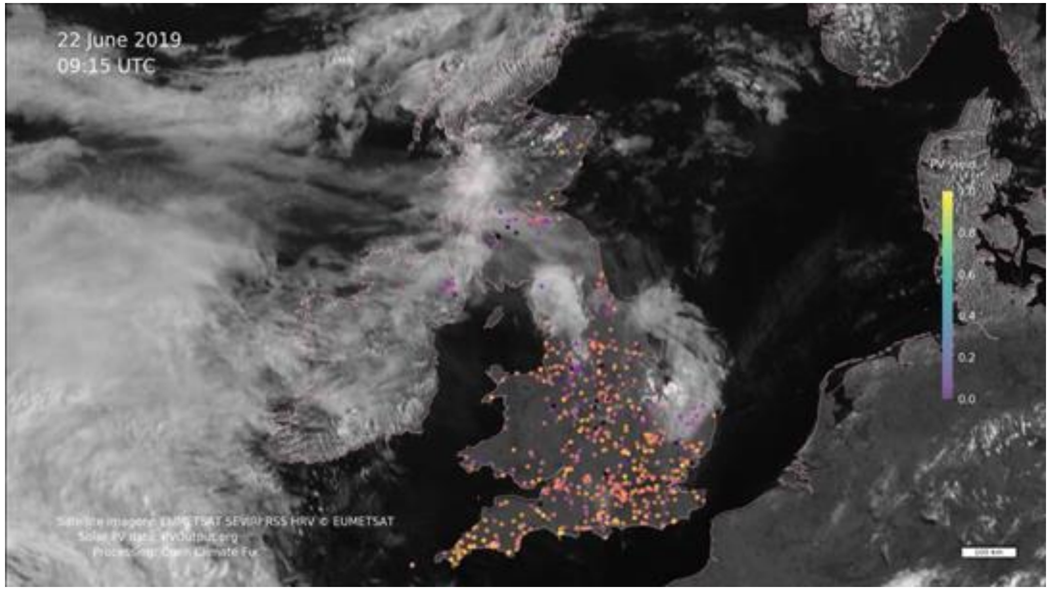


Image source: Open Climate Fix

AI for climate action: Recurring themes

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Improving predictions (renewables, transportation demand, extreme events)

Optimizing complex systems (heating and cooling, power grids, freight)

Images: Public domain

AI for climate action: Recurring themes

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Predictive maintenance (methane leaks, resilient infrastructure)

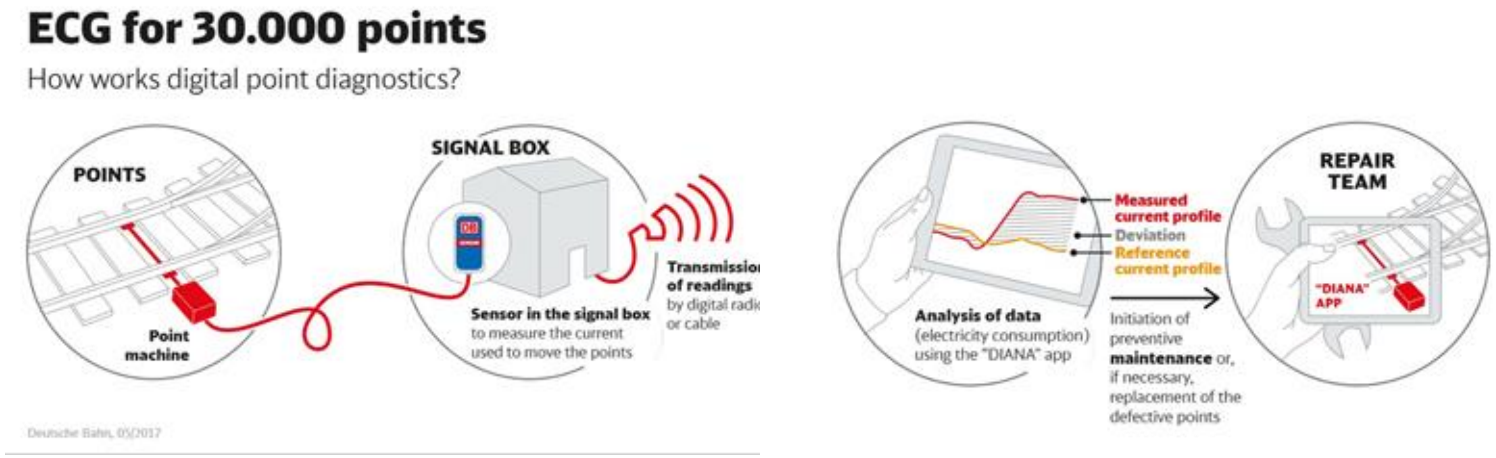

Image source: Deutsche Bahn

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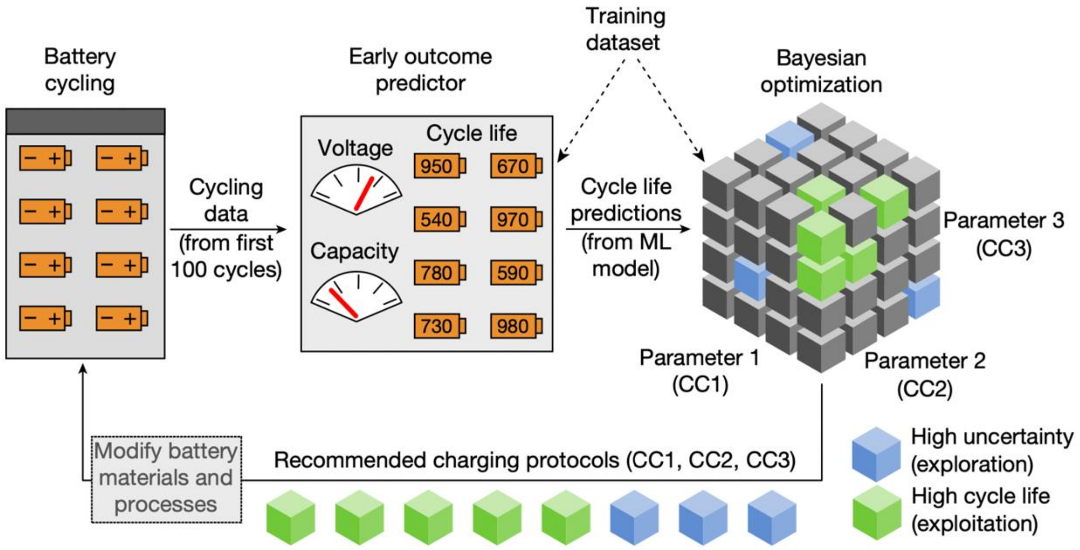

Figure source: Attia et al. (2020)

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Approx. time-intensive simulations (climate, energy, city planning)

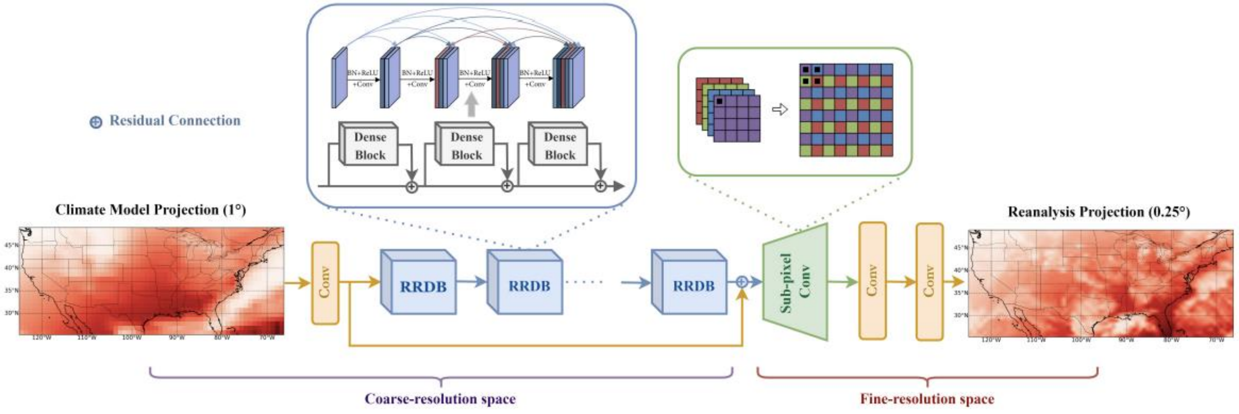

Figure source: Harilal, Hodge, Monteleoni, Subramanian (2022)

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Approx. time-intensive simulations
(climate, energy, city planning)

Data management & scenario generation
(entity matching, time series generation)

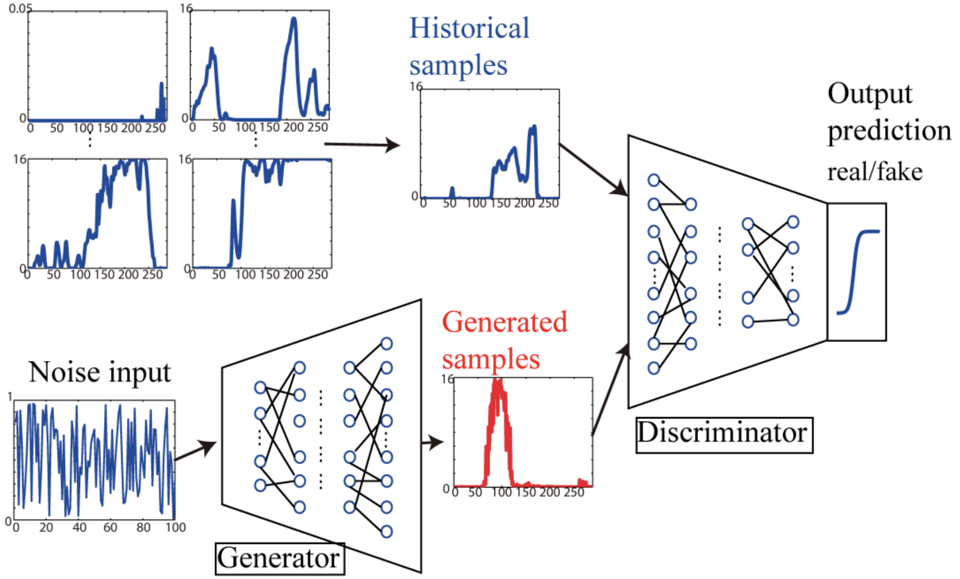


Image source: Chen, Wang, Kirschen, Zhang, 2018

Diverse settings require diverse approaches

Dominant ML paradigm (e.g.)	Differences on the ground (e.g.)
Big data	Less data; data hard to move
Big compute	Less compute; edge devices; reducing energy/emissions
Data is all you need	Useful knowledge from task/domain
Performance = average accuracy	Diverse set of metrics (e.g., group-weighted accuracy, safety, robustness, privacy, interpretability, explainability, uncertainty quantification, …)

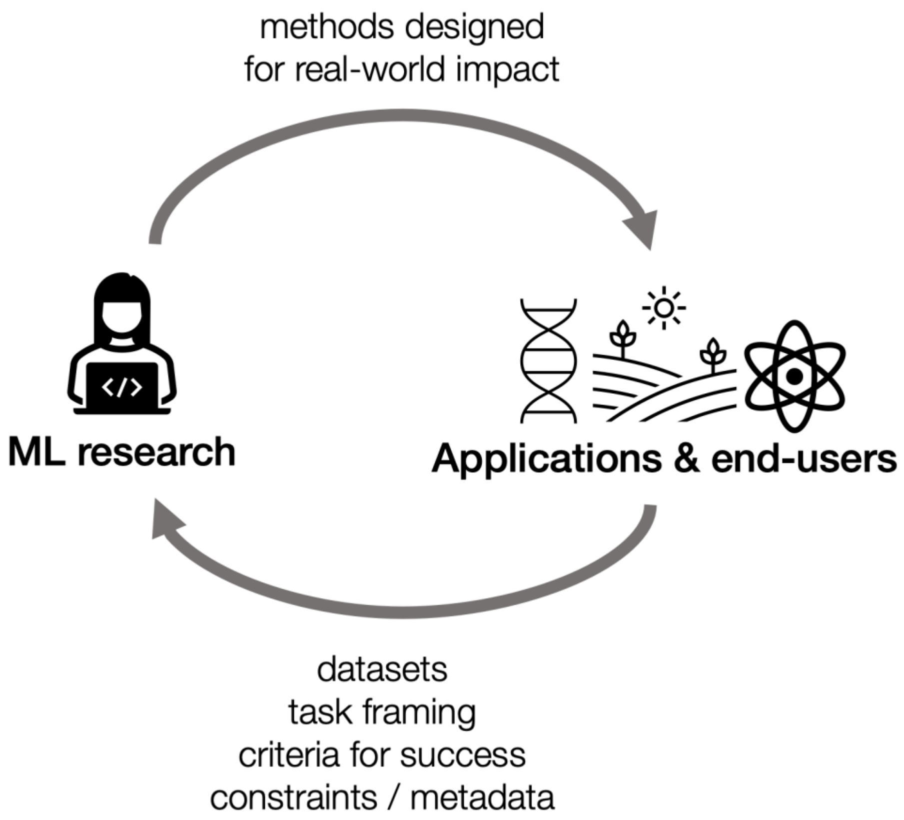
See also: Birhane, Abeba, et al. "The values encoded in machine learning research." *ACM Conference on Fairness, Accountability, and Transparency*. 2022.

Demands of applications should shape innovations

Specific notions of robustness, interpretability, generalization, etc. differ across areas

Need to source data, requirements, success criteria, etc. from a diverse set of tasks

… and foster a diverse set of methods to serve these diverse tasks



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

Many opportunities for innovation

Physics-informed and robust ML

Interpretable ML & uncertainty quantification

Generalization and causality

Energy efficient ML & TinyML

AutoML

….

		Causal inference	Computer vision	Interpretable models	NLP	RL & Control	Time-series analysis	Transfer learning	Uncertainty quantification	Unsupervised learning
Mitigation	**Electricity systems**									
	Enabling low-carbon electricity		•	•		•	•		•	•
	Reducing current-system impacts		•				•		•	•
	Ensuring global impact		•					•		•
	Transportation									
	Reducing transport activity		•				•		•	•
	Improving vehicle efficiency		•			•				
	Alternative fuels & electrification					•				•
	Modal shift	•	•				•		•	
	Buildings and cities									
	Optimizing buildings	•				•	•	•		
	Urban planning		•				•	•		•
	The future of cities				•			•	•	•
	Industry									
	Optimizing supply chains		•			•	•			
	Improving materials									•
	Production & energy		•	•		•				
	Farms & forests									
	Remote sensing of emissions		•							
	Precision agriculture		•			•	•			
	Monitoring peatlands		•							
	Managing forests		•			•	•			
	Carbon dioxide removal									
	Direct air capture									•
	Sequestering CO_2		•						•	•
Adaptation	**Climate prediction**									
	Uniting data, ML & climate science		•	•			•		•	
	Forecasting extreme events		•	•			•		•	
	Societal impacts									
	Ecology		•					•		
	Infrastructure					•	•		•	
	Social systems		•				•			•
	Crisis		•		•					
	Solar geoengineering									
	Understanding & improving aerosols						•		•	
	Engineering a control system					•			•	
	Modeling impacts						•		•	
Tools for Action	**Individual action**									
	Understanding personal footprint	•			•	•	•			
	Facilitating behavior change				•					•
	Collective decisions									
	Modeling social interactions			•		•				
	Informing policy	•	•		•				•	•
	Designing markets					•	•			•
	Education				•	•				
	Finance				•		•		•	

Responsible AI for climate action

Mitigating biases in data and models

- E.g., Buildings data: Housing discrimination, geographic disparities in availability
- 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 ag vs. smallholder farmers
- Avoiding centralization: Democratized capacity and compute, digital divide
- Avoiding digital colonialism: E.g., smart meters, analysis of remote sensing data

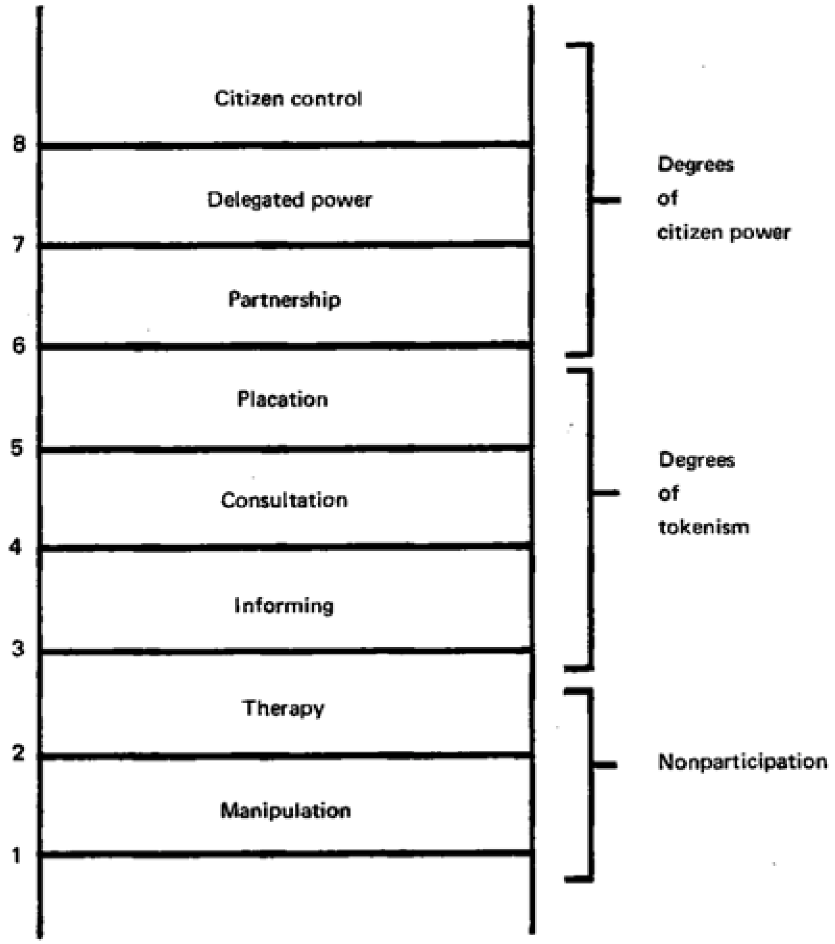
Accounting for potential "dual use"

Importance of stakeholder engagement

Stakeholder types (e.g.)

- Researchers (tech & social sciences)
- Implementing entities and industries
- End users
- Policymakers
- Other affected parties

Meaningful engagement required



Arnstein's Ladder of Citizen Participation

Figure source: Arnstein, S. R. (1969). A ladder of citizen participation. *Journal of the American Institute of Planners*, *35*(4), 216-224.

AI and climate change

AI applications for climate action

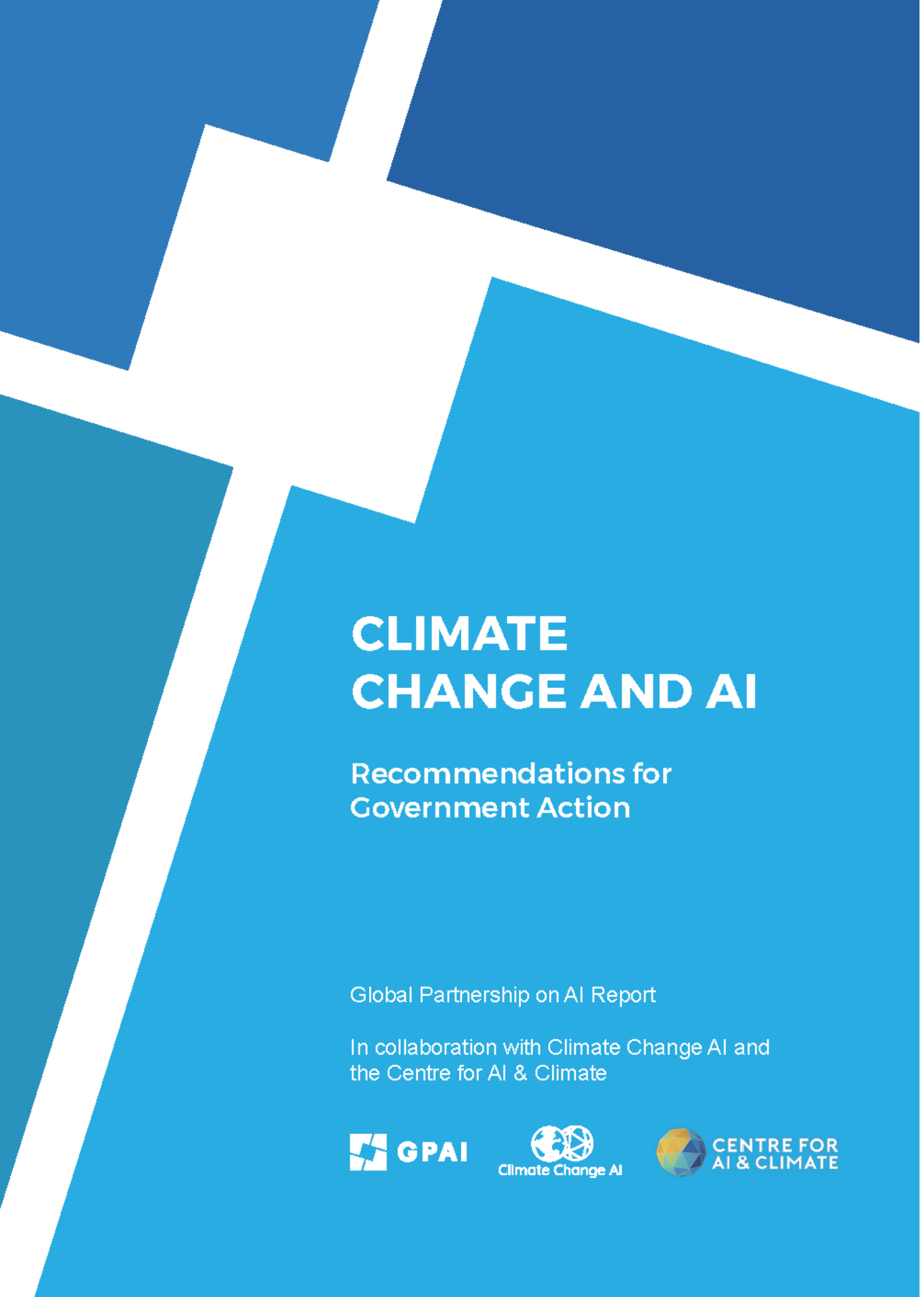
Impacts from AI computation & hardware

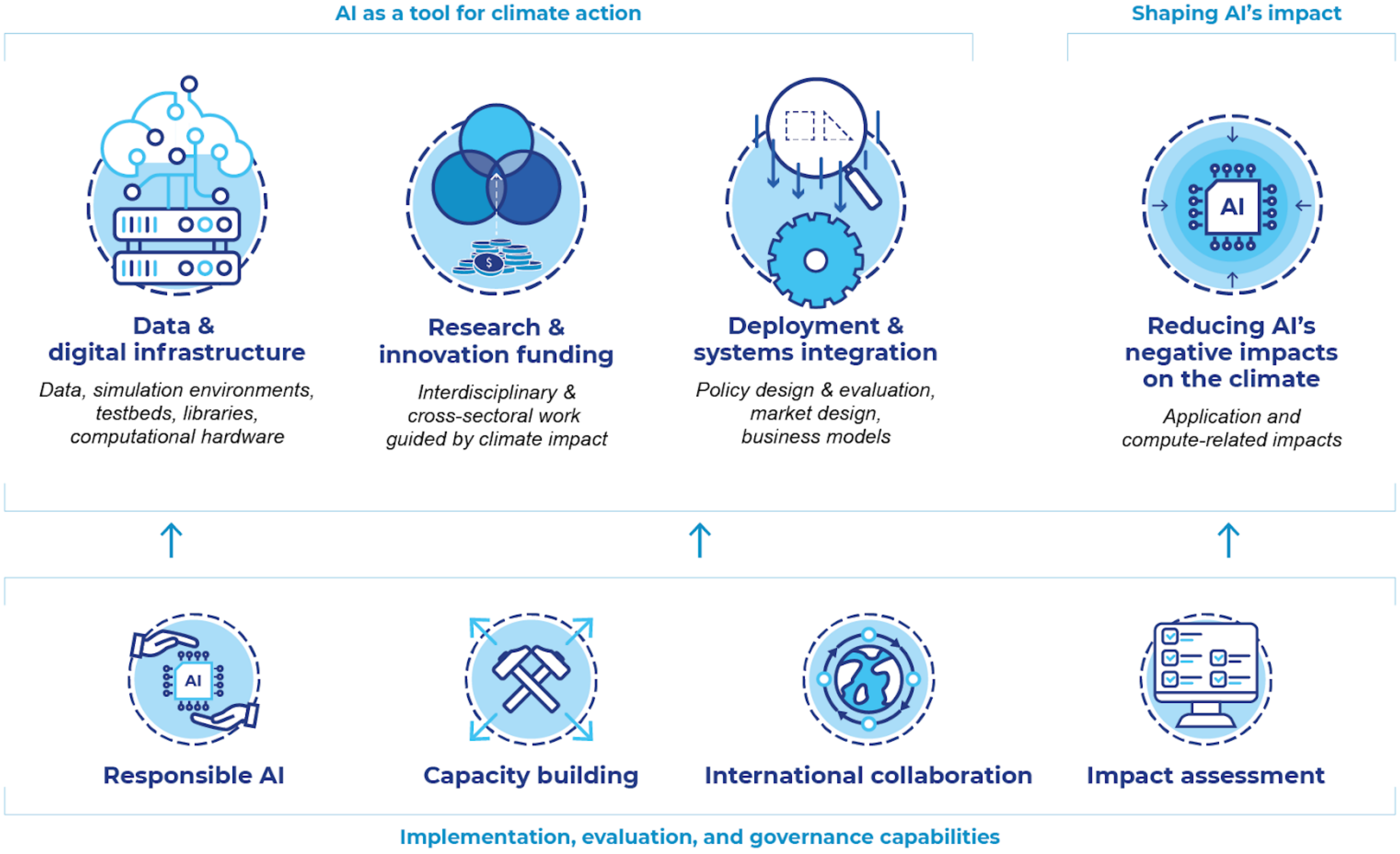
AI's system-level impacts

AI applications that increase emissions

Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 1-10.

Levers for policymakers





Available at:
https://www.climatechange.ai/reports/gpai

Takeaways

💪 **Axes of climate action:** Climate science, mitigation, adaptation

🤖 **AI is not a silver bullet, but can play and important role**

- Applications across energy, biodiversity, climate science, etc.
- Importance of application-driven innovation (and deployment)
- Considerations of responsible AI and stakeholder engagement

🎭 **AI's climate impacts are multifaceted** (inputs, applications, systemic)

🌎 **We are excited to learn and create knowledge together** to make an impact on one the most important issues of our time