Why your work matters for climate in more ways than you think

Priya L. Donti
Assistant Professor, MIT EECS and LIDS
Co-founder and Chair, Climate Change AI

Climate change warrants rapid action


Filippo Monteforte | AFP | Getty Images


David Mcnew | Getty Images


NASA


Piyaset | Shutterstock.com

Impacts felt globally

- Disproportionate effects on most disadvantaged populations

Need net-zero greenhouse gas emissions by 2050 [IPCC 2018]

- Across energy, transport, buildings, industry, agriculture, forestry, etc.

Need large-scale adaptation efforts

- Inherently local, at a global scale

How does AI factor in?

AI and climate change

AI applications for climate action

Impacts from AI computation & hardware

AI's system-level impacts

AI applications that increase emissions

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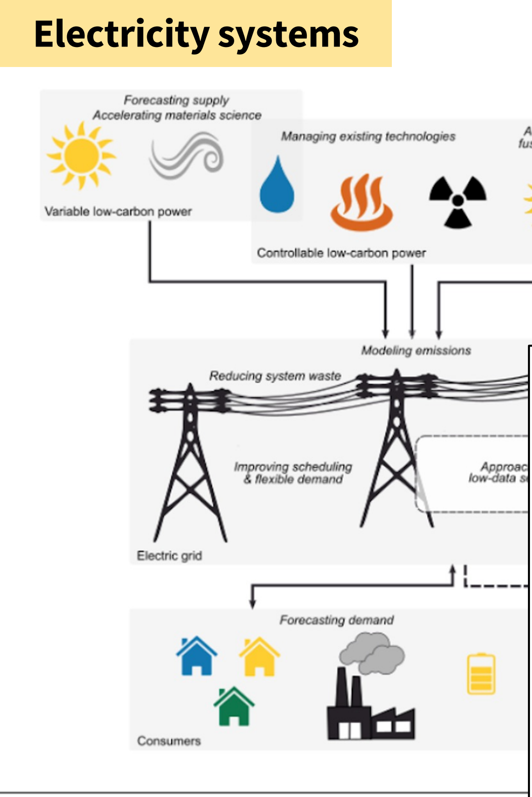
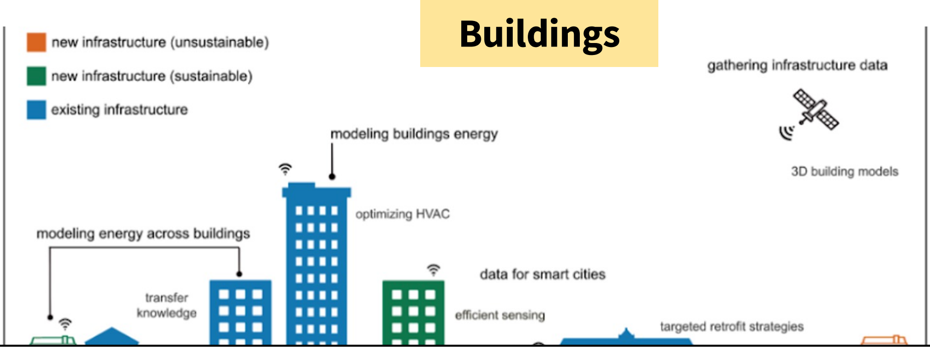
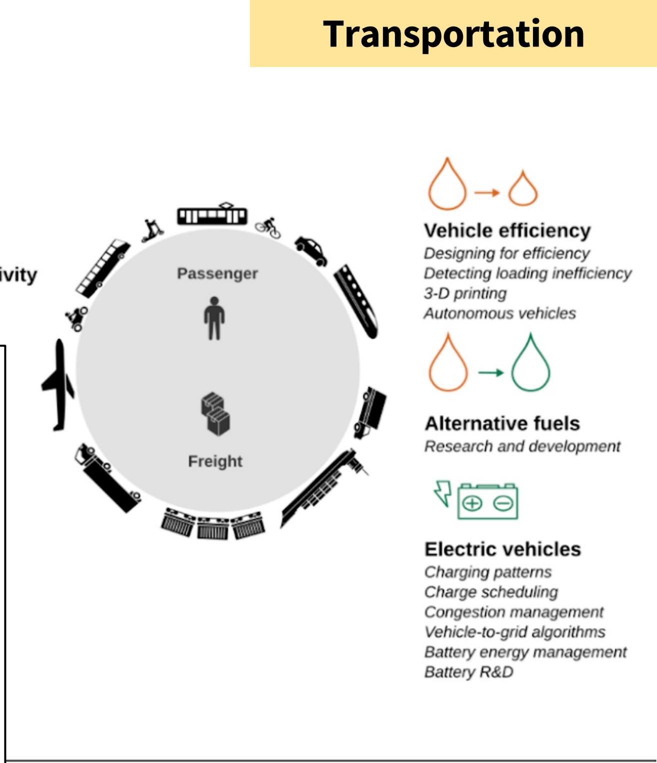


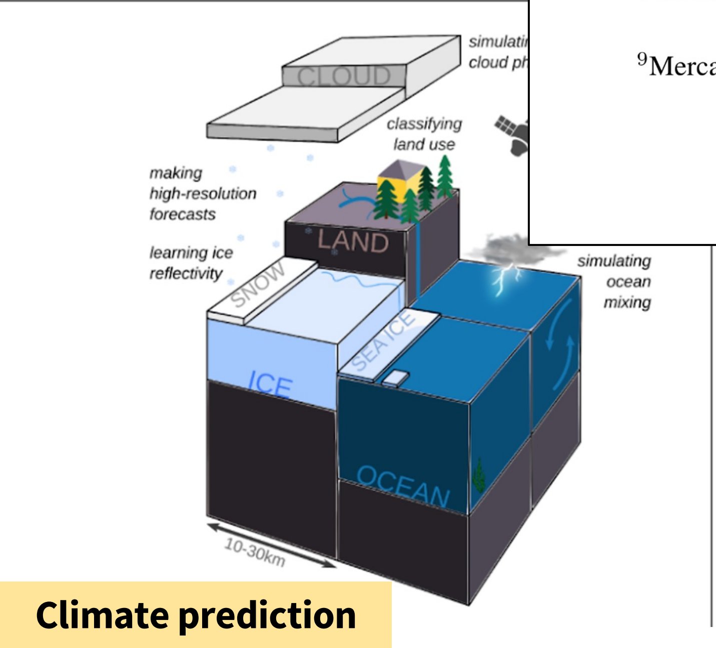


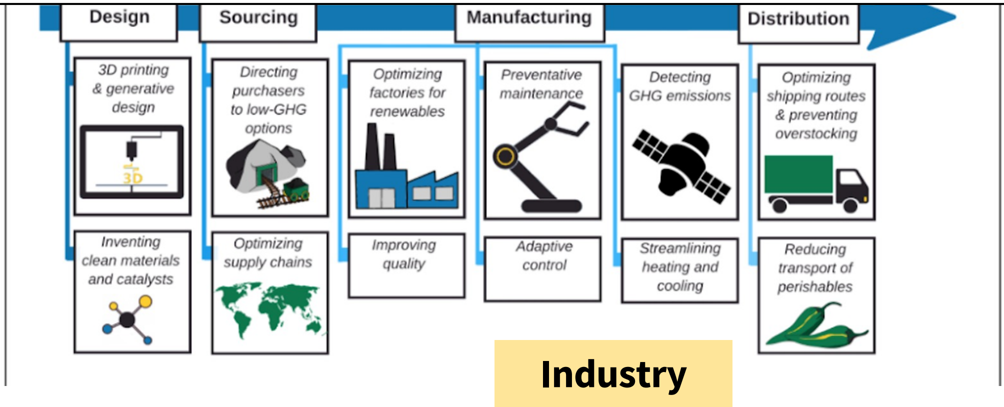


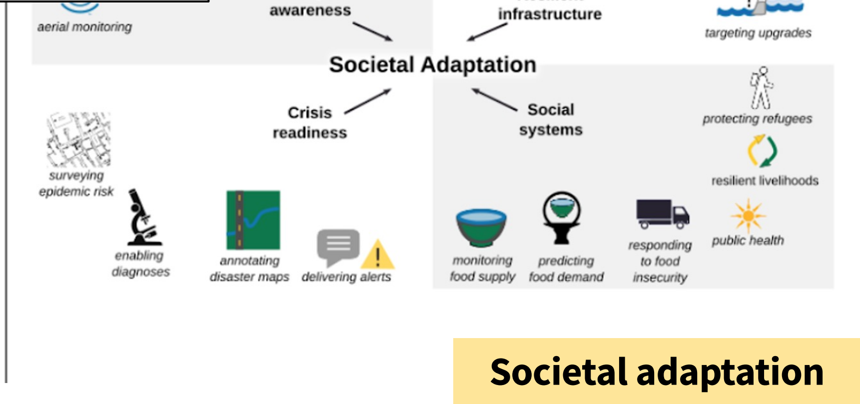
Tackling Climate Change with Machine Learning

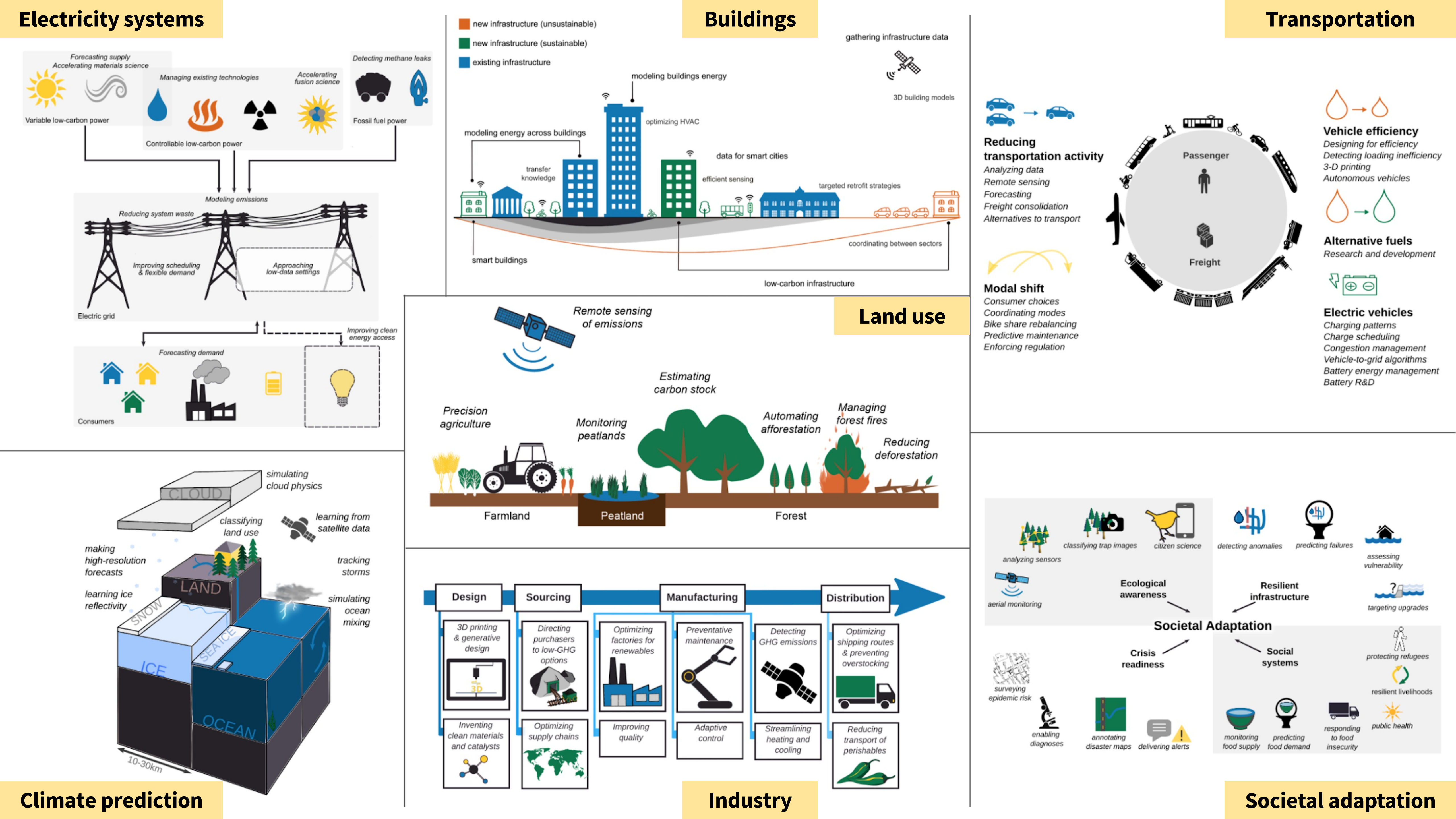
David Rolnick[1]*, Priya L. Donti[2], Lynn H. Kaack[3], Kelly Kochanski[4], Alexandre Lacoste[5], Kris Sankaran[6,7], Andrew Slavin Ross[8], Nikola Milojevic-Dupont[9,10], Natasha Jaques[11], Anna Waldman-Brown[11], Alexandra Luccioni[6,7], Tegan Maharaj[6,7], Evan D. Sherwin[2], S. Karthik Mukkavilli[6,7], 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





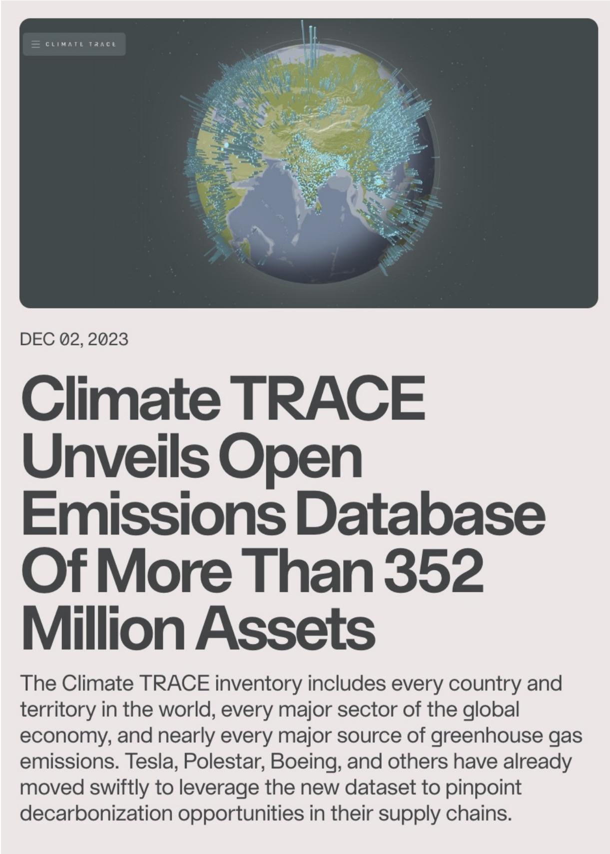




Electricity systems
Forecasting supply
Accelerating materials science
Variable low-carbon power
Managing existing technologies
Accelerating fusion science
Controllable low-carbon power
Detecting methane leaks
Fossil fuel power
Modeling emissions
Reducing system waste
Improving scheduling & flexible demand
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
CLOUD
simulating cloud physics
classifying land use
learning from satellite data
making high-resolution forecasts
tracking storms
LAND
learning ice reflectivity
SNOW
simulating ocean mixing
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
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

AI for climate action: Recurring themes

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



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, policy)

Improving predictions (renewables, transportation demand, extreme events)

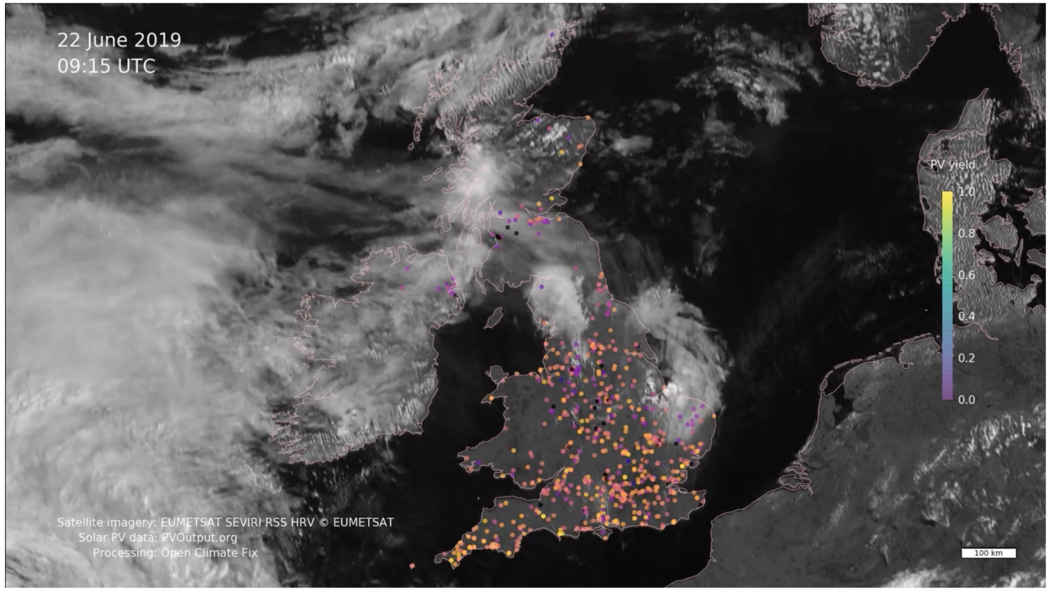


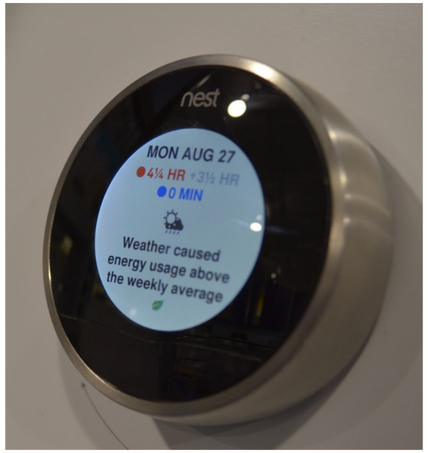
Image source: Open Climate Fix

AI for climate action: Recurring themes

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

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)

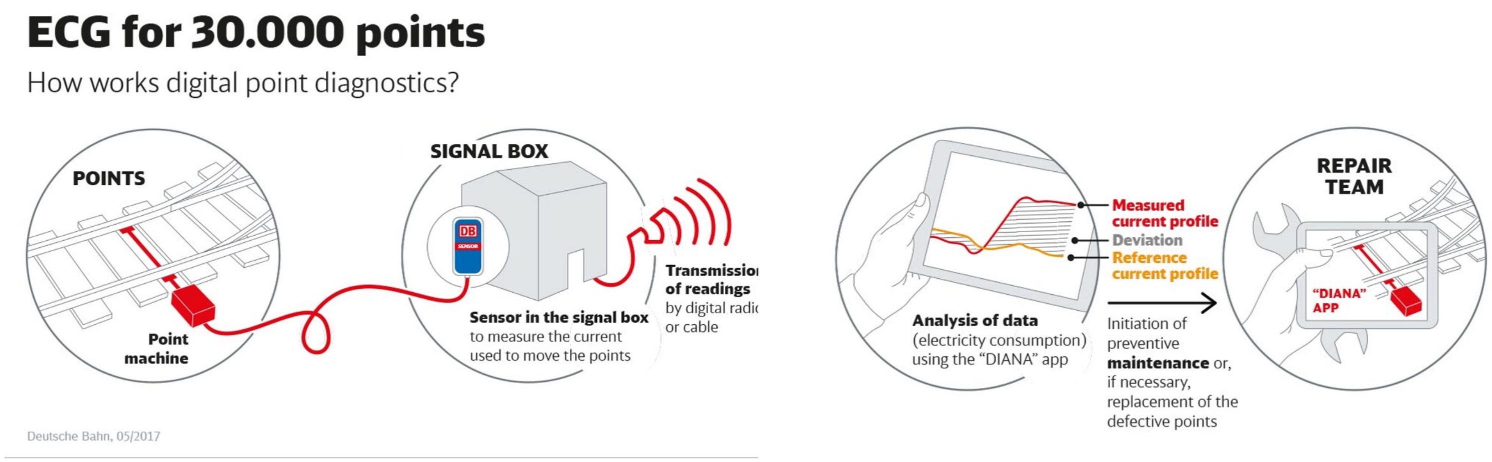

Image source: Deutsche Bahn

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Accelerating scientific discovery
(batteries, electrofuels, CO_2 sorbents)

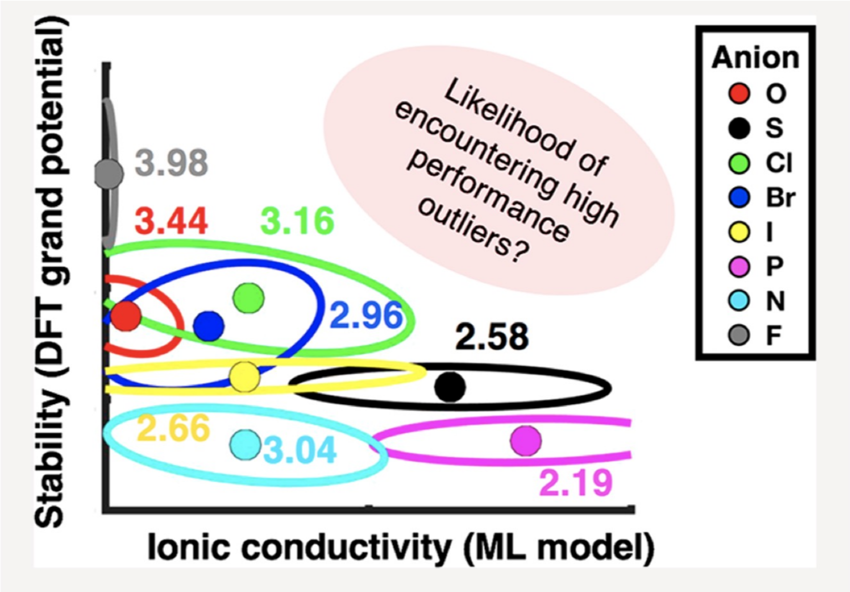

Image source: Sendek et al., 2020

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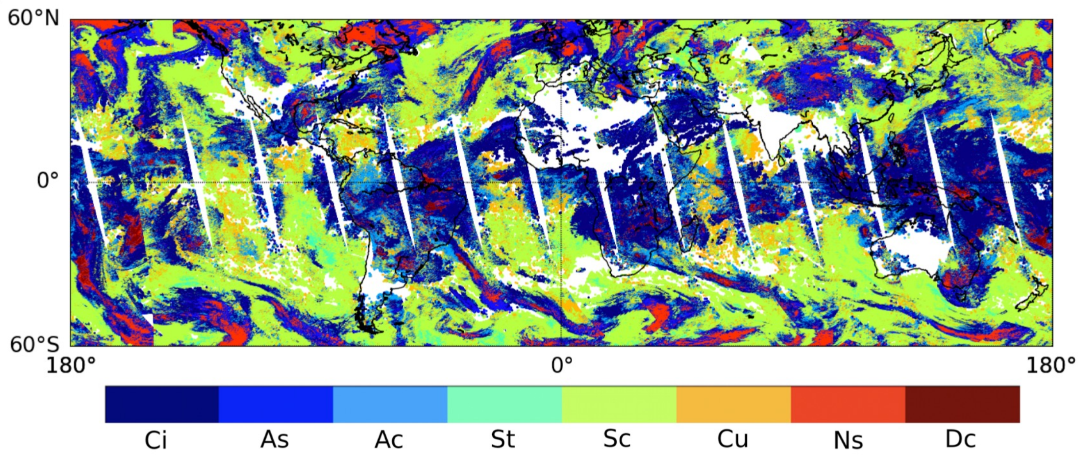
Approximating time-intensive simulations
(climate, energy, city planning)



(a) Predictions of one day.

Image source: Zantedeschi et al., 2019

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Data management
(data matching/fusion, data generation)

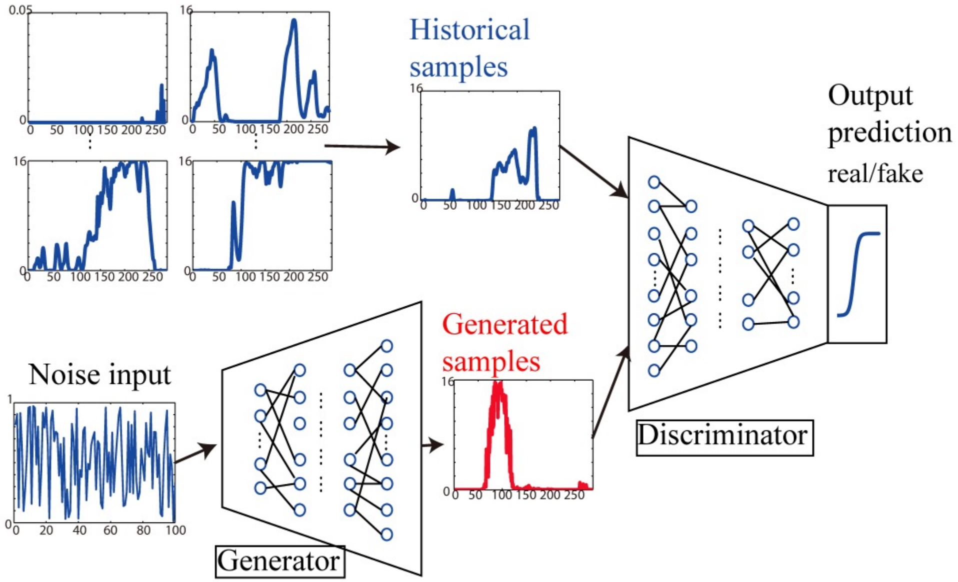

Image source: Chen, Wang, Kirschen, Zhang, 2018

Many opportunities for innovation

Physics-informed and robust ML

Interpretable ML

Uncertainty quantification

Generalization and causality

….

Demands of the climate change domain should shape innovations

- See ICML 2022 climate change tutorial (icml.cc/virtual/2022/tutorial/18443)

		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				•		•		•	

AI and climate change

AI applications for climate action

Impacts from AI computation & hardware

AI's system-level impacts

AI applications that increase emissions

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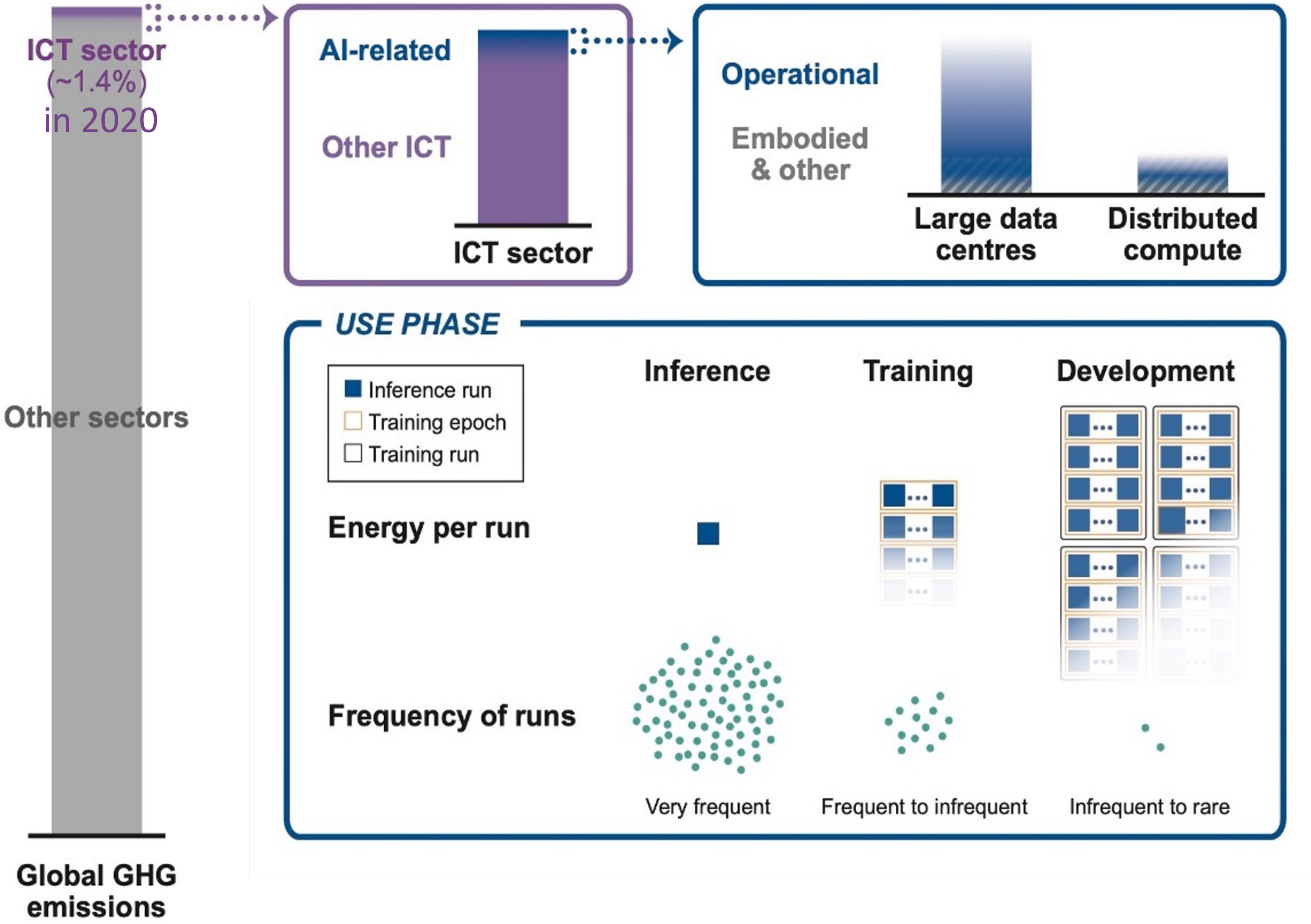
Impacts from AI computation & hardware

Operational impacts from energy & water consumed during computation

Embodied emissions & materials impacts from production, transport, and disposal of hardware



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Electricity demand is rapidly growing

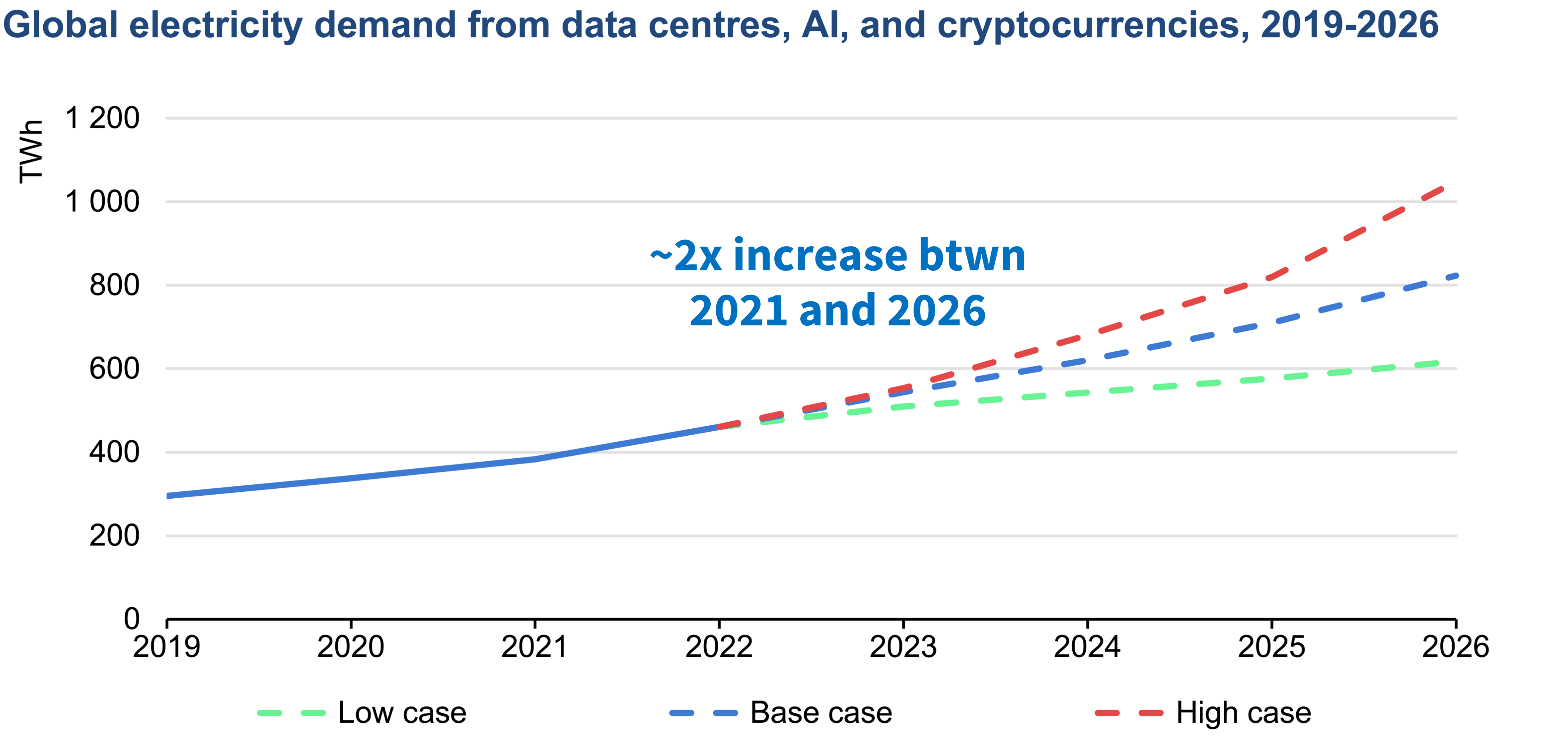

Figure source: IEA (International Energy Agency), “Electricity 2024: Analysis and forecast to 2026” [DATE]

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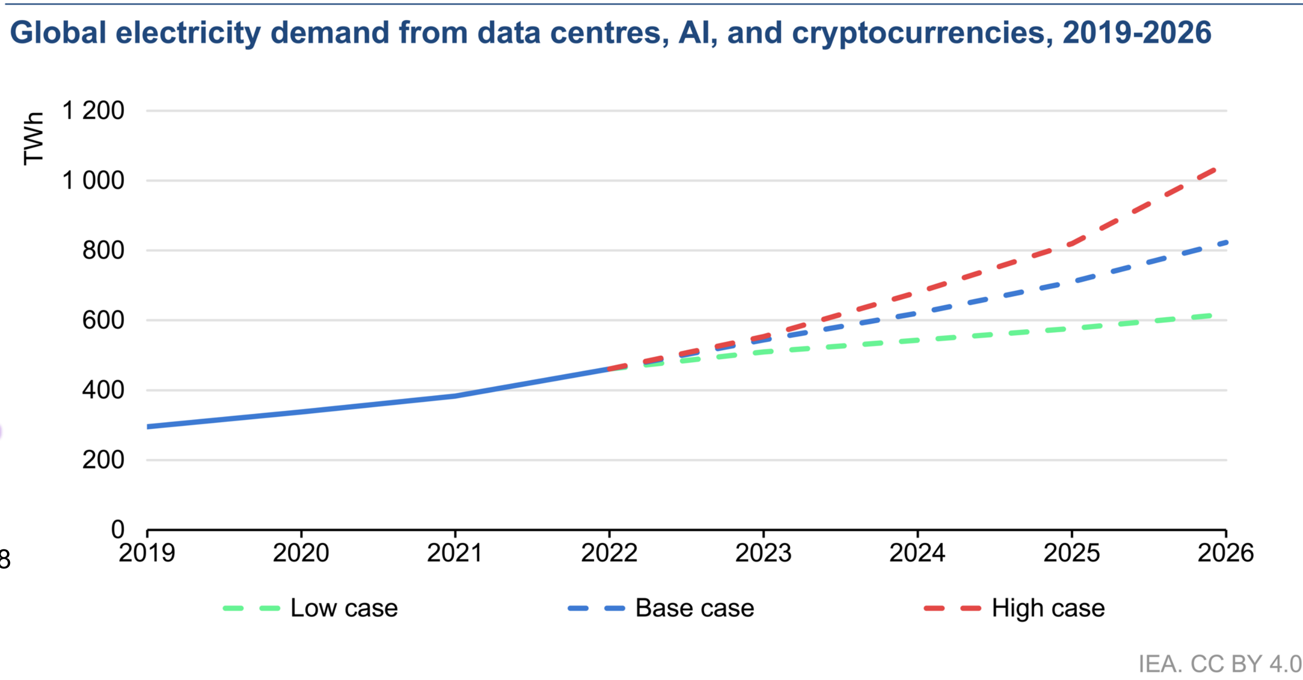


6% increase
btwn 2010 and 2018

(despite 5.5x increase in compute instances)

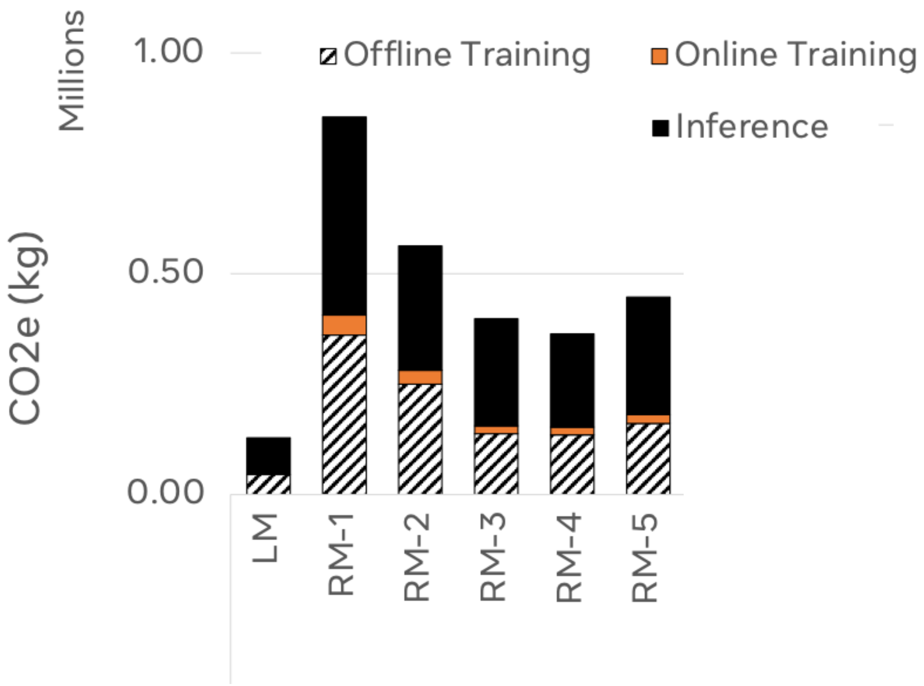
> 2x increase
btwn 2019 and 2026

Rough estimates, based on:
Masanet, Eric, et al. "Recalibrating global data center energy-use estimates." Science (2020)

Source: IEA, “Electricity 2024: Analysis and forecast to 2026”

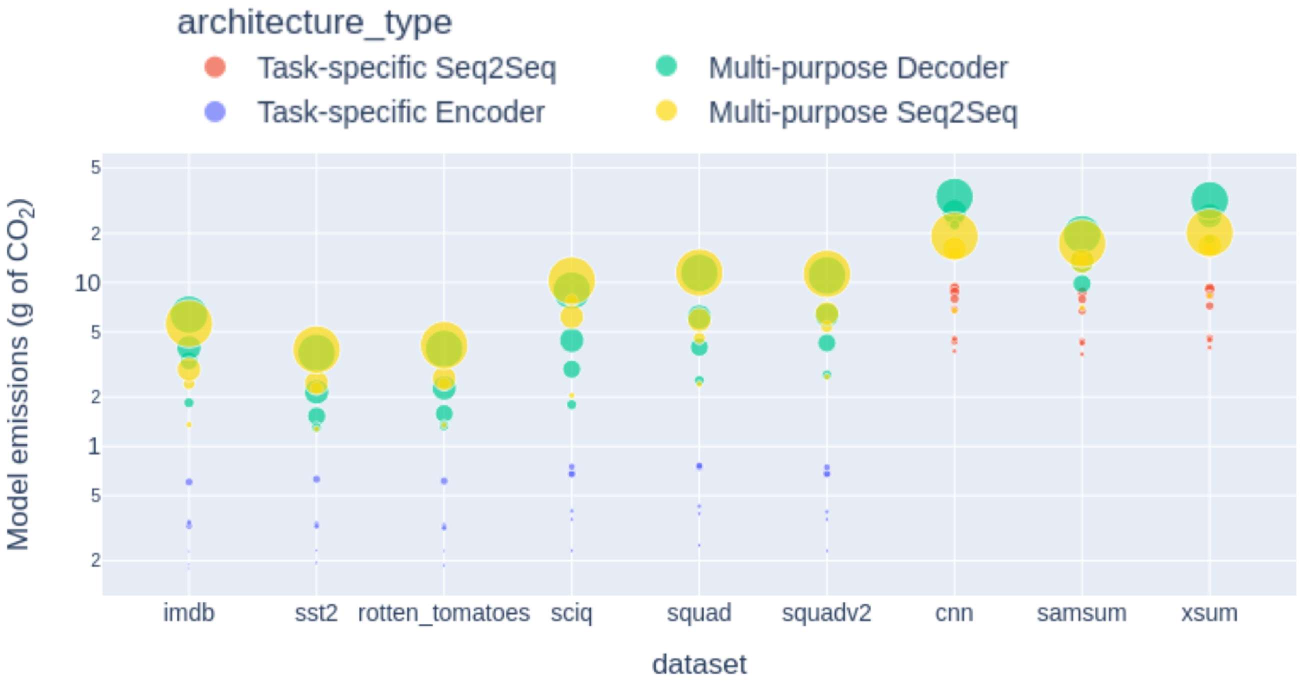
Changing emissions impacts of training vs. inference

Facebook: “The carbon footprint of the LM model is dominated by Inference whereas, for RM1 – RM5, the carbon footprint of Training versus Inference is roughly equal”



Wu, Carole-Jean, et al. "Sustainable AI: Environmental implications, challenges and opportunities." *Proceedings of Machine Learning and Systems* 4 (2022): 795-813.

Per inference, multi-purpose models can be orders of magnitude more expensive than task-specific models



Luccioni, Alexandra Sasha, Jernite, Yacine, and Strubell, Emma. "Power Hungry Processing: ⚡Watts ⚡ Driving the Cost of AI Deployment?" *arXiv preprint arXiv:2311.16863 (2023)*

“Greening the grid” is important but insufficient

The path to net zero emissions is narrow: staying on it requires immediate and massive deployment of all available clean and efficient energy technologies. In the net zero emissions pathway presented in this report, the world economy in 2030 is some 40% larger than today but uses 7% less energy. A major worldwide push to increase energy efficiency is an essential part of these efforts, resulting in the annual rate of energy intensity improvements averaging 4% to 2030 – about three-times the average rate achieved over the last two decades.

Source: IEA, “Net Zero by 2050: A Roadmap for the Global Energy Sector” (2021)

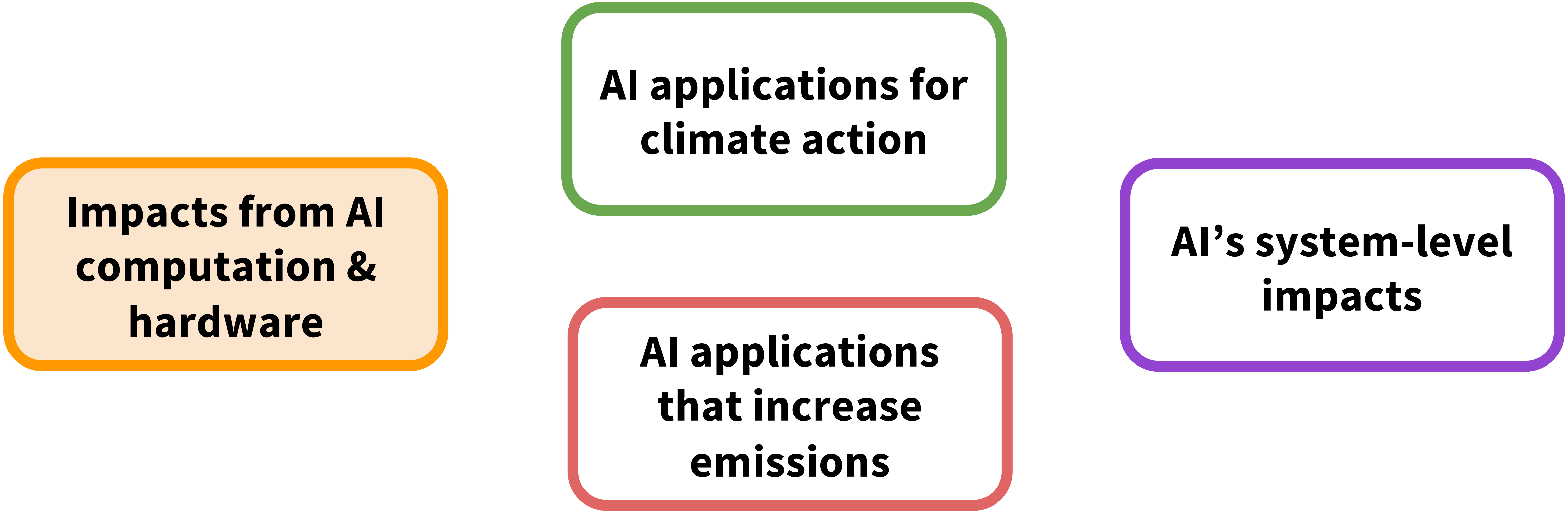
While the carbon costs of data centers have been the primary focus of attention in the news, data centers also rely on immense amounts of water for both electricity production and cooling. To supply their centers, many tech firms draw from public water supplies and aquifers, adding to regional water stress—while being built in some of the world’s most drought-prone areas.

Source: Amba Kak and Sarah Myers West, “AI Now 2023 Landscape: Confronting Tech Power,” AI Now Institute (2023).

The term “artificial intelligence” may invoke ideas of algorithms, data, and cloud architectures, but none of that can function without the minerals and resources that build computing’s core components.

Source: Kate Crawford, “Atlas of AI” (2021)

AI and climate change



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AI applications increasing emissions

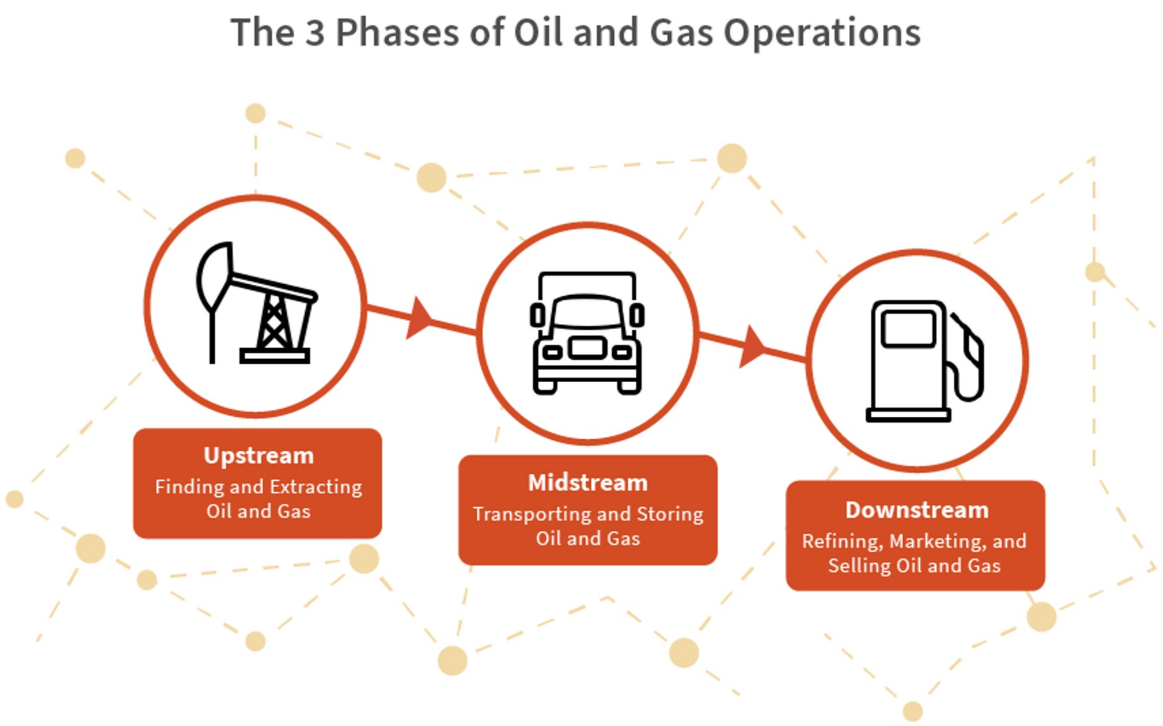

Image source: Greenpeace

AI use to accelerate **emissions-intensive industries**

Example: Oil and gas applications
[Greenpeace “Oil in the Cloud” 2020]

- AI has boosted production levels in some cases by as much as 5%
- AI could generate $425 billion in value for oil/gas sector by 2025

Example: AI use in “Internet of Cows” to manage livestock at scale

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System-level impacts of AI applications

Potential **rebound** and **lock-in** effects

- Autonomous vehicles, ridesharing

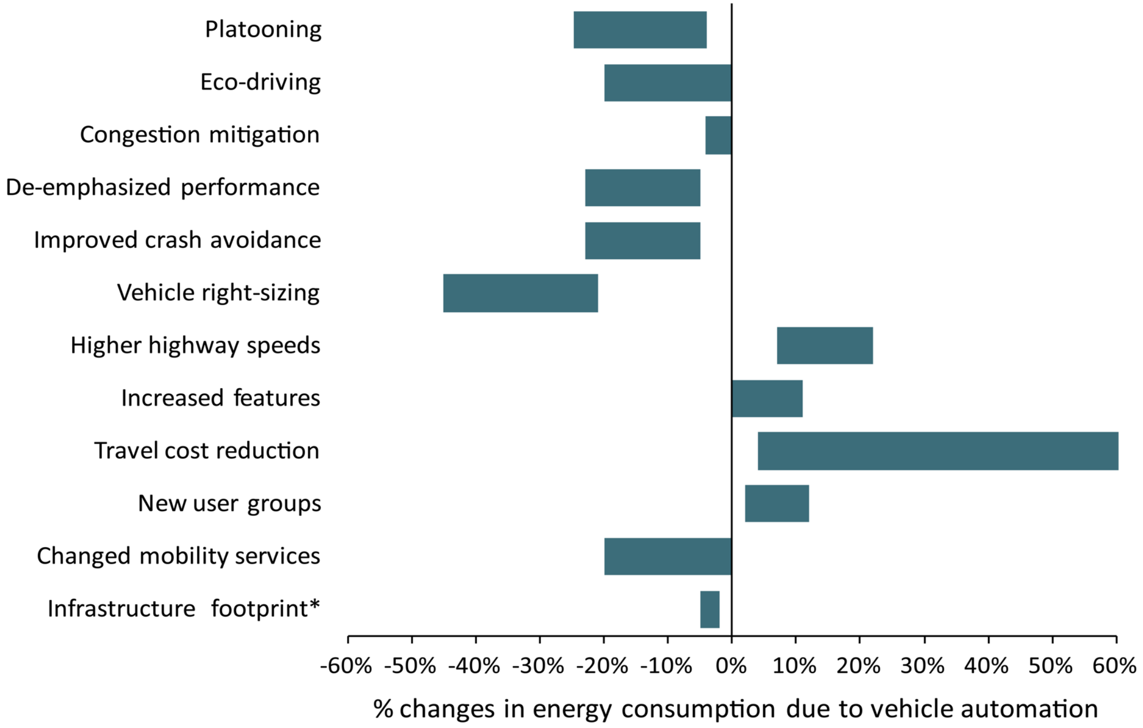

Image source: Wadud et al. 2016

System-level impacts of AI applications

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- Autonomous vehicles, ridesharing

Increasing **societal consumption**

- Personalized ads, on-demand delivery

Image credit: Megan_Rexazin_Conde / Pixabay.com

System-level impacts of AI applications

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(Mis)information and **polarization**

- Content personalization/amplification

Image credit: Rose Wong / for NBC News

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Increasing **societal consumption**
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(Mis)information and **polarization**
- Content personalization/amplification

Inducing **societal power shifts** due to access and agency

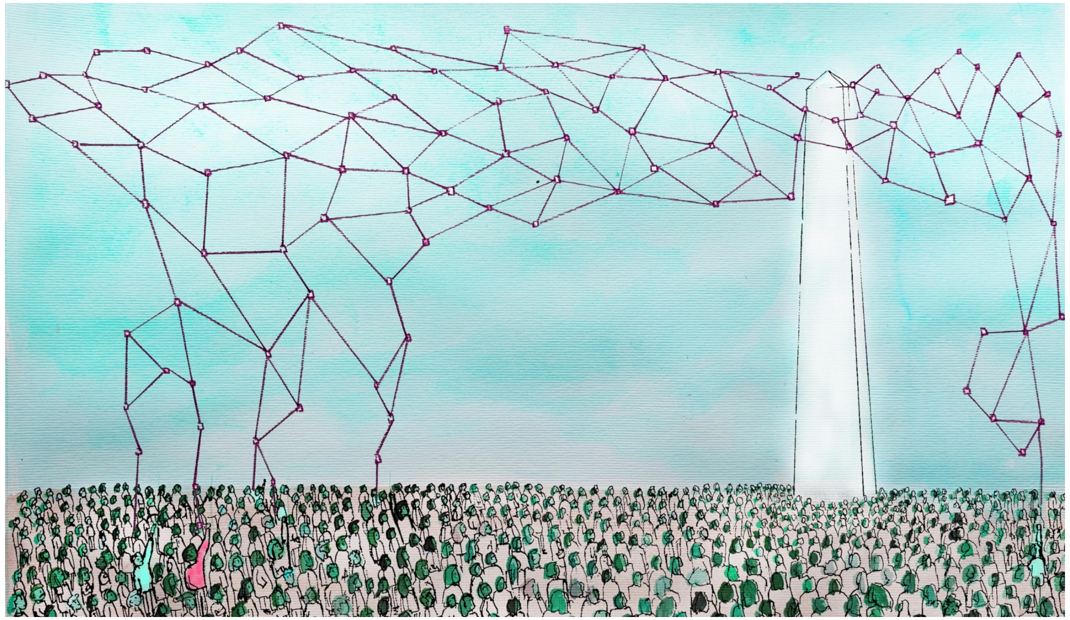

Image credit: Jamillah Knowles & We and AI / Better Images of AI / People and Ivory Tower AI / CC-BY 4.0

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Levers of impact for the AI community

Impacts from AI computation & hardware

AI applications for climate action

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AI's system-level impacts

Methodological innovation

Applications (what & how)

Practices

Public communication

Levers of impact for the AI community

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Methodological innovation

Applications (what & how)

Practices

Public communication

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.

Methodological frontiers with climate relevance

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

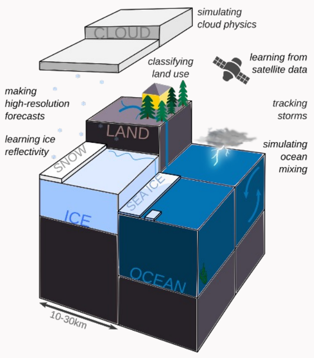
Methodological frontiers with climate relevance

Physics-informed ML

Safe and robust ML

Climate prediction

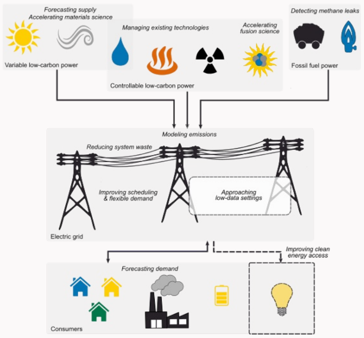
Earth, atmospheric, oceanic modeling



Electricity systems

Wind farm optimization

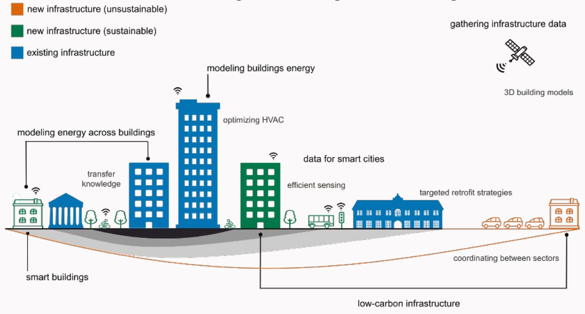
Power system optimization & control



Buildings & cities

Urban environmental simulations

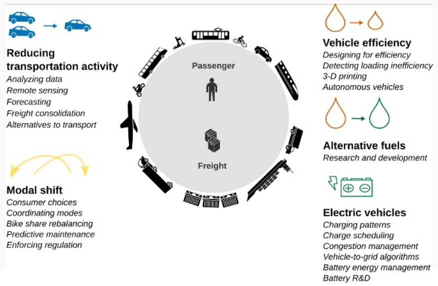
Building heating & cooling control



Transportation

Aerodynamic efficiency modeling

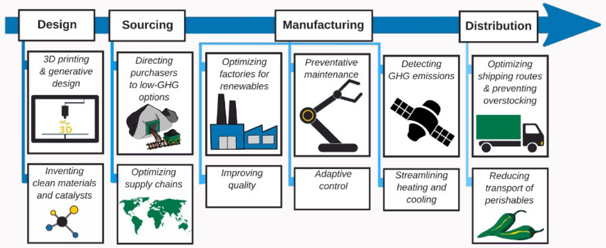
Battery and alternative fuel R&D



Industry

Equipment control & demand response

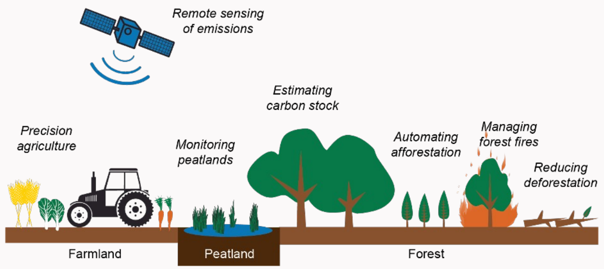
Design of low-materials structures



Land use (agriculture)

Precision agriculture

Cleaner ammonia production



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

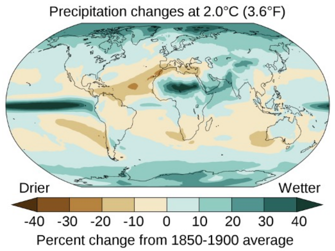
Methodological frontiers with climate relevance

Physics-informed ML

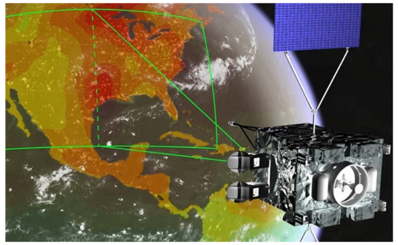
Safe and robust ML

Interpretable ML

Uncertainty quantification



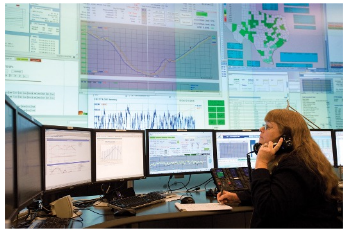
Scientific understanding and predictions of climate change



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

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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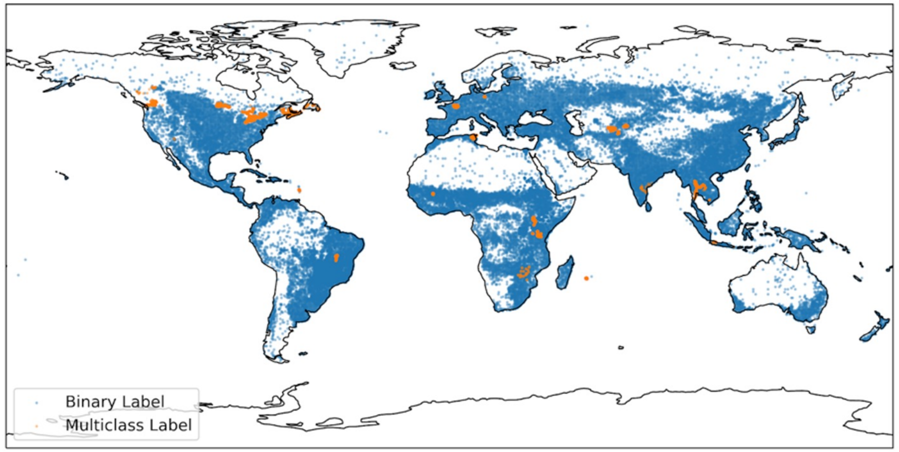
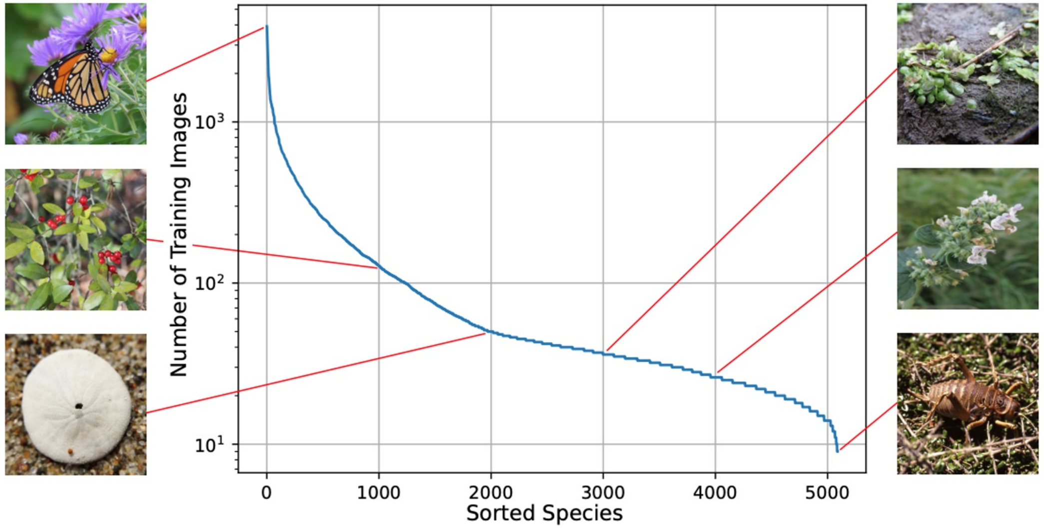
Uncertainty quantification

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.

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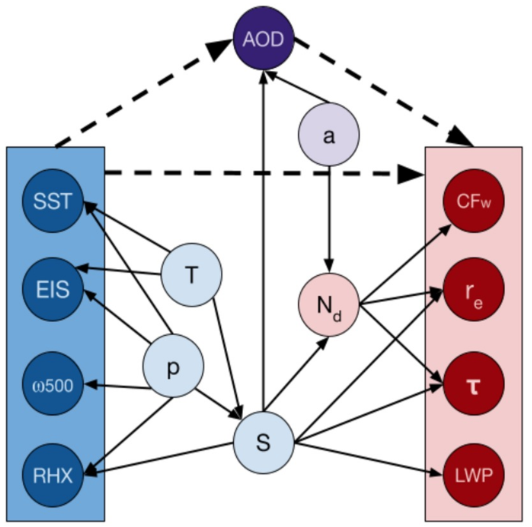
Causality



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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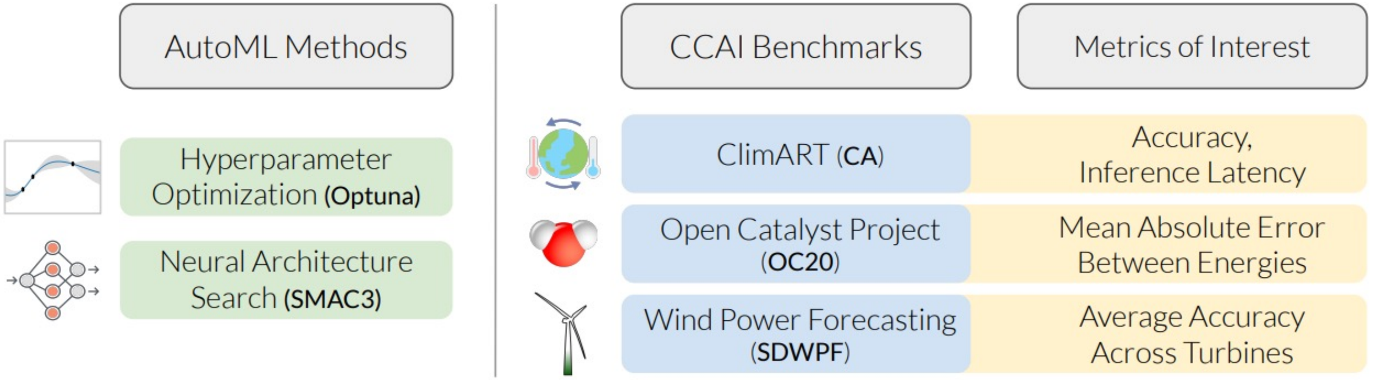
Energy efficient ML & TinyML

AutoML



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

AI applications for climate action

Impacts from AI computation & hardware

AI's system-level impacts

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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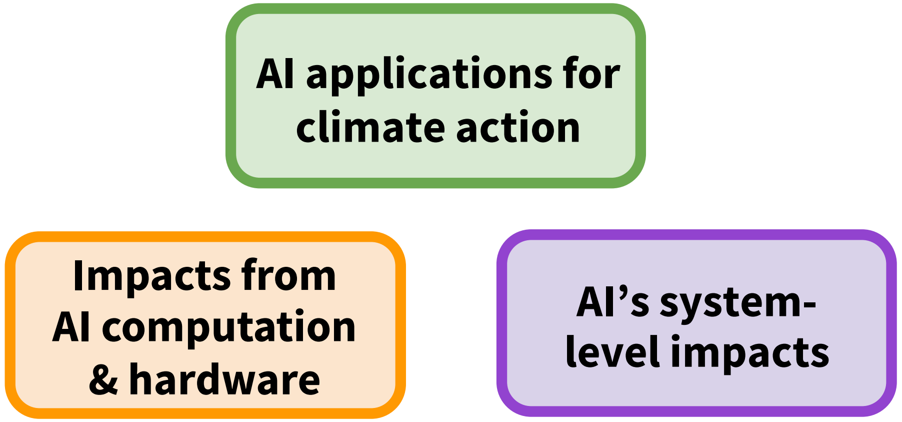
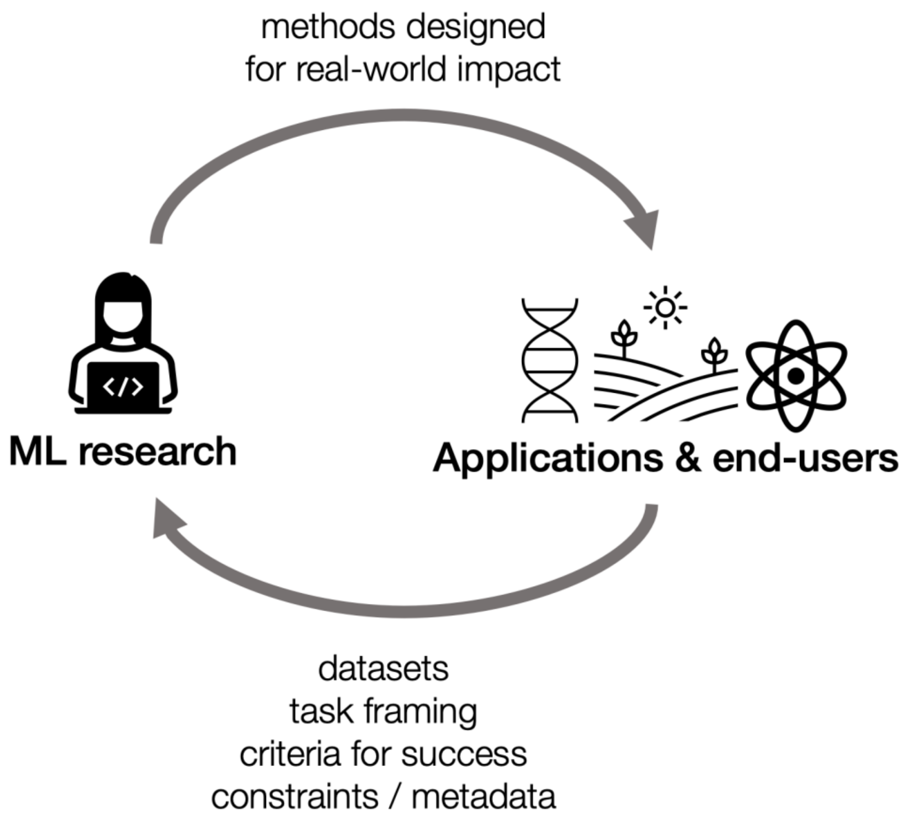


See also: Priya L. Donti, David Rolnick, Lynn H. Kaack, "Climate Change and ML: Opportunities, Challenges, and Considerations," *ICML 2022 tutorial*.

Demands of applications should shape innovations

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

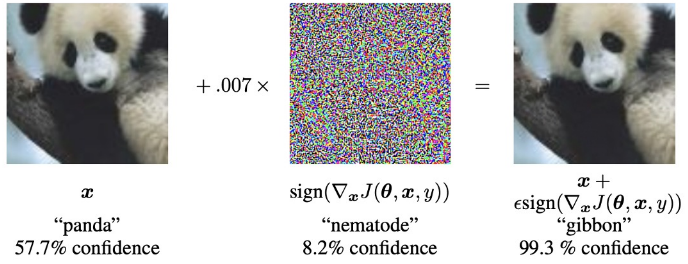
Need to source datasets, requirements, success criteria, and constraints/metadata from a diverse set of tasks



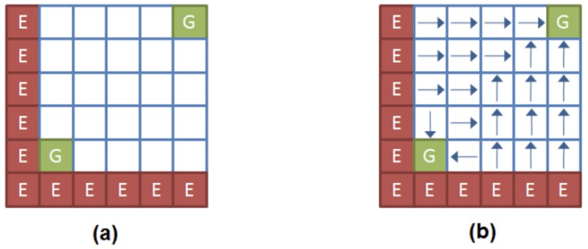
See: David Rolnick, Alan Aspuru-Guzik, Sara Beery, Bistra Dilkina, Priya L. Donti, Marzyeh Ghassemi, Hannah Kerner et al. "Application-Driven Innovation in Machine Learning." Forthcoming in *International Conference on Learning Representations* (2024).

Example: Differing notions of “robustness”

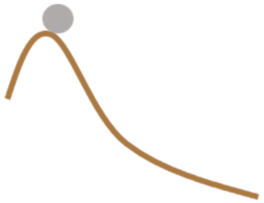
Adversarial robustness [ML]: Robustness to perturbations of inputs



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



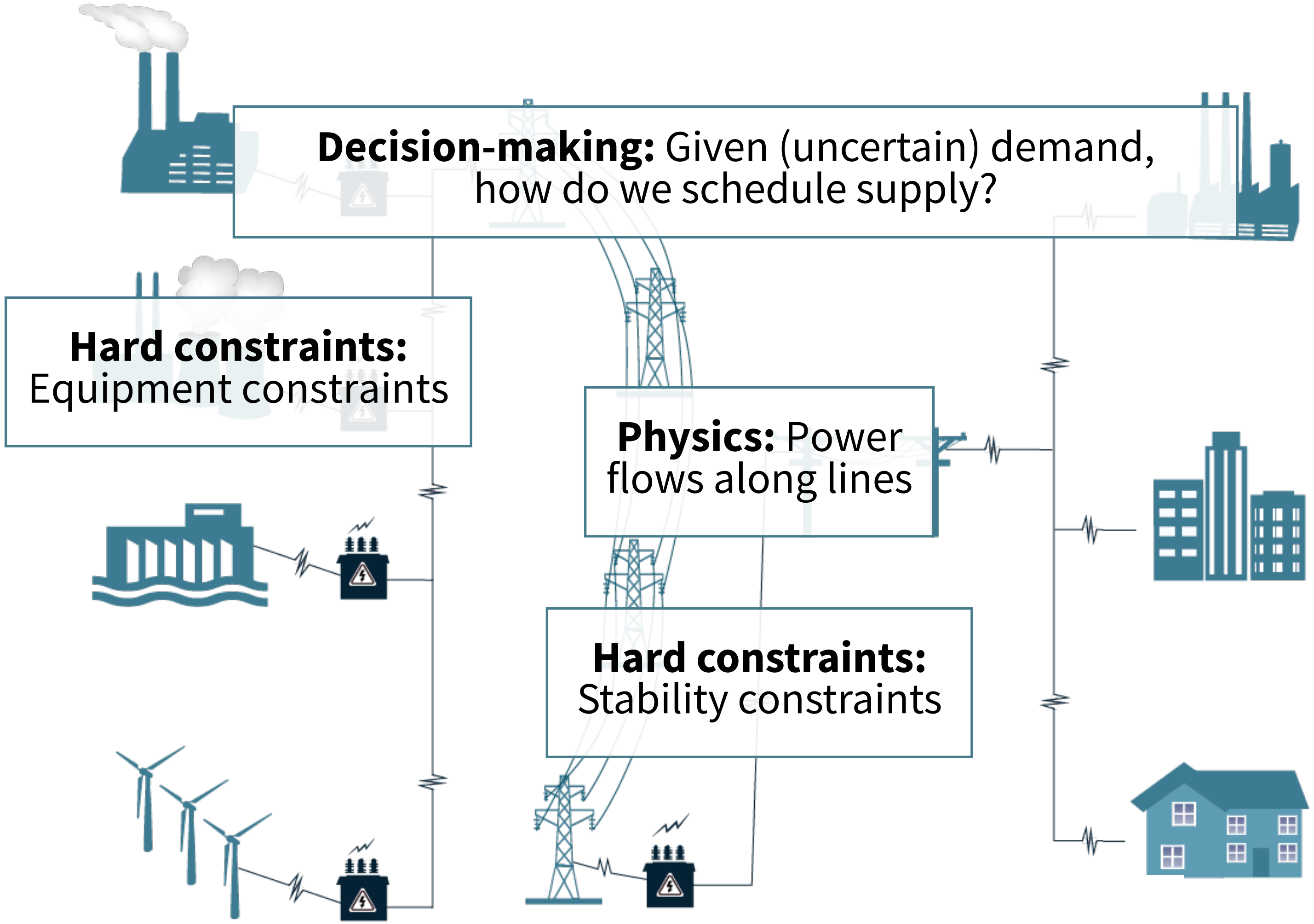
Robust control [e.g., power systems, buildings]: Bring system to an equilibrium (e.g., Lyapunov stability)



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.

Our work: ML with engineering constraints (power grids)



Trad. optimization & control
- Satisfies (many) constraints
- Struggles with speed / scale

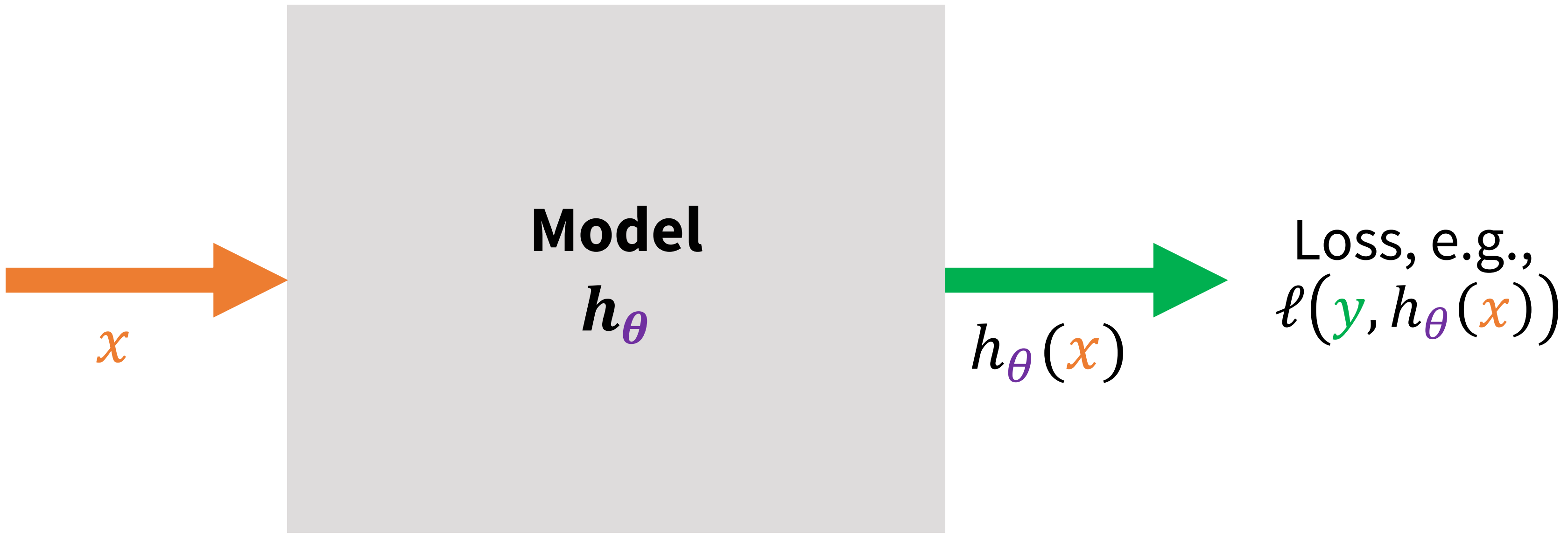
Machine learning (ML)
- Fast and scalable
- Struggles with constraints

Donti, Priya L. *Bridging Deep Learning and Electric Power Systems*. Diss. Carnegie Mellon University, 2022.

Figure adapted from: US Congressional Budget Office

Optimization-in-the-loop ML

Framework for developing ML methods that incorporate knowledge of physics, hard constraints, or downstream decision-making procedures, via optimization problems



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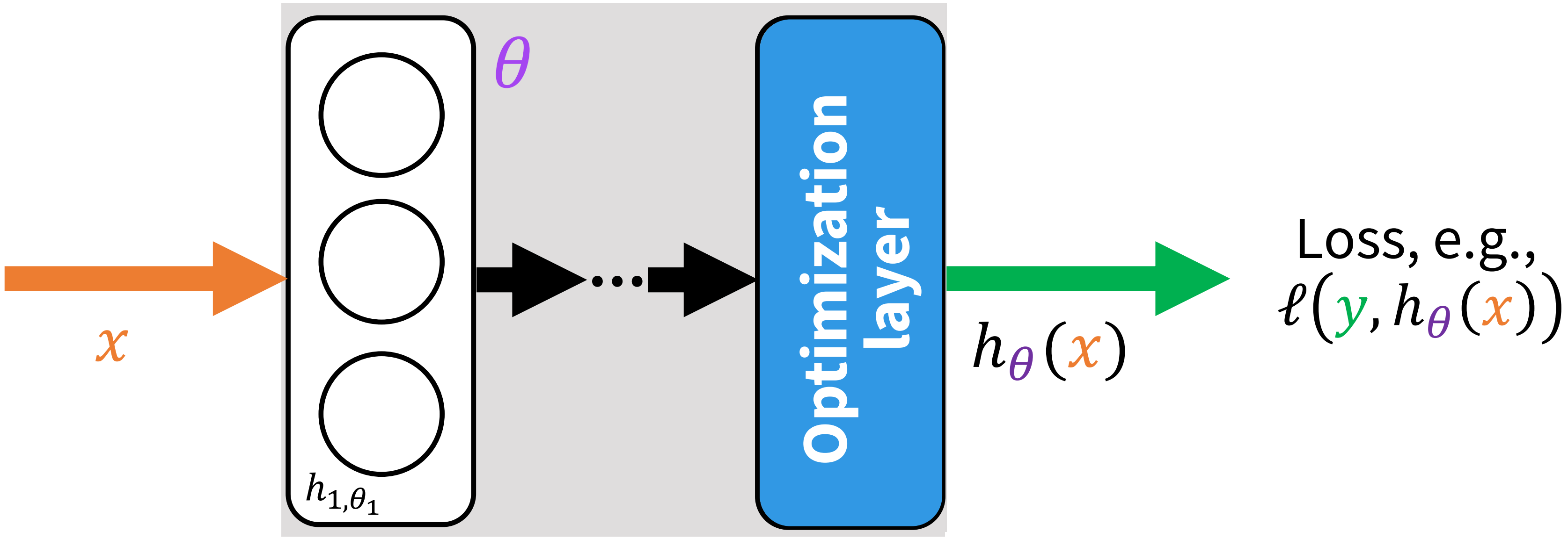
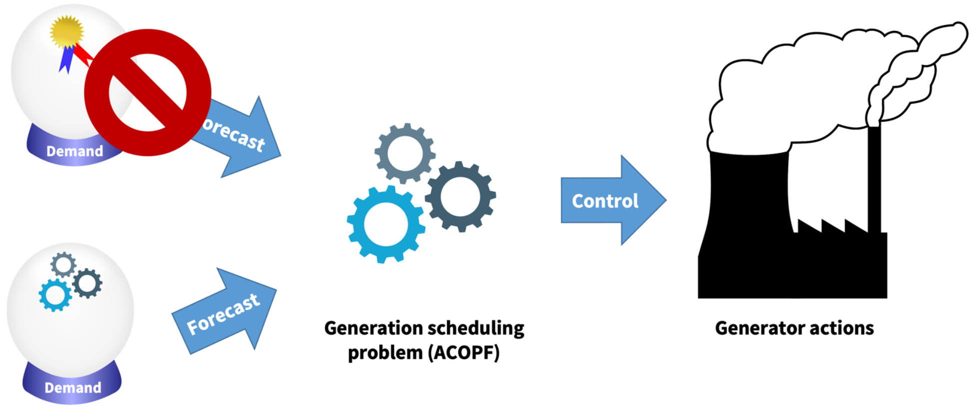
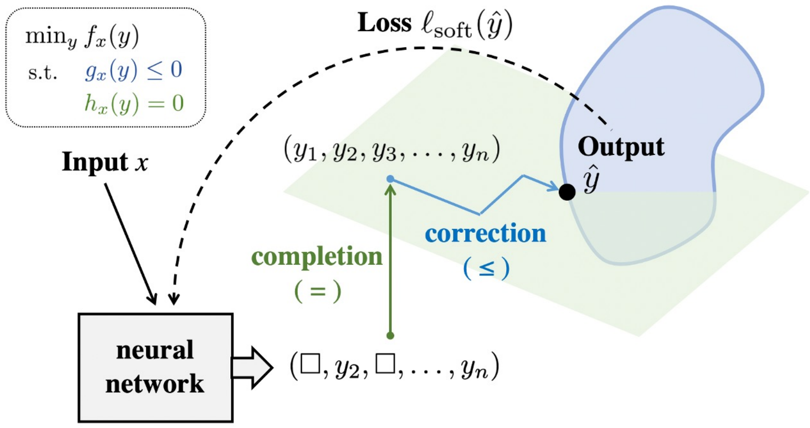


Donti, Priya L. *Bridging Deep Learning and Electric Power Systems*. Diss. Carnegie Mellon University, 2022.

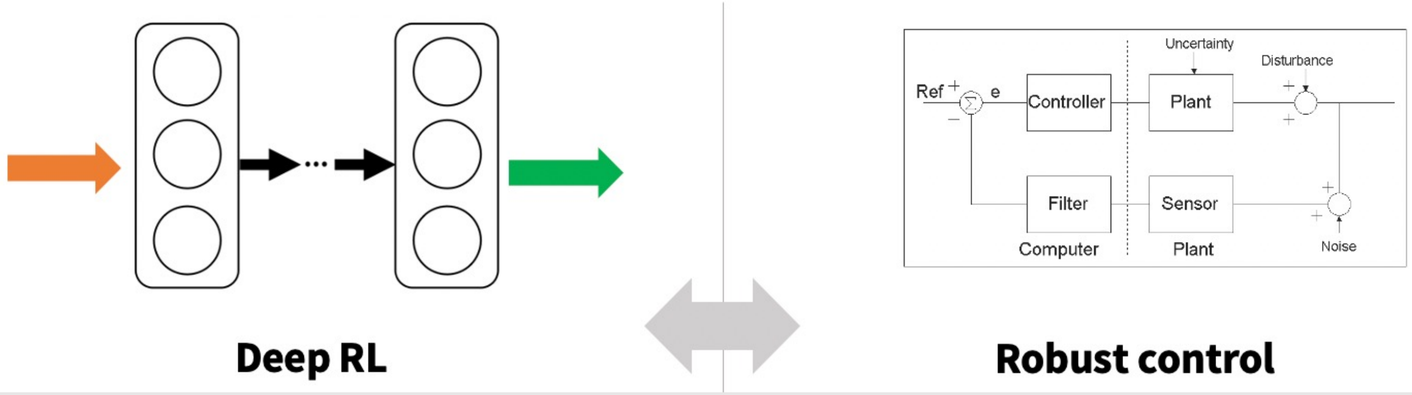
Optimization-in-the-loop ML for power systems



Decision-cognizant forecasting of supply & demand



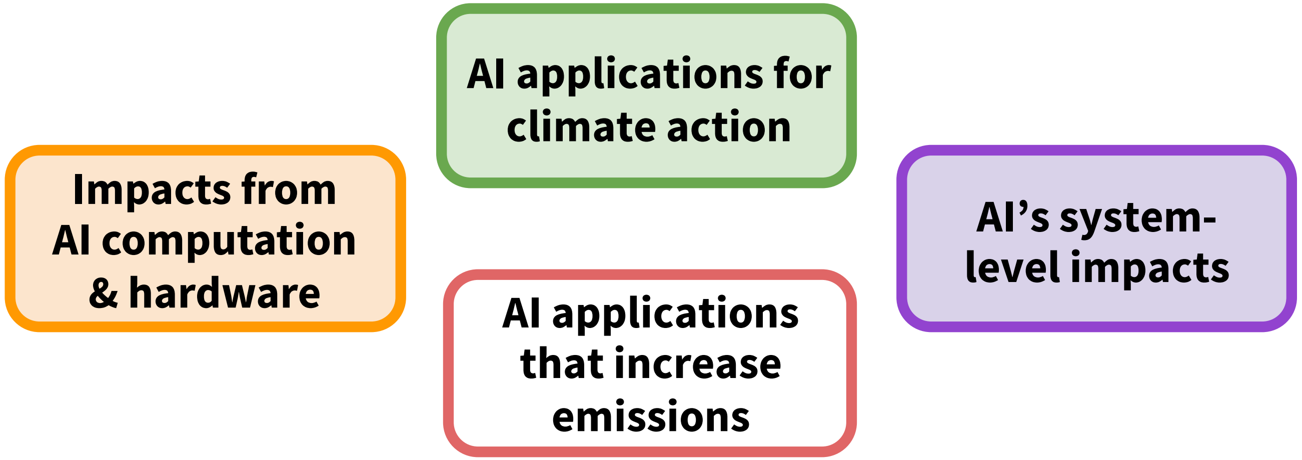
Fast, feasible approximations to power systems optimization (ACOPF, SCOPF)



Provably robust control via deep reinforcement learning (power, buildings)

Donti, Priya L. *Bridging Deep Learning and Electric Power Systems*. Diss. Carnegie Mellon University, 2022.

Levers of impact for the AI community



Methodological innovation

Applications (what & how)

Practices

Public communication

Levers of impact for the AI community

Impacts from AI computation & hardware

AI applications for climate action

AI applications that increase emissions

AI's system-level impacts

Methodological innovation

Applications (what & how)

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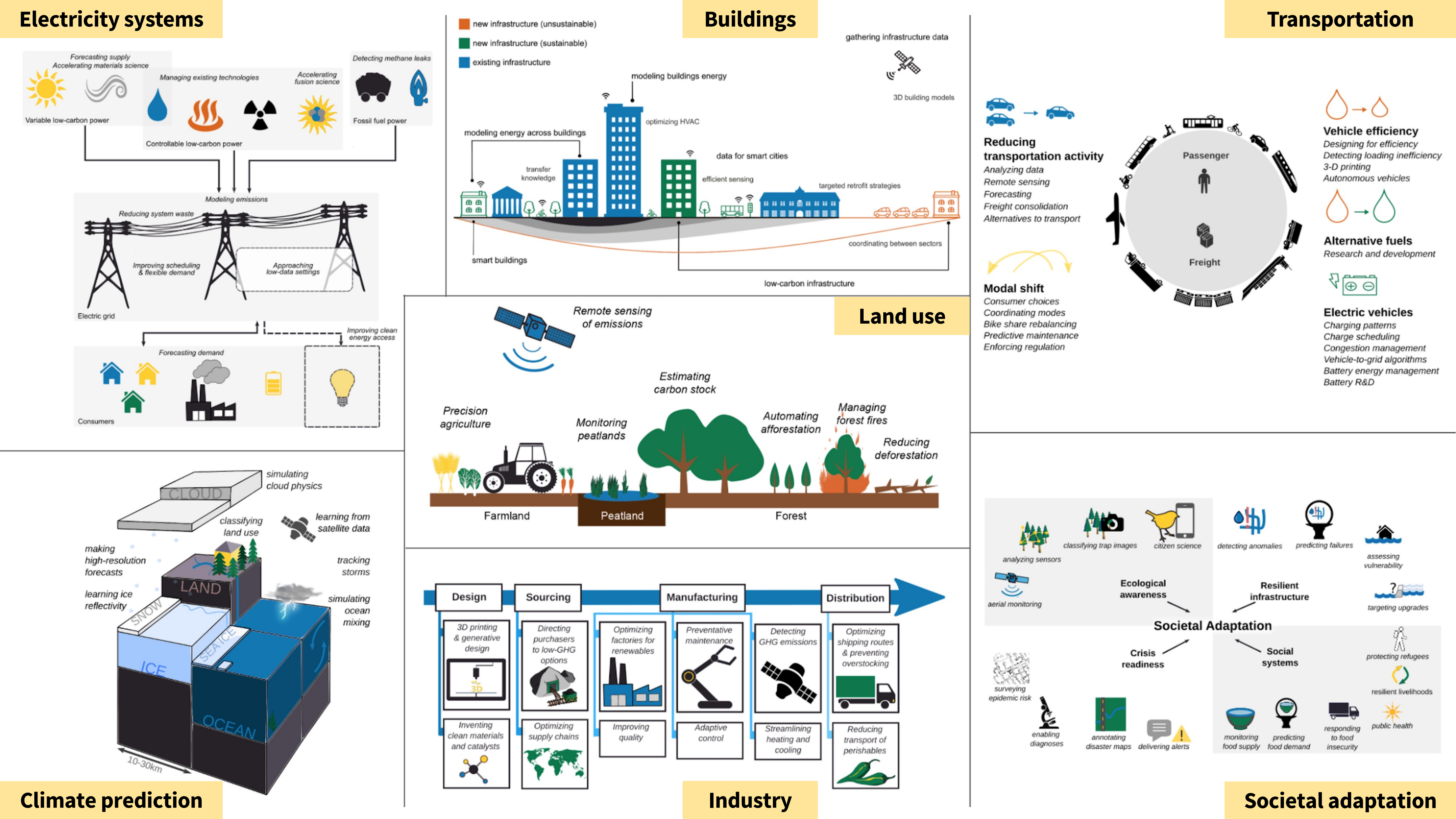


Electricity systems
Forecasting supply
Accelerating materials science
Variable low-carbon power
Managing existing technologies
Accelerating fusion science
Controllable low-carbon power
Detecting methane leaks
Fossil fuel power
Modeling emissions
Reducing system waste
Improving scheduling & flexible demand
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
LAND
learning ice reflectivity
simulating ocean mixing
SNOW
SEA ICE
ICE
OCEAN
10-30km
Industry
Design
Sourcing
Manufacturing
Distribution
3D printing & generative design
3D
Inventing clean materials and catalysts
Directing purchasers to low-GHG options
Optimizing supply chains
Optimizing factories for renewables
Improving quality
Preventative maintenance
Adaptive control
Detecting GHG emissions
Streamlining heating and cooling
Optimizing shipping routes & preventing overstocking
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
surveying epidemic risk
resilient livelihoods
enabling diagnoses
annotating disaster maps
delivering alerts
monitoring food supply
predicting food demand
responding to food insecurity
public health

Applications

AI applications for climate action

Work on climate-relevant applications ☺

AI applications that increase emissions

Avoid work on applications clearly countering climate goals

AI's system-level impacts

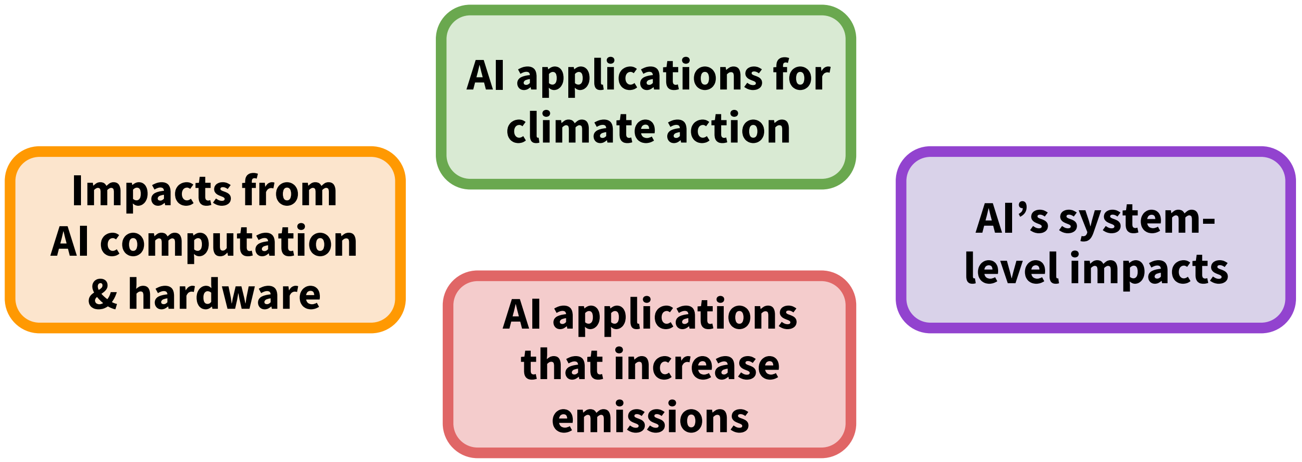
Shape emissions impacts of "other" AI applications

- Autonomous vehicles *[methods for public/multi-modal transit]*
- On-demand delivery *[fuel efficiency, bundling shipments]*
- Content personalization/amplification *[change objective functions]*

Adopt an equity-focused lens (implications for climate justice/climate equity)

- Who am I working with? Whose problems am I centering?
- Who has ownership/agency?

Levers of impact for the AI community



Methodological innovation

Applications (what & how)

Practices

Public communication

Practices

All

Advocate for organizational policies, e.g.

- Internal carbon pricing (covering scopes 1, 2, and 3)
- Ethics/best practices on work to pursue (consider emissions, equity)
- Transparency of reporting and impact assessment

AI's system-level impacts

Brainstorm ways to align "business as usual" AI with climate goals

Ensure education, capacity-building, and ownership among a diverse set of stakeholders

Impacts from AI computation & hardware

Develop cost-benefit frameworks (accuracy vs. efficiency)

Implement infrastructure for emissions-aware load scheduling

Avoid wasteful runs (e.g., better hyperparameter tuning)

Levers of impact for the AI community

- Impacts from AI computation & hardware
- AI applications for climate action
- AI applications that increase emissions
- AI's system-level impacts

Methodological innovation

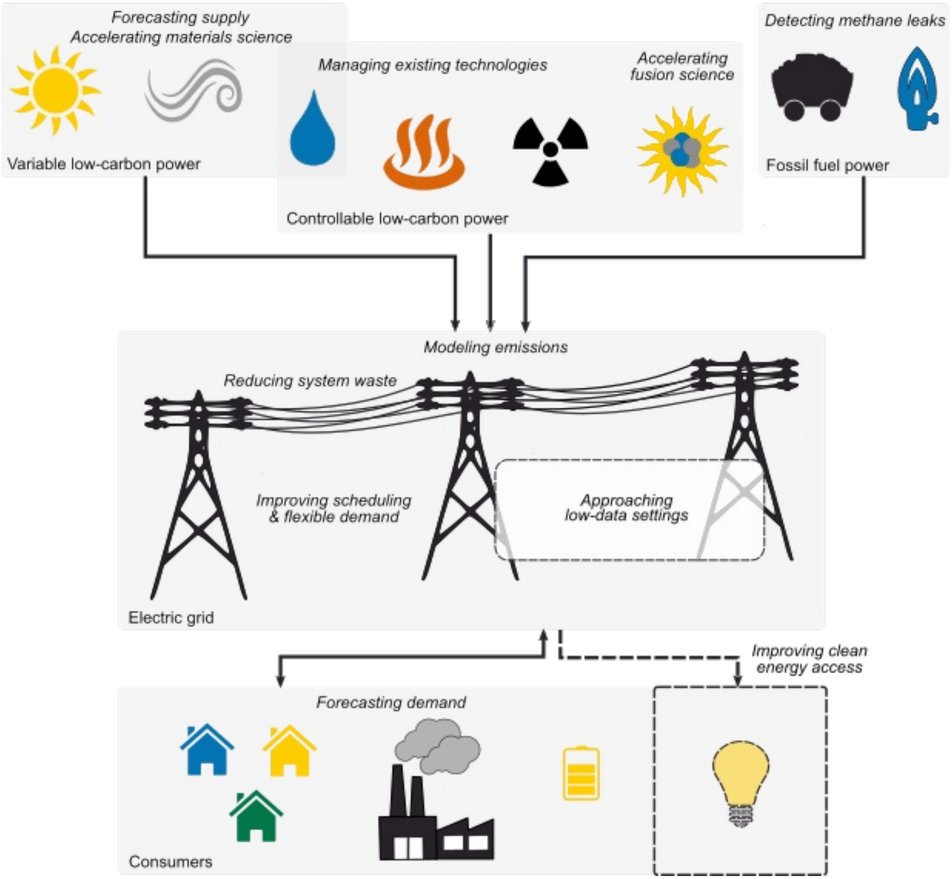
Applications (what & how)

Practices

Public communication

Public excitement for AI, but lack of mental model

AI for power grids – diverse tasks, methods, data modalities



Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., et al. (2022). Tackling climate change with machine learning. *ACM Computing Surveys (CSUR)*, *55*(2), 1-96.

US AI Executive Order, on AI for power grids – anchored on foundation models & text

(g) Within 180 days of the date of this order, to support the goal of strengthening our Nation's resilience against climate change impacts and building an equitable clean energy economy for the future, the Secretary of Energy [...] shall:

(i) issue a public report describing the potential for AI to improve planning, permitting, investment, and operations for electric grid infrastructure [...]

(ii) develop tools that facilitate building foundation models useful for basic and applied science, including models that streamline permitting and environmental reviews while improving environmental and social outcomes; [...]

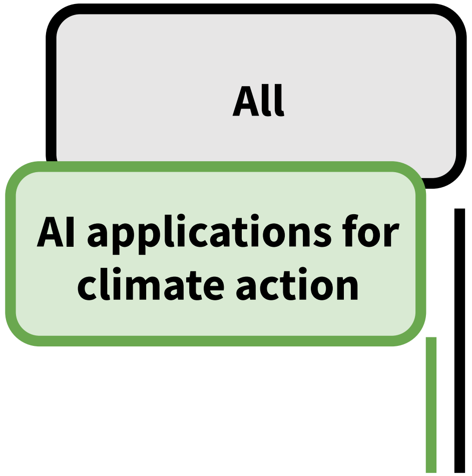
(iv) take steps to [...] utilize the Department of Energy's computing capabilities and AI testbeds to build foundation models that support new applications in science and energy [...]

Public communication

We are increasingly communicating to a non-AI audience [to many, AI = ChatGPT]

Sound understanding can facilitate widespread, on-the-ground impact

Poor mental models and misunderstandings can lead to
- Diversion of funding/attention from impactful but less flashy work
- Opportunity costs with respect to fostering impactful work
- Unsound, irresponsible, or ill-informed AI use



Communicate with both the AI *and* general audiences in mind
- Be transparent about strengths, limitations, and risks
- Highlight diversity of methods & perspectives (in and outside AI)

Engage in thoughtful education of policymakers & general public

Levers of impact for the AI community

Impacts from AI computation & hardware

AI applications for climate action

AI applications that increase emissions

AI's system-level impacts

Methodological innovation

Applications (what & how)

Practices

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Climate Change AI

ICLR 2024 Workshop

Tackling Climate Change with Machine Learning

May 11, 2024

Vienna, Austria & Virtual (hybrid format)

Free livestream: www.climatechange.ai/events/iclr2024#livestream

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Our work on AI matters for climate –
and there's a lot we can do about it.