ICML 2022 Tutorial

Climate Change and ML: Opportunities, Challenges, and Considerations

Priya L. Donti, David Rolnick, Lynn H. Kaack

Climate change warrants rapid action


Filippo Monteforte | AFP | Getty Images


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NASA


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Impacts felt globally

Disproportionate impacts on most disadvantaged populations

Need net-zero greenhouse gas emissions by 2050 (IPCC 2018)

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

How does ML fit into this picture?

Tutorial outline

Introduction to climate change

Opportunities for ML in climate action

Research challenges

- Physics-informed and robust ML
- Interpretable ML and uncertainty quantification
- Generalization and causality

Is ML a help or hindrance for climate action?

Considerations for research and deployment

Takeaways and how to get involved

Tutorial presenters

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David Russell
Duncan Watson-Parris
The Climate Change AI team

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State of
climate change

Approaches for
climate action

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.

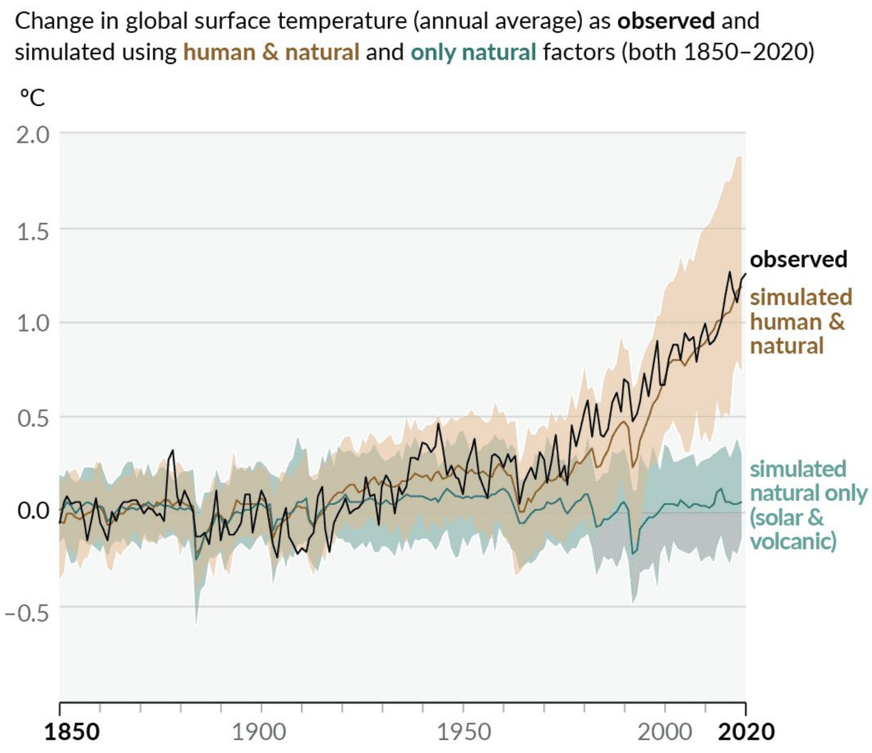

Figure source: IPCC AR6 WG1 Report (2021)

Rapid action is needed to limit warming

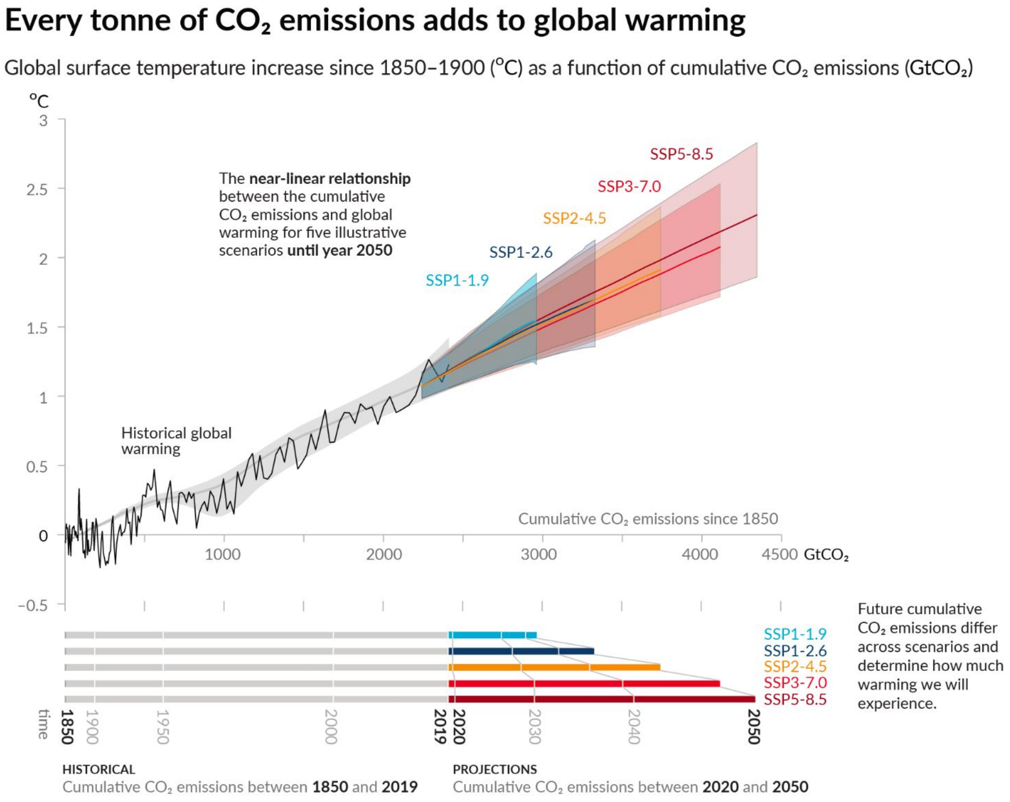

Figure source: IPCC AR6 WG1 Report (2021)

Speed and scale of systemic changes affects total warming

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

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

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

Approaches to addressing climate change

See NeurIPS tutorials by McKinnon & Poppick (2021) and Monteleoni & Banerjee (2014)

Axes of action

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Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

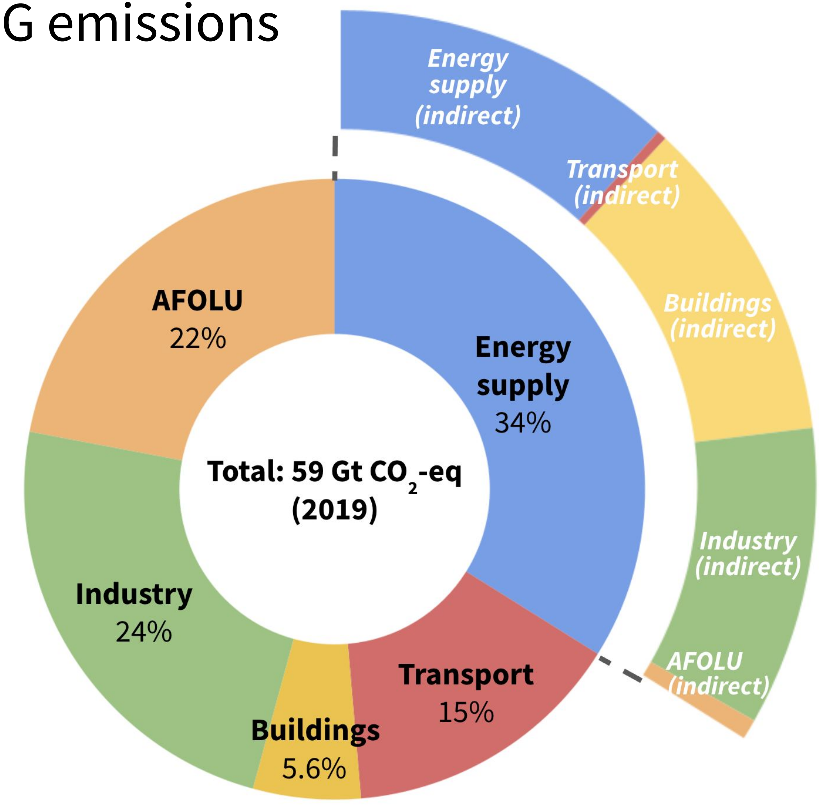


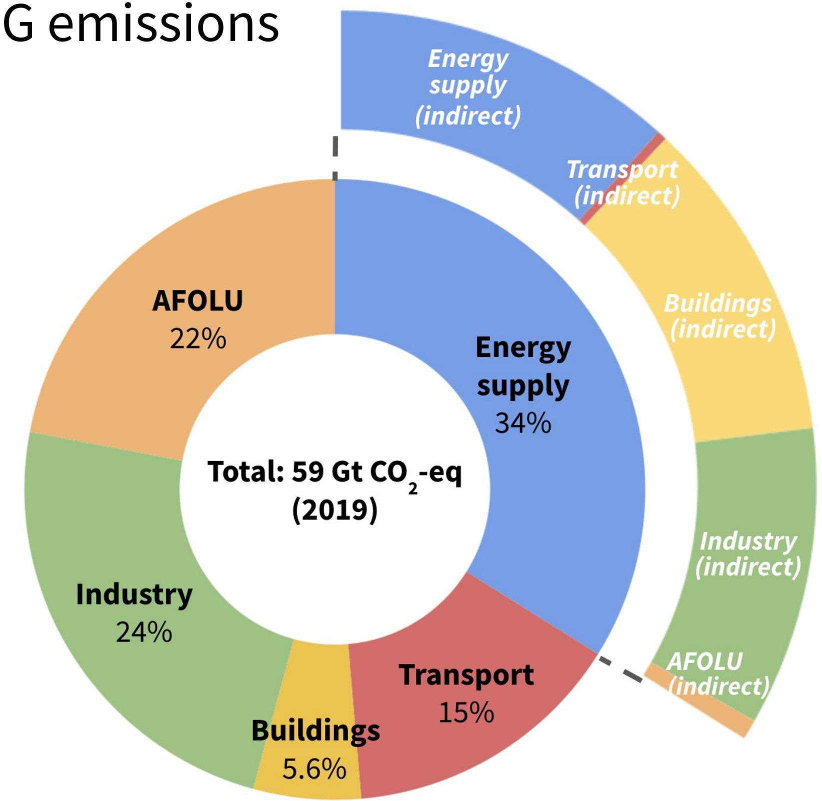
Figure data based on IPCC AR6 WG3 Report (2022). Percentages shown do not add to exactly 100% due to rounding to two significant figures.

Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

Sectors

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



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Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

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Energy-related emissions

Mitigation: Energy-related emissions

Conceptual framework based on **Kaya identity:**

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}} \right)$$

Mitigation: Energy-related emissions

Conceptual framework based on **Kaya identity:**

$$\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}}$$

Reducing consumption

Example: Passenger cars *Service = vehicle-kilometers* 	Reduce number of miles driven ▸ Individual change: Move closer to work ▸ Systemic change: Dense urban areas Increase passengers per trip and vehicle
General energy-related sectors	Individual behavior changes Systemic changes & structural improvements

Mitigation: Energy-related emissions

Conceptual framework based on **Kaya identity:**

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}} \right)$$

Improving efficiency

Example: Passenger cars *Service = vehicle-kilometers* 	Improve vehicle efficiency (e.g., fuel economy) Drive more efficiently Switch to other transport modes (e.g., bikes)
General energy-related sectors	Efficient end-use technologies Efficient generation technologies

Mitigation: Energy-related emissions

Conceptual framework based on **Kaya identity:**

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}} \right)$$

Switching to clean energy

Example: Passenger cars *Service = vehicle-kilometers* 	Switch to battery electric vehicles Switch to alternative fuels (e.g., electrofuels, solar fuels, hydrogen)
General energy-related sectors	Electrify & switch to low-carbon power Replace fossil fuels with clean alternative fuels

Mitigation: Energy-related emissions

Conceptual framework based on **Kaya identity:**

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}}\right)$$

Reducing consumption

Improving efficiency

Switching to clean energy

Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

Sectors

Energy supply Transportation Buildings Industry	**Energy-related emissions**
Agriculture Forestry Other land use	**Land use (AFOLU) emissions**
CO_2 removal	

Mitigation: Land use emissions

GHG emissions result from (e.g.)

- Land use changes (forests, peatlands, etc.)
- Fertilizer use
- Livestock

Complex to assess effects of interventions

- Natural systems are in complex carbon cycle
- Interactions between climate system, natural factors, socioeconomic factors

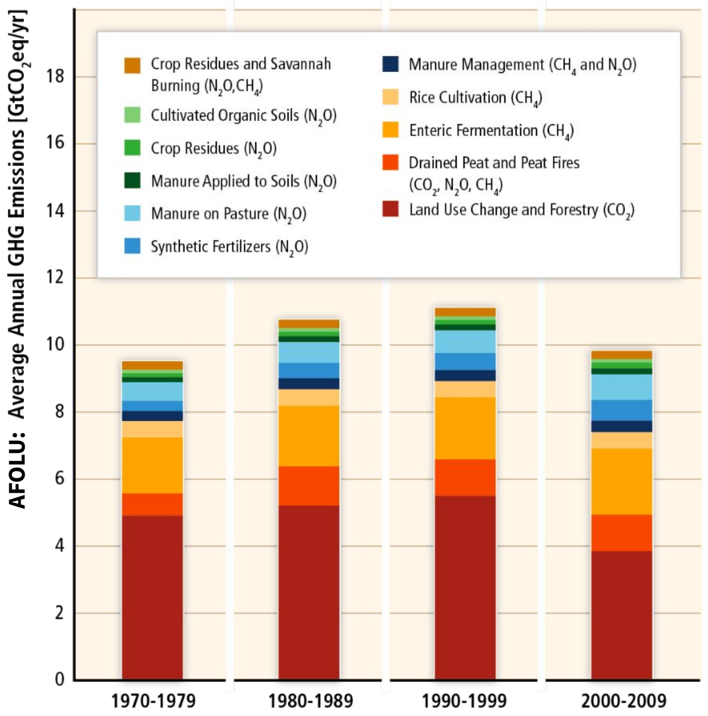

Figure source: IPCC AR5 WG3 Report (2014)

Example mitigation strategies: Land use

GHG emissions result from (e.g.): Land use changes Fertilizer use Livestock

Natural systems	**Agriculture**	**Demand-side measures**
Prevent deforestation Preserve peatlands and coastal wetlands Protect biodiversity Protect indigenous rights	Reduce fertilizer use Reduce cows and other ruminant animals Improve land management	Reduce losses in food supply chain Dietary change Change wood procurement practices

Monitoring: E.g., via remote sensing

See also: IPCC AR5 WG3 Report (2014) and IPCC AR6 WG3 Report (2022)

Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

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Transportation
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Industry

Energy-related emissions

Agriculture
Forestry
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Land use (AFOLU) emissions

CO_2 removal

"Negative emissions"

Mitigation: Negative emissions strategies

Negative emissions strategies remove CO_2 from the atmosphere

- **Carbon capture and storage** (CCS): Use sorbents to capture CO_2 from exhaust or directly from air
  - Related: Bioenergy with carbon capture and storage (BECCS)
- **Enhancing natural sinks:** Afforestation, reforestation, soil carbon restoration, peatland restoration, etc.
- **Biochar:** Pyrolize plant materials & store underground

Climate change mitigation

Mitigation: Reducing or preventing GHG emissions

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Land use (AFOLU) emissions

CO_2 removal

"Negative emissions"

Total GHG emissions

Economy-wide strategies to limit total GHGs

Targets (mandatory or voluntary)

- International: UNFCCC and COP (Kyoto Protocol, Paris Agreement)
- At national or sub-national levels

Regulation, **standards**, and **investments**

Carbon pricing

- Carbon tax: Tax per unit of CO_2 or CO_2-eq emissions
- Carbon markets: Emissions trading under some agreed-upon CO_2-eq cap (i.e., cap-and-trade or emissions trading system)

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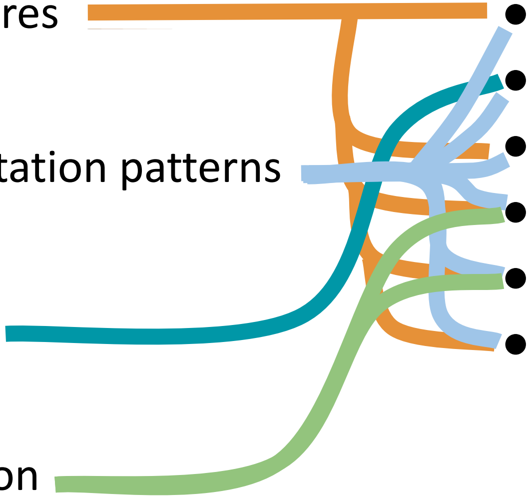
Climate impacts and downstream effects

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

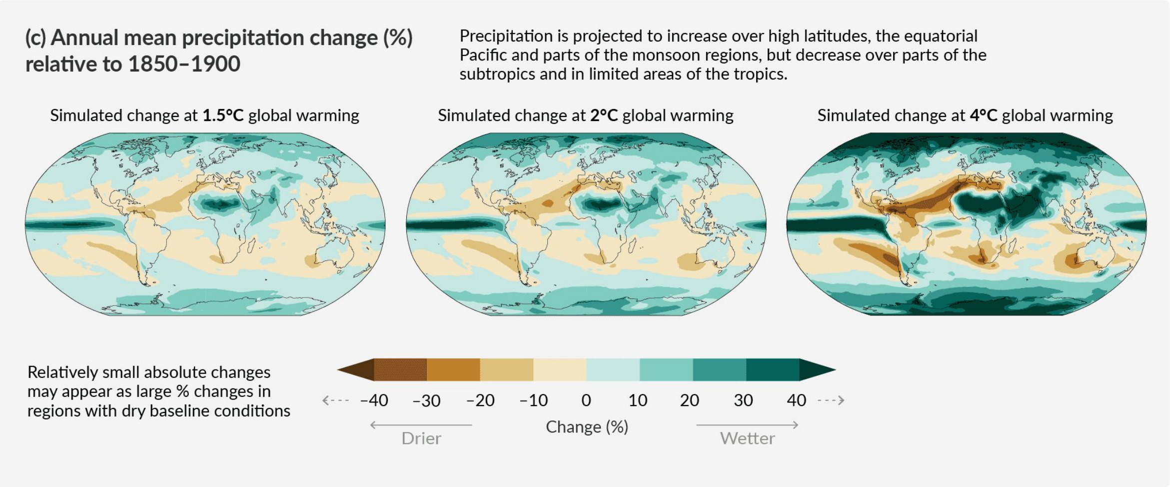


Figure source: IPCC AR6 Summary for Policymakers (2021)

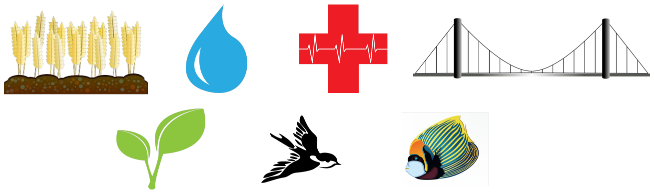
Climate change adaptation

Adaptation: Responding to the effects of a changing climate

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

2. Strengthening adaptive capacity
   - **Robustness:** 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

Solar geoengineering

"Cool the planet" by increasing the Earth's albedo (reflectivity)

- E.g., Release stratospheric aerosols to increase reflectance for a few years

Viewed as last resort: Uncertainty, moral hazard, termination shock, governance

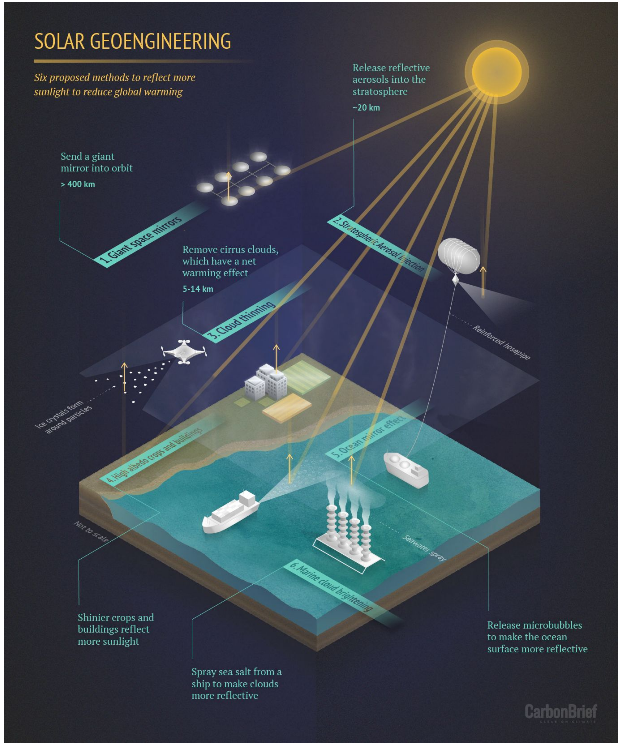


Figure source: CarbonBrief.org

Takeaways: Introduction to climate change

Rapid action is needed on climate change

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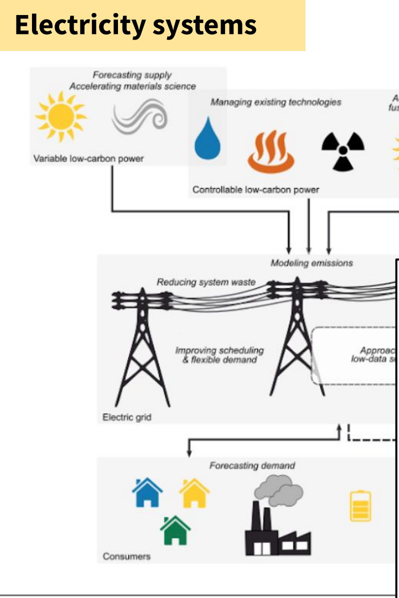
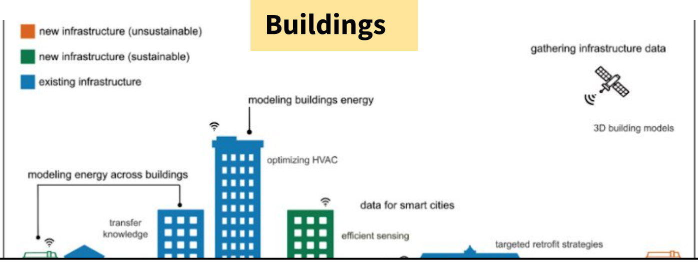
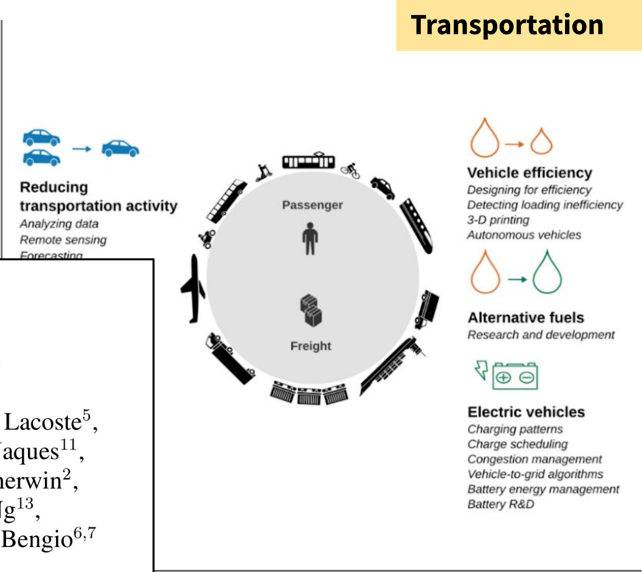
Roles for ML in climate action

Considerations in evaluating applications







Tackling Climate Change with Machine Learning

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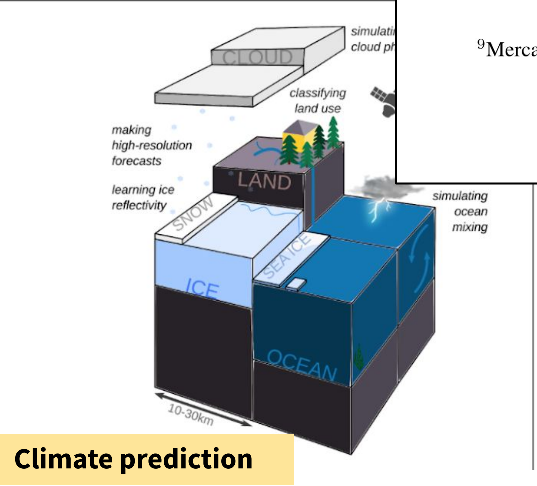
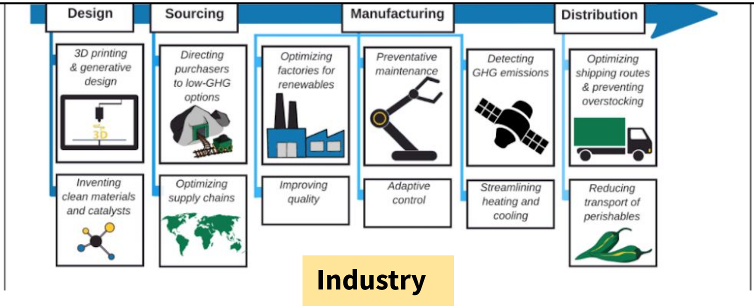
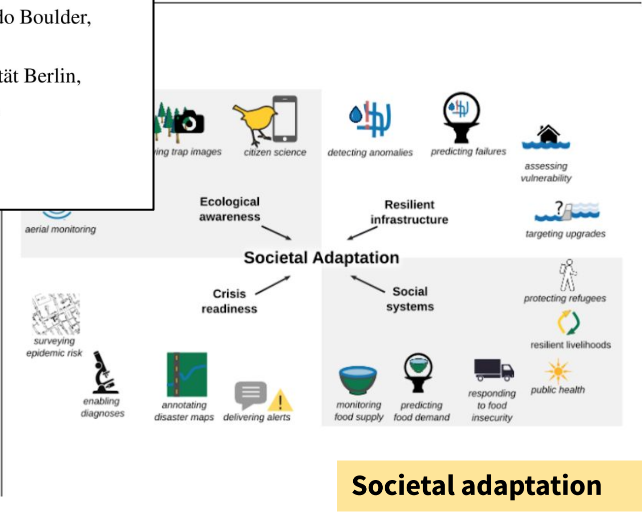
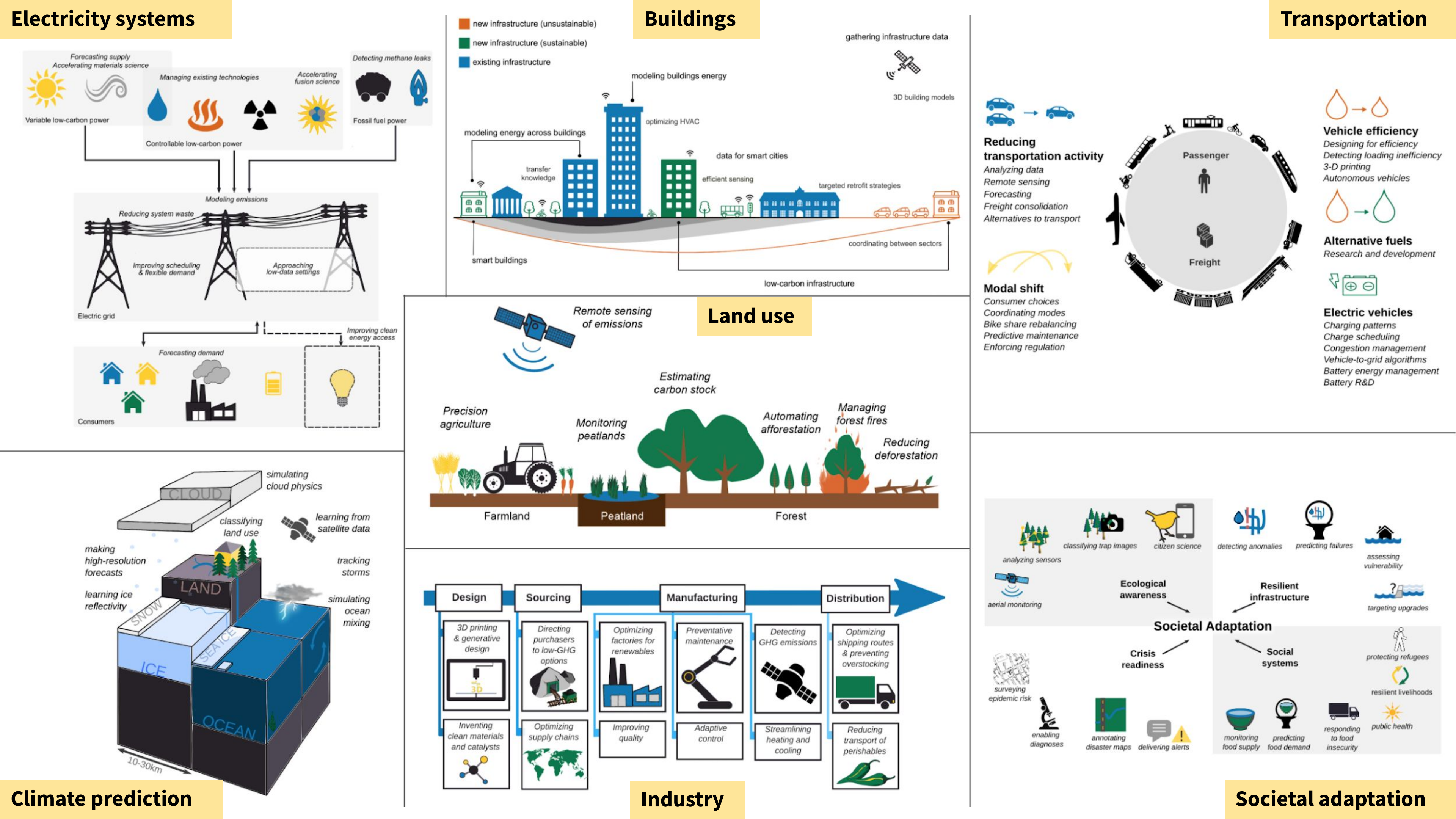
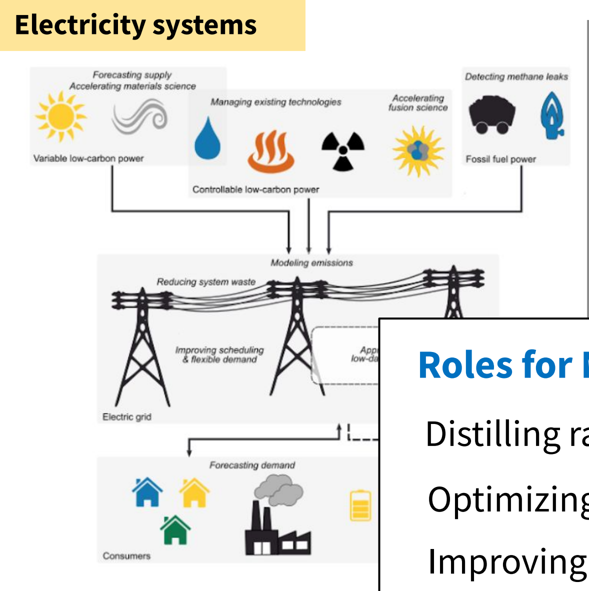


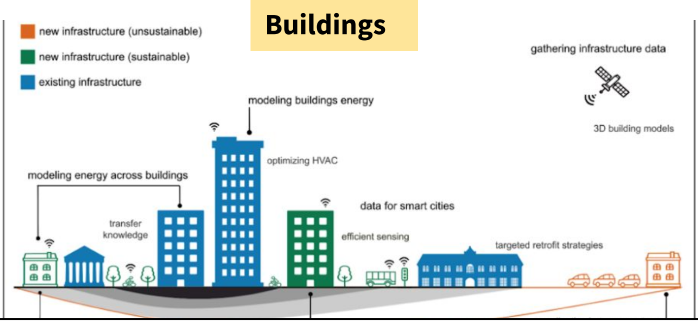


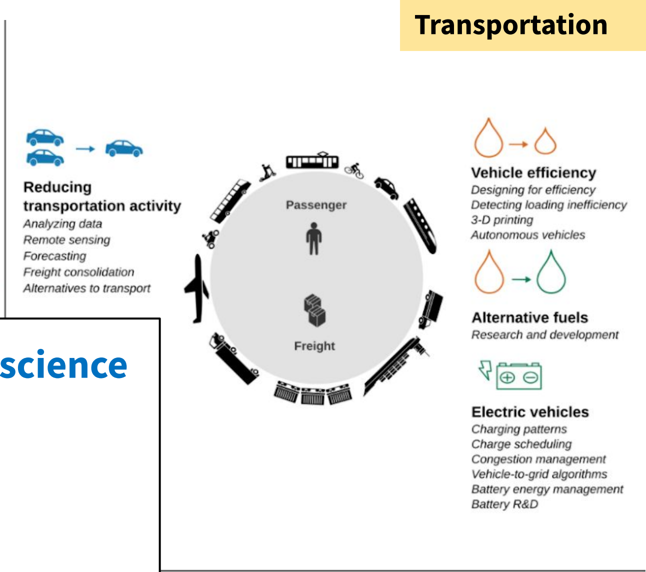




Electricity systems
Forecasting supply
Accelerating materials science
Managing existing technologies
Accelerating fusion science
Detecting methane leaks
Variable low-carbon power
Controllable low-carbon power
Fossil fuel power
Modeling emissions
Reducing system waste
Improving scheduling & flexible demand
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
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
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







Roles for ML in mitigation, adaptation, & climate science

Distilling raw data into actionable information

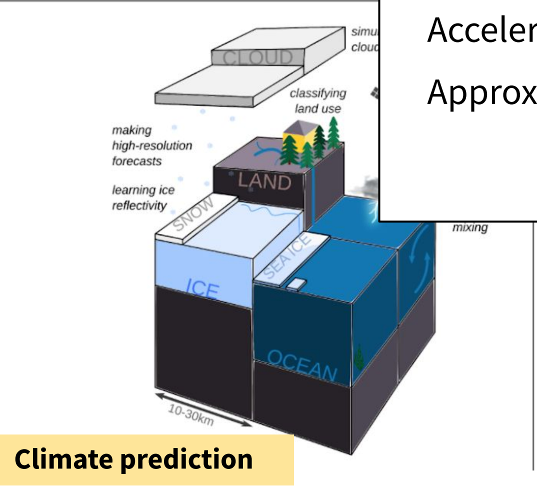
Optimizing complex systems

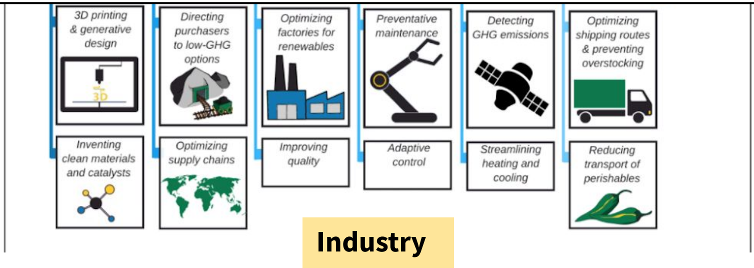
Improving predictions

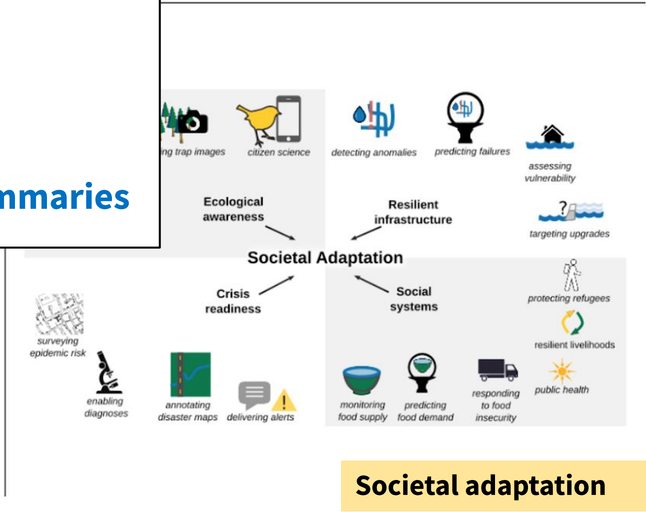
Accelerating scientific discovery

Approximating time-intensive simulations

See also: **https://www.climatechange.ai/summaries**



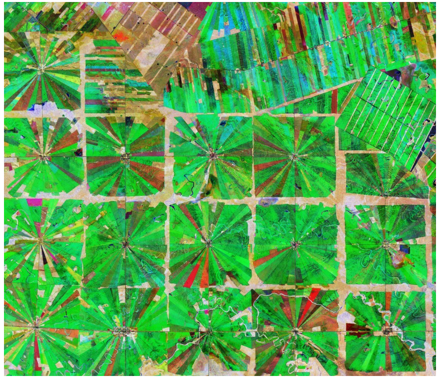




1. Distilling raw data

Role: Distilling raw data into actionable information

Some relevant ML areas: Computer vision, natural language processing



Examples

- Mapping deforestation and carbon stock [M]
- Gathering data on building footprints/heights [M]
- Evaluating coastal flood risk [A]
- Parsing corporate disclosures for climate-relevant info [A]

2. Optimizing complex systems

Role: Improving efficient operation of complex, automated systems

Some relevant ML areas: Optimization, control, reinforcement learning

Examples

- Controlling heating/cooling systems efficiently [M]
- Optimizing rail and multimodal transport [M]
- Demand response in electrical grids [M]

Note: Beware of misaligned objectives and rebound effects

3. Improving predictions

Role: Forecasts and time series predictions

Some relevant ML areas: Time series analysis, computer vision, Bayesian methods

Examples

- "Nowcasting" for solar/wind power [M]
- Forecasting electricity demand [M]
- Predicting crop yield from remote sensing data [A]

4. Accelerating scientific discovery

Role: Suggesting experiments in order to speed up the design process

Some relevant ML areas: Generative models, active learning, reinforcement learning, graph neural networks

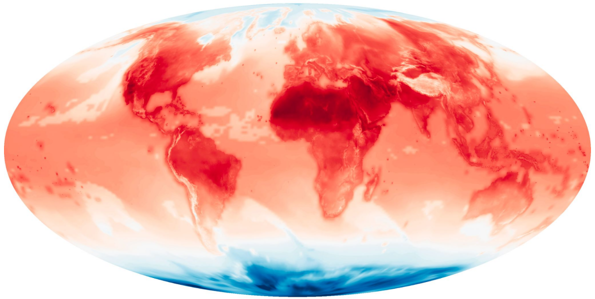
Examples

- Identifying candidate materials for batteries, photovoltaics, and energy-related catalysts [M]
- Algorithms for controlling fusion reactors [M]

5. Approximating simulations

Role: Accelerating time-intensive, often physics-based, simulations

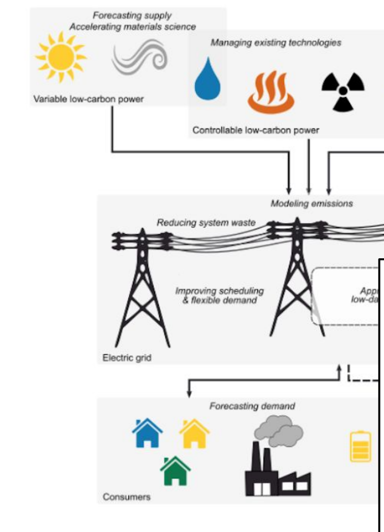
Some relevant ML areas:
Physics-informed ML, computer vision, interpretable ML, causal ML



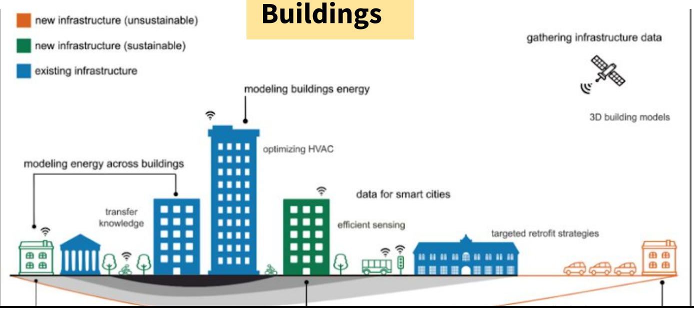
Examples

- Superresolution of predictions from climate models [A]
- Simulating portions of car aerodynamics [M]
- Speeding up planning models for electrical grids [M]

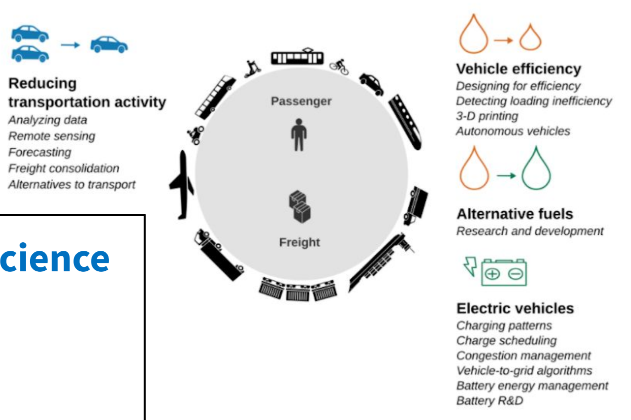
Electricity systems



Buildings



Transportation



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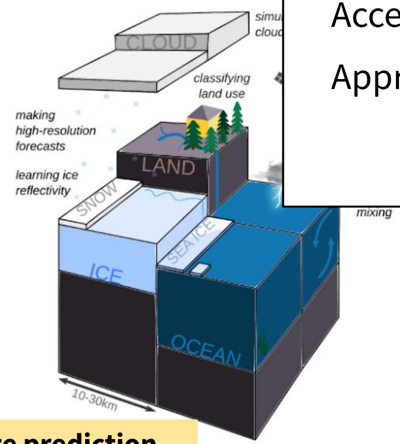
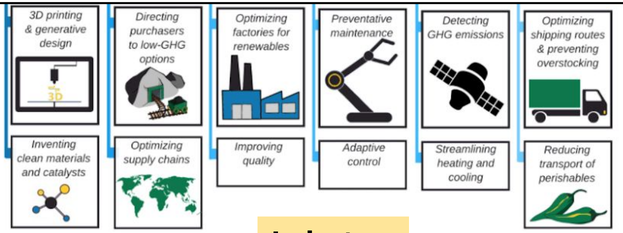
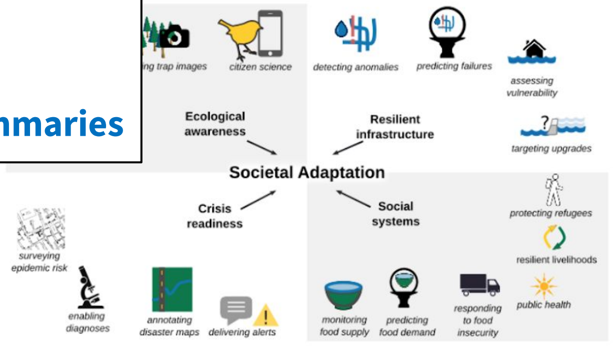


Climate prediction



Industry



Societal adaptation

Questions that we asked in identifying priorities

- **Is ML needed** to address the problem?
- What is the **scope** of the impact? (in rough terms)
- What is the **time horizon** of the impact?
- What is the **likelihood** that a solution can be found?
- Can a solution feasibly be **deployed**?
- What are the potential **side effects** of deploying the candidate solution?
- Who are the **relevant stakeholders** who are involved in or affected by the application?

Key considerations

ML is not a silver bullet and is only relevant sometimes

High-impact applications are not always flashy

Sophisticated algorithms can be required, but aren't always

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

Tutorial outline

Introduction to climate change

Opportunities for ML in climate action

Research challenges

- Physics-informed and robust ML
- Interpretable ML and uncertainty quantification
- Generalization and causality

Is ML a help or hindrance for climate action?

Considerations for research and deployment

Takeaways and how to get involved

Example areas for ML innovation in climate work

How problem demands inform novel methods

Tutorial outline

Introduction to climate change

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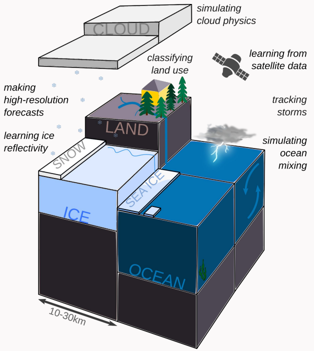
Physics & engineering are central to climate action

Climate prediction

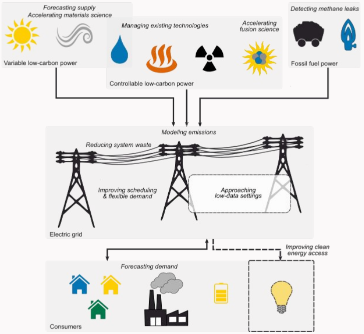
Earth, atmospheric, oceanic modeling



Electricity systems

Wind farm optimization

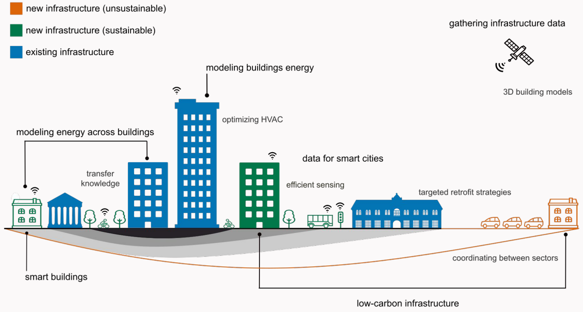
Power system optimization & control



Buildings & cities

Urban environmental simulations

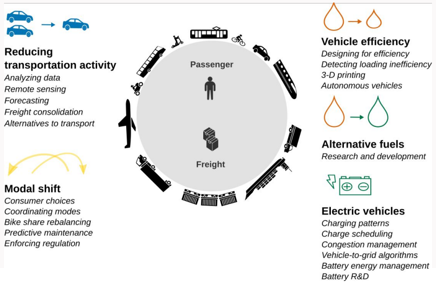
Building heating & cooling control



Transportation

Aerodynamic efficiency modeling

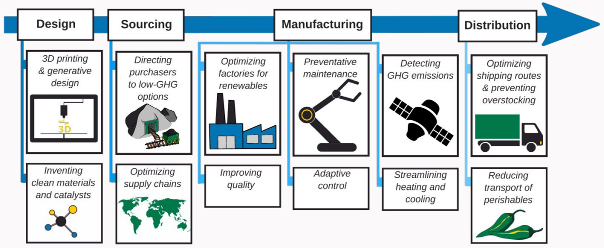
Battery and alternative fuel R&D



Industry

Equipment control & demand response

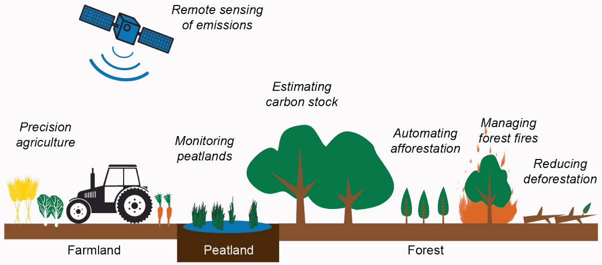
Design of low-materials structures



Land use (agriculture)

Precision agriculture

Cleaner ammonia production



Types of {physics, engineering} + ML approaches

Physics-informed approaches:
Improve performance and/or data efficiency by employing physical knowledge or priors

Robust and safety-critical approaches:
Ensure adherence to system requirements (e.g., engineering constraints)

Types of {physics, engineering} + ML approaches

Physics-informed approaches:
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Why physics-informed ML?

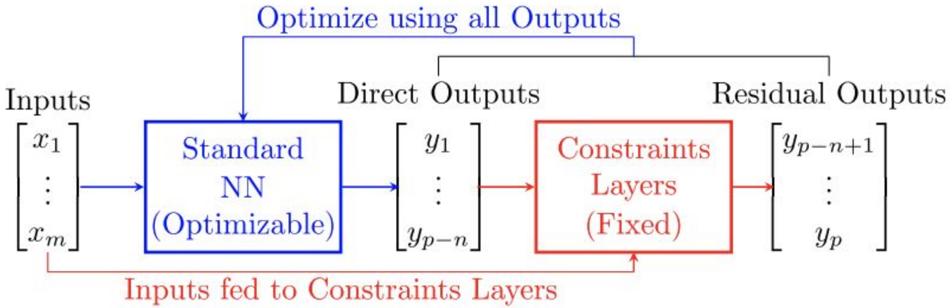
	Physics-based approaches	"Pure" ML approaches	Hybrid approaches
Efficiently leverage physical knowledge	✅	❌	✅?
Transparent & robust behavior	✅	❌	✅?
Adaptive, data-driven	❌	✅	✅?
Fast to run	❌	✅	✅?

Caveat: This is an oversimplification!

Example: Emulating subgrid-scale processes

Difficult to cheaply represent subgrid-scale processes in coarse-scale atmospheric models (“subgrid parameterization”), while respecting conservation laws

Approach: Design NN-based emulator, with architecture constrained to satisfy conservation laws



See related challenge: Climate Bench (emulating Earth System Models)

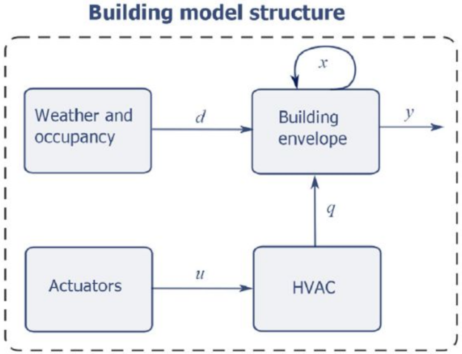
Beucler, T., et al. (2021). Enforcing analytic constraints in neural networks emulating physical systems. *Physical Review Letters*, *126*(9), 098302.
See also: Kashinath, K., et al (2021). Physics-informed machine learning: case studies for weather and climate modelling. *Philosophical Transactions of the Royal Society A*, *379*(2194), 20200093.

Example: Modeling building dynamics

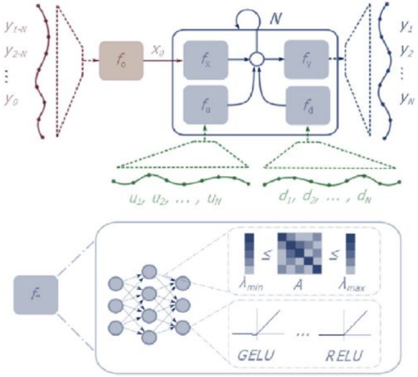
Modeling dynamics of buildings can be difficult & expensive, but is needed for implementing simulators and/or control strategies

Approach: Learn differentiable surrogate using physics-informed ML model

- Can employ within end-to-end "differentiable predictive control" workflow



(a) Structure of physics-based building thermal model.



(b) Structured recurrent neural dynamics model.

See related platforms: COBS (building control) and City Learn (city-scale control)

Drgoňa, J., Tuor, A. R., Chandan, V., & Vrabie, D. L. (2021). Physics-constrained deep learning of multi-zone building thermal dynamics. *Energy and Buildings*, *243*, 110992.
Drgoňa, J., Tuor, A., Skomski, E., Vasisht, S., & Vrabie, D. (2021). Deep learning explicit differentiable predictive control laws for buildings. *IFAC-PapersOnLine*, *54*(6), 14-19.

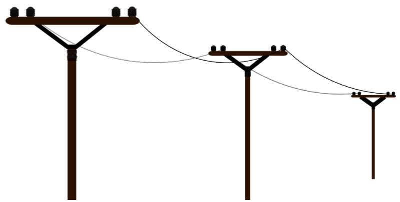
Directions: Physics-informed ML and climate change

Incorporating **more complex constraints** into architectures and losses

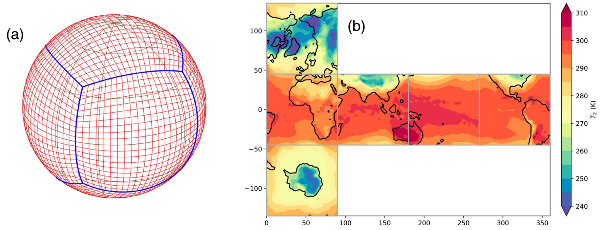
Improving **stability & convergence** of physics-informed model training

Improving **data representations** to capture physical considerations

Improving **out-of-distribution generalization**
(See also tutorial section: “Research challenges: Generalization and causality)



E.g., Power grids: DC power flow (linear) → AC power flow (nonlinear)



E.g., Cubed-sphere grid data representation

Cubed-sphere grid figure source: Weyn, J. A., Durran, D. R., & Caruana, R. (2020). Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. *Journal of Advances in Modeling Earth Systems*, *12*(9), e2020MS002109.

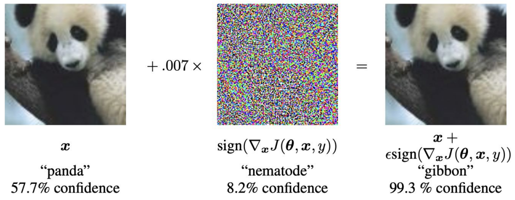
Types of {physics, engineering} + ML approaches

Physics-informed approaches:
Improve performance and/or data efficiency by employing physical knowledge or priors

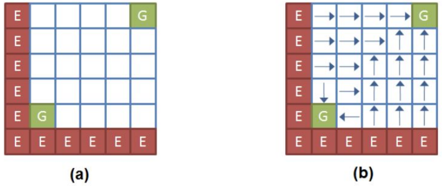
Robust and safety-critical approaches:
Ensure adherence to system requirements (e.g., engineering constraints)

Example notions of “robustness” in ML and climate

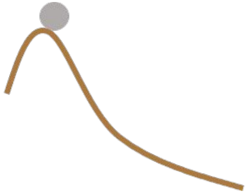
Adversarial robustness [ML]: Robustness to perturbations of inputs



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)



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.

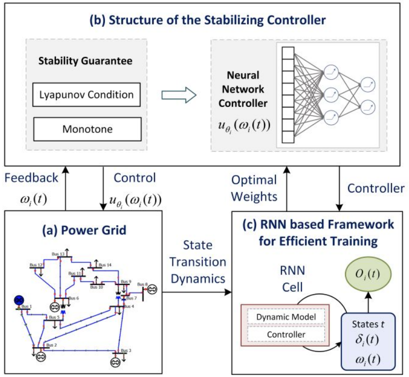
Example: RL for robust power grid control

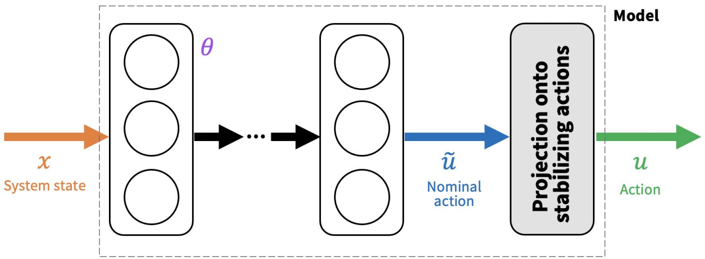
Want to control power system devices in a robust manner

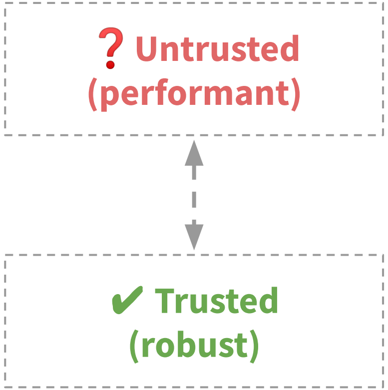
- Notion of robustness: Lyapunov stability [robust control]

Ideas

- Enforce Lyapunov stability guarantees in NN architecture
- Mix between robust and untrusted controllers







Cui, W., Jiang, Y., & Zhang, B. (2022). Reinforcement learning for optimal primary frequency control: A Lyapunov approach. *IEEE Transactions on Power Systems*.
Donti, P. L., Roderick, M., Fazlyab, M., & Kolter, J. Z. (2021). Enforcing robust control guarantees within neural network policies. *ICLR.*
Rutten, D., Christianson, N., Mukherjee, D., & Wierman, A. (2022). Online Optimization with Untrusted Predictions. *arXiv preprint arXiv:2202.03519*.

Example: Adversarially robust power grid optimization

Intractable to dispatch power generators to be robust to *k* failures (N-k SCOPF)

- Notion of robustness: Feasibility against contingency constraints [optimization]

Approach: Re-cast as an adversarially robust optimization problem [ML-style]

- "Solve" using adversarial training techniques (plus implicit layers)

minimize maximize ℓ (🔌 , 💥)
🔌 💥

See related challenge: [ARPA-E GO Competition] (secure power system optimization)

Donti, P. L., Agarwal, A., Bedmutha, N. V., Pileggi, L., & Kolter, J. Z. (2021). Adversarially robust learning for security-constrained optimal power flow. *NeurIPS*.

Takeaways: Physics-informed and robust ML

Many fruitful directions for merging physics & engineering knowledge with ML approaches, with benefits across many climate-relevant areas

Physics-informed approaches: Accommodate new and more complex physics within data, deep learning architectures, and loss functions

Robust and safety-critical approaches: Implement, exchange, and/or combine notions of robustness from ML and climate-relevant domains

Deep domain understanding can yield new methodological directions

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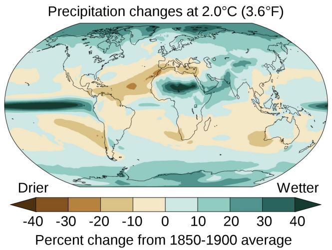
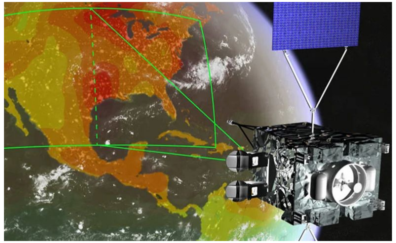
Interpretability and uncertainty in climate change

Climate change mitigation and adaptation require **trust** and **robust decision-making**



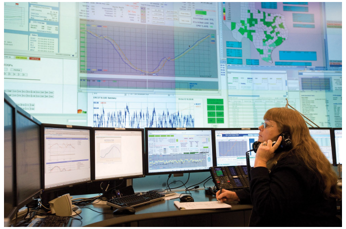
Scientific understanding and predictions of climate change



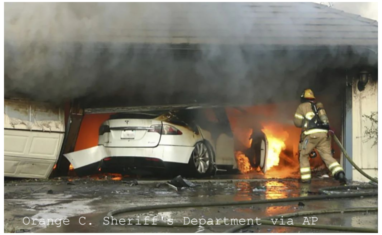
Monitoring, reporting, and verification of emissions and climate change effects

Early warning and emergency response

Policy-making on international, national, and local levels



Planning and operation of critical infrastructure



Innovation and technology assessment

Interpretability and uncertainty in climate change

Interpretability aims:

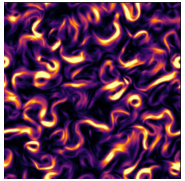
Oversight	Regulatory oversight and recourse Real-time settings: Intervening & overriding model outputs Domain-informed model debugging
Credibility	Allowing stakeholders to decide whether to trust
Scientific discovery	Working with and expanding domain knowledge

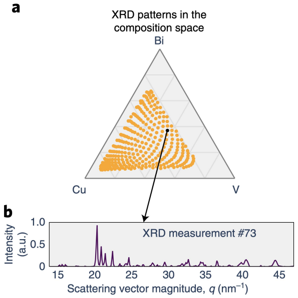
Uncertainty quantification aims:

Assessing risks	Input to making robust decisions
Communication	Avoiding overconfidence and increasing credibility

Examples

Ocean sub-grid scale modeling with equation-discovery

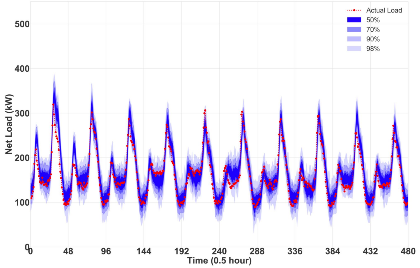




Crystal-structure phase mapping with deep reasoning networks

Bird species classification with a prototypical part network

Net load forecasting with Bayesian deep learning

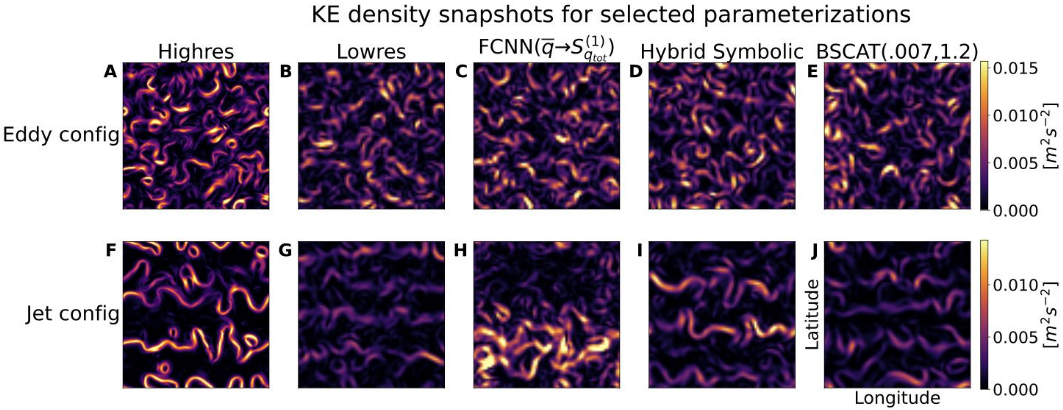


Example 1: Ocean sub-grid scale modeling with equation-discovery

Human-in-the-loop guidance and scientific interpretation may help improve ML-based emulators for subgrid-scale processes within coarse-grained climate models

Approach: (Interpretable) **hybrid symbolic equation-discovery** approach

- Compared to (physics constrained) neural networks, generalizes better to unseen flow regimes



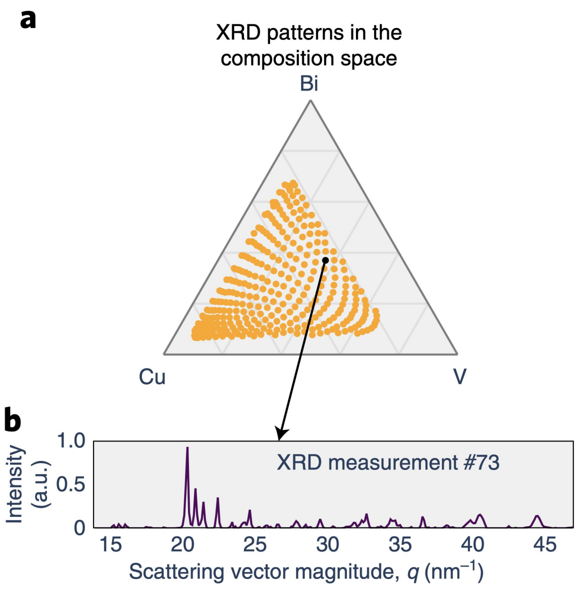
Ross, Li, Perezhogin, Fernandez-Granda & Zanna (in review) Benchmarking of machine learning ocean subgrid parameterizations in an idealized model

Example 2: Crystal-structure phase mapping with deep reasoning networks

Discovery of solar fuel materials requires separating noisy mixtures of X-ray diffraction patterns into source signals of the corresponding crystal structures (unsupervised pattern demixing problem)

Approach: (Interpretable) **deep reasoning network**

- Exploiting scientific prior knowledge about rules that govern the mixtures of crystals
- **Interpretable latent space** constructed with scientific variables that are learned in an unsupervised setting



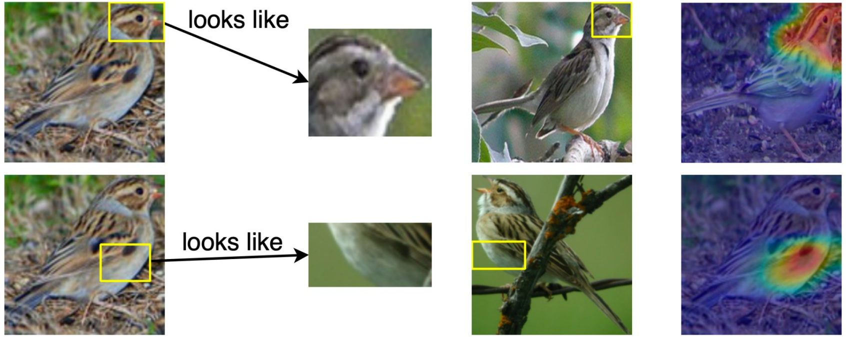
Chen, D., Bai, Y., Ament, S., Zhao, W., Guevarra, D., Zhou, L., ... & Gomes, C. P. (2021). Automating crystal-structure phase mapping by combining deep learning with constraint reasoning. Nature Machine Intelligence, 3(9), 812-822.

Example 3: Bird species identification with a prototypical part network

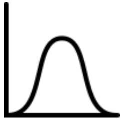
Computer vision can help with ecosystem monitoring as the habitats of species change with a changing climate

Approach: Interpretable **prototypical part network** for bird species identification reasons in a similar way to ornithologists

- Explanations generated are used during classification and are not created posthoc



Chen, C., Li, O., Tao, D., Barnett, A., Rudin, C., & Su, J. K. (2019). This looks like that: deep learning for interpretable image recognition. Advances in neural information processing systems, 32.

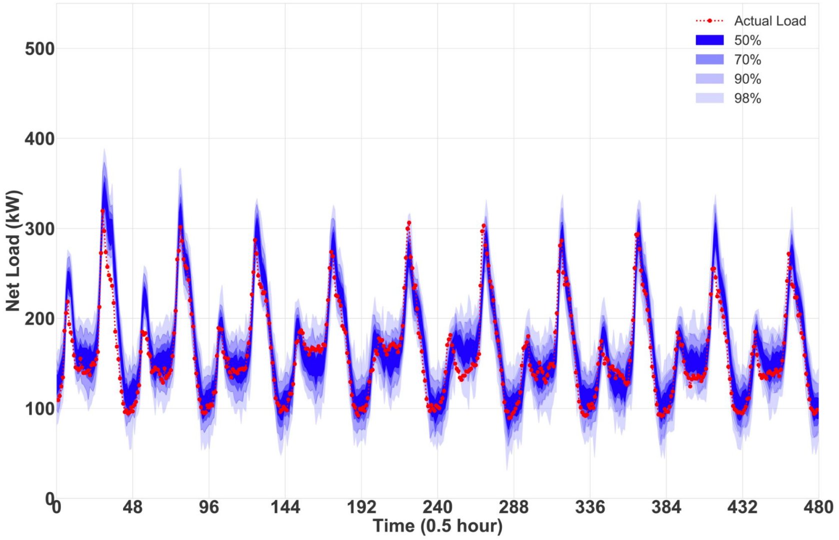


Example 4: Net load forecasting with Bayesian deep learning

Residential net electricity load is uncertain due to climate variability, variable power generation and aperiodic human activities

Approach: **Bayesian theory combined with deep LSTM networks** for probabilistic day-ahead net load forecasts

- Using smart meter data and (partially available) PV output data



Sun, M., Zhang, T., Wang, Y., Strbac, G., & Kang, C. (2019). Using Bayesian deep learning to capture uncertainty for residential net load forecasting. IEEE Transactions on Power Systems, 35(1), 188-201.

Takeaways: Interpretable ML & uncertainty quantification

- Decision-making and discovery crucial for many areas of climate change: need for interpretability and uncertainty quantification
- **Domain-specific goals** should drive the specific notion of interpretability used
- Lack of documented use cases from practice where interpretability and uncertainty quantification in ML is used for improving decision-making
- Research challenge: **user-focused method development**

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nat. Machine Intelligence, 1(5), 206-215
Amarasinghe, K., Rodolfa, K., Lamba, H., & Ghani, R. (2020). Explainable machine learning for public policy: Use cases, gaps, and research directions. arXiv:2010.14374.

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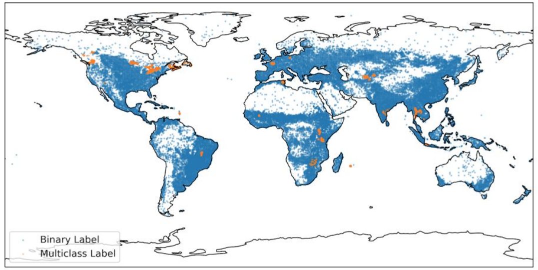
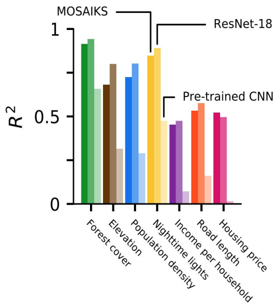
Takeaways and how to get involved

Several notions of generalization

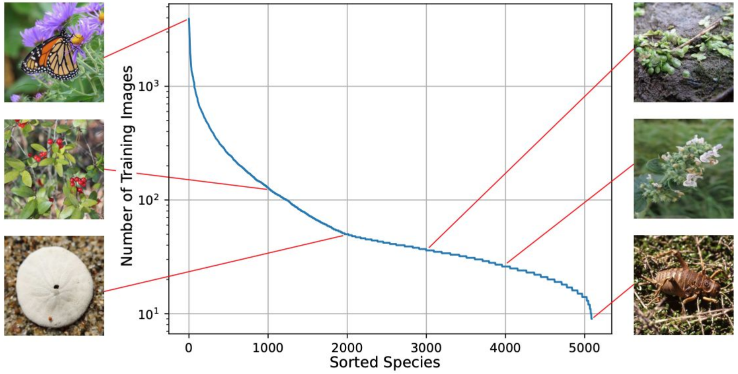
- Generalization across tasks





- Generalization under concept drift

- Generalization from limited data



Generalization across tasks

Contexts include:

- Performing a similar task across geographies or communities, e.g. classifying land cover or predicting power demand

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- Data embeddings designed for fast transfer to new tasks
- Meta-learning algorithms

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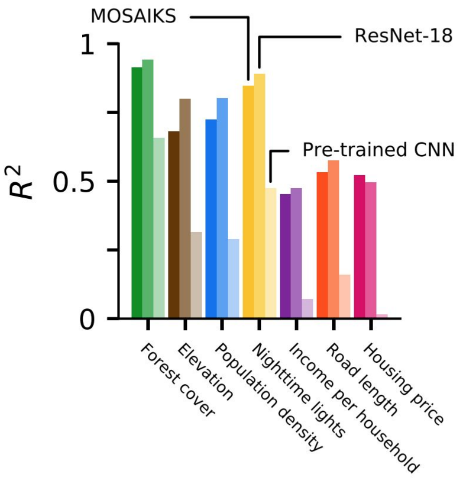
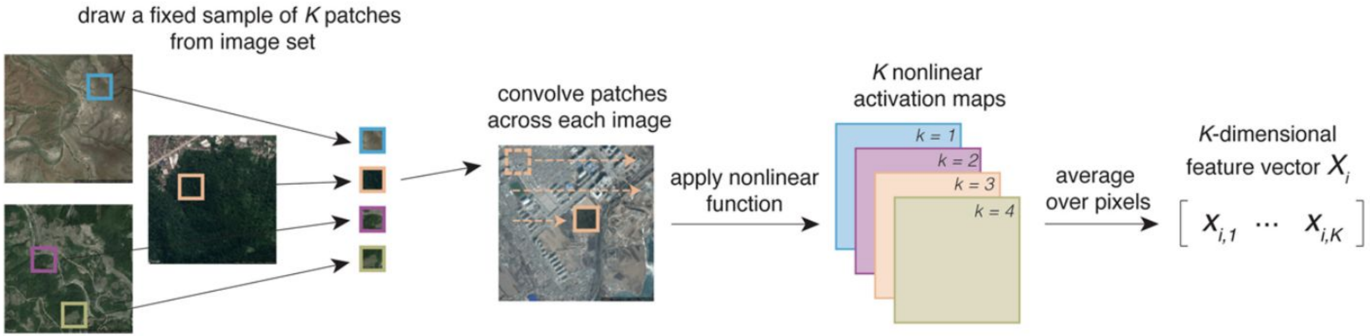
Example: Task-agnostic features for satellite images

Unsupervised featurization of satellite images

MOSAIKS: Convolutional "random kitchen sink," then apply nonlinear function & average over pixels

Ridge regression on features almost matches task-specific ResNets on wide array of tasks





E. Rolf et al., "A generalizable and accessible approach to machine learning with global satellite imagery," Nature Communications 2021.

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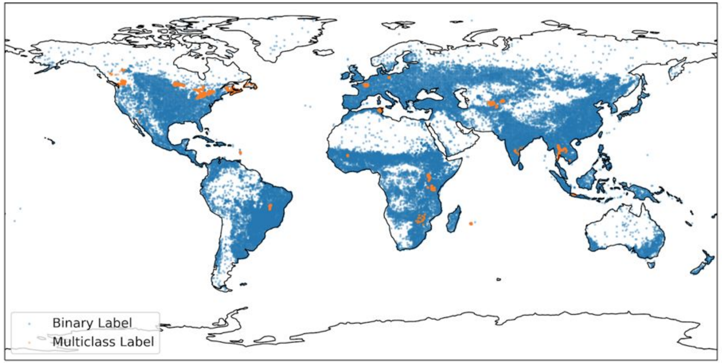
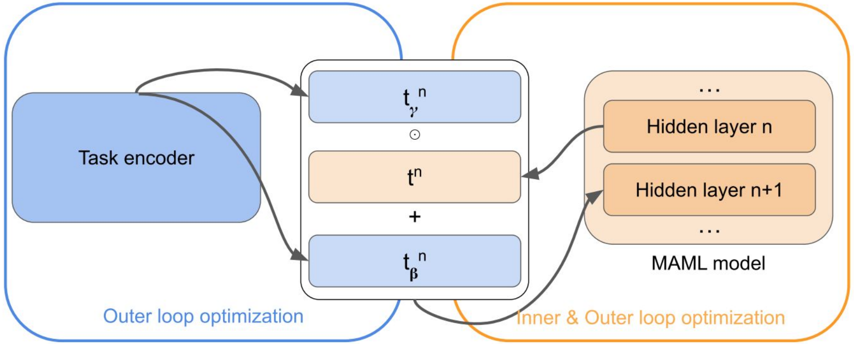
Example: Task-informed meta-learning

Remote sensing to map crops & forecast yield can help avoid food insecurity under climate change, but data are imbalanced by location/crop



TIML builds in location/task metadata to meta-learning via a task encoder

Added to MAML/other meta-learning methods to improve performance on classification & regression tasks



G. Tseng, H. Kerner, D. Rolnick, "TIML: Task-Informed Meta-Learning for agriculture," arXiv 2202.02124, 2022.

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

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Contexts include:

- Performing a similar task across geographies or communities, e.g. classifying land cover or predicting power demand

Strategies include:

- Data embeddings designed for fast transfer to new tasks
- Meta-learning algorithms
- Treating tasks separately and ensuring enough data for each

See Birhane et al. "The Values Encoded in Machine Learning Research," FAccT 2022.

Generalization under concept drift

Contexts include:

- Climate & weather data
- Things affected by climate change, e.g. mapping crops, assessing species distributions, predicting energy supply

Strategies include:

- Physics-informed models that generalize better to new regimes (see also tutorial section: "Research challenges: Physics-informed and robust ML")
- Synthetic data from physics-based simulations

Generalization from limited data

Contexts include:

- Long-tailed data distributions, e.g. identifying species from photos
- Rare or extreme events, e.g. predicting wildfires or hurricanes

Strategies include:

- Algorithms designed to learn from imbalanced/few-shot data
- Unsupervised or self-supervised algorithms for anomaly detection

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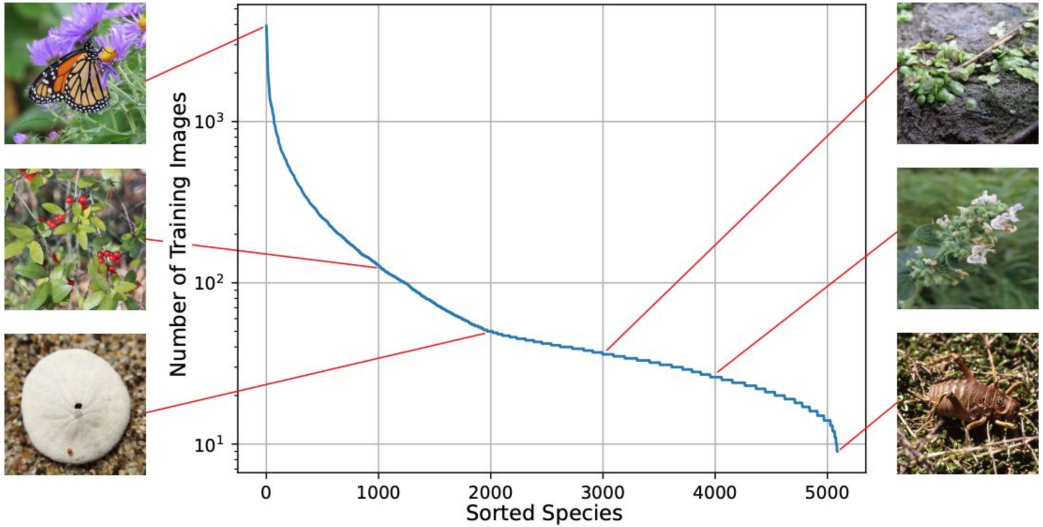
- Unsupervised or self-supervised algorithms for anomaly detection

Example: Data from citizen science observations

iNaturalist dataset: citizen-science observations of animals, plants, etc. used to assess changing biodiversity, labeled by domain experts

Fine-grained classification: 859,000 images, 5,000 classes, many very similar

Long tails in distribution from rare or rarely observed species



Benchmark for highly imbalanced visual classification & localization

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

Generalization from limited data

Contexts include:

- Long-tailed data distributions, e.g. identifying species from photos
- Rare or extreme events, e.g. predicting wildfires or hurricanes

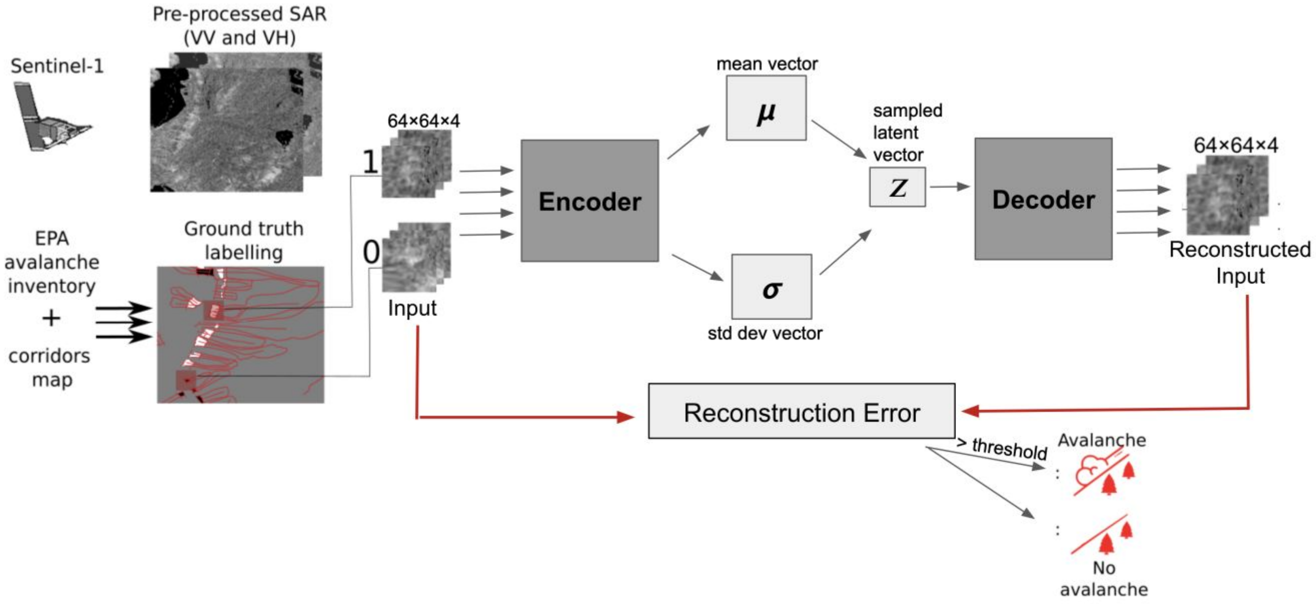
Strategies include:

- Algorithms designed to learn from imbalanced/few-shot data
- Unsupervised or self-supervised algorithms for anomaly detection

Example: Detecting avalanches using VAEs

Avalanches are rare events, so few annotated images of them

Can use VAE reconstruction error to find anomalies, often avalanches



S. Sinha et al, "Detecting avalanche deposits using variational autoencoder on sentinel-1 satellite imagery," Tackling Climate Change with Machine Learning workshop at NeurIPS 2019.

Causality and ML

In complicated physical systems, e.g. climate & weather models

- Identifying causal relations between variables, e.g. teleconnections
- Attributing causes to rare/extreme events
- Assessing the strength of relations in a known causal graph

In settings where policy decisions must be made

- Predicting optimal interventions under known or inferred causal models
- Estimating the causal effect of implemented policies

J. Runge et al., "Inferring causation from time series in Earth system sciences," Nature Communications.

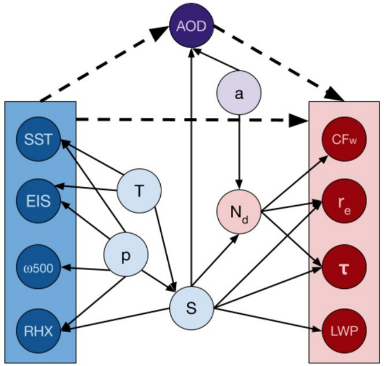
S. Athey. Beyond prediction: "Using big data for policy problems," Science.

Example: Quantifying aerosol-cloud interactions

Clouds affect the climate and are in turn affected by aerosols in the atmosphere

Causal graph structure for aerosol-cloud interactions is known, but is mediated by the local environment in unknown ways

The Quince deep learning-based causal-effect estimator can predict the strengths of these causal relations from data



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.

A. Jesson et al., "Quantifying ignorance in individual-level causal-effect estimates under hidden confounding," ICML 2021.

Takeaways: Generalization and causality

Important climate change applications lead to **interesting methodological challenges** related to generalization and causality

Generalization-related challenges can arise from **geographic variation**, **nonstationarity**, and **imbalanced data** or **rare events**

Causality-related challenges can arise in **understanding complicated physical systems** and in working with **policy interventions**

Tutorial outline

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Opportunities for ML in climate action

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Is ML a help or hindrance for climate action?

Considerations for research and deployment

Takeaways and how to get involved

What is ML's carbon footprint?

What can one do to shape the overall impact?

ML’s carbon footprint

ML applications in climate change mitigation

Emissions from ML computation & hardware

ML’s system-level impacts

ML 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.

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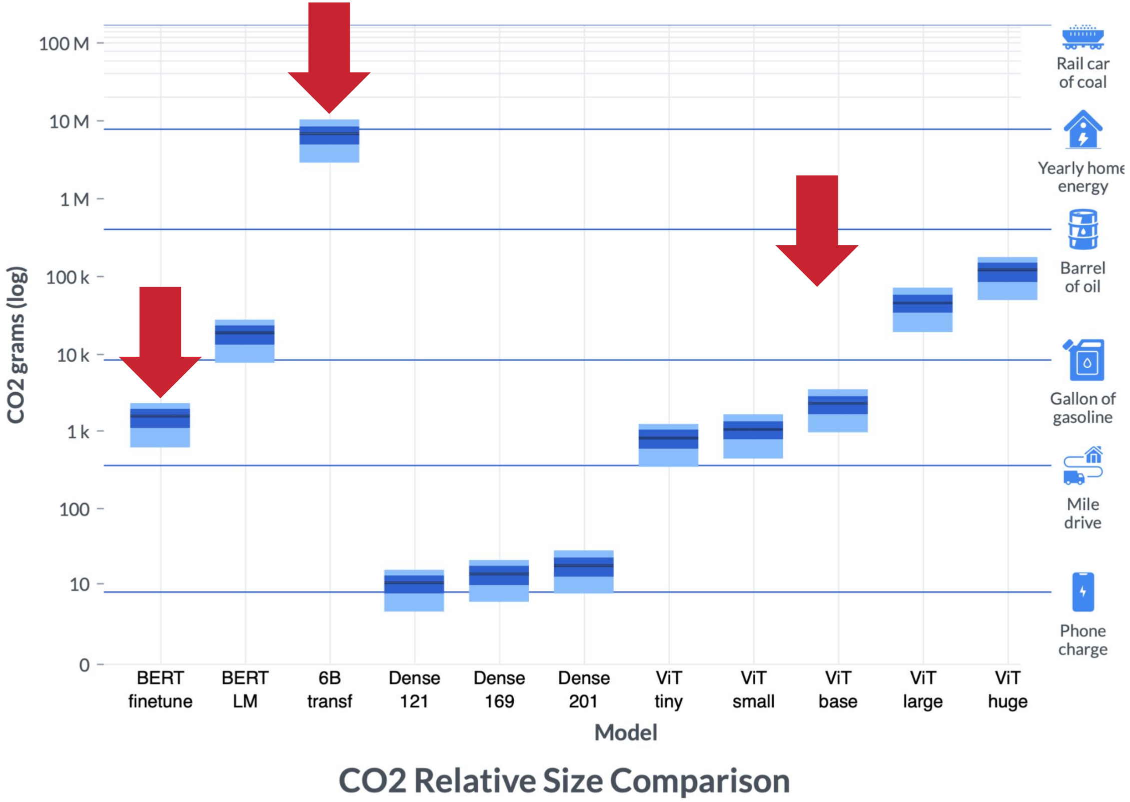
Emissions from ML computation

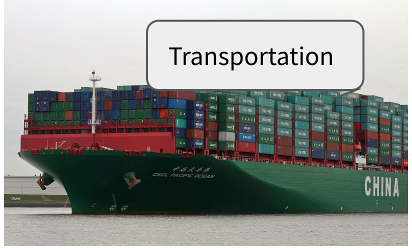


Dodge, J., Prewitt, T., Tachet des Combes, R., Odmark, E., Schwartz, R., Strubell, E., ... & Buchanan, W. (2022, June). Measuring the Carbon Intensity of AI in Cloud Instances. In *2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1877-1894).

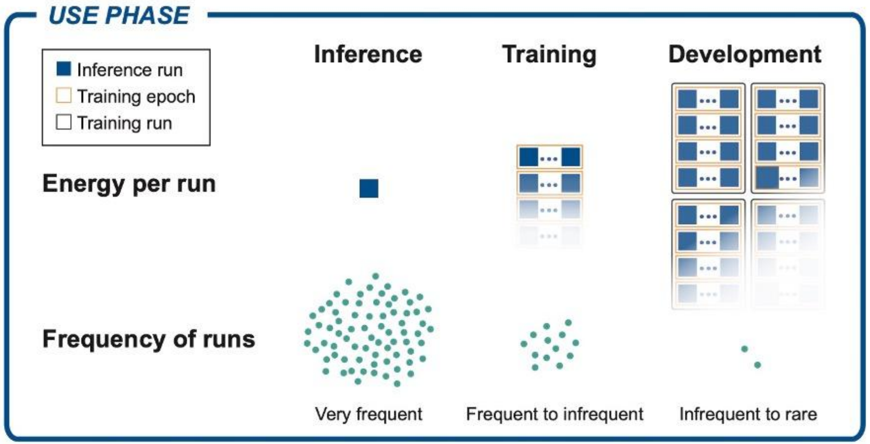
Impacts from ML computation & hardware

Operational emissions from energy consumed during computation

Embodied emissions from production and end-of-life of hardware



Computing-related emissions from ML



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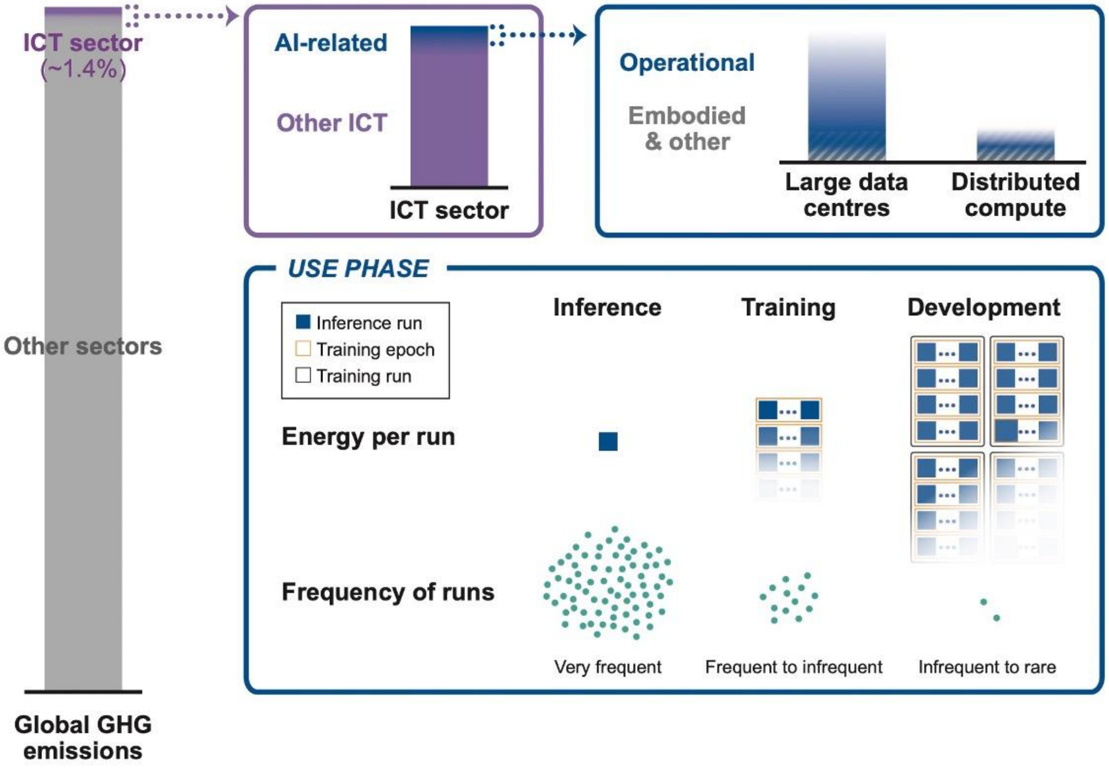
Computing-related emissions from ML



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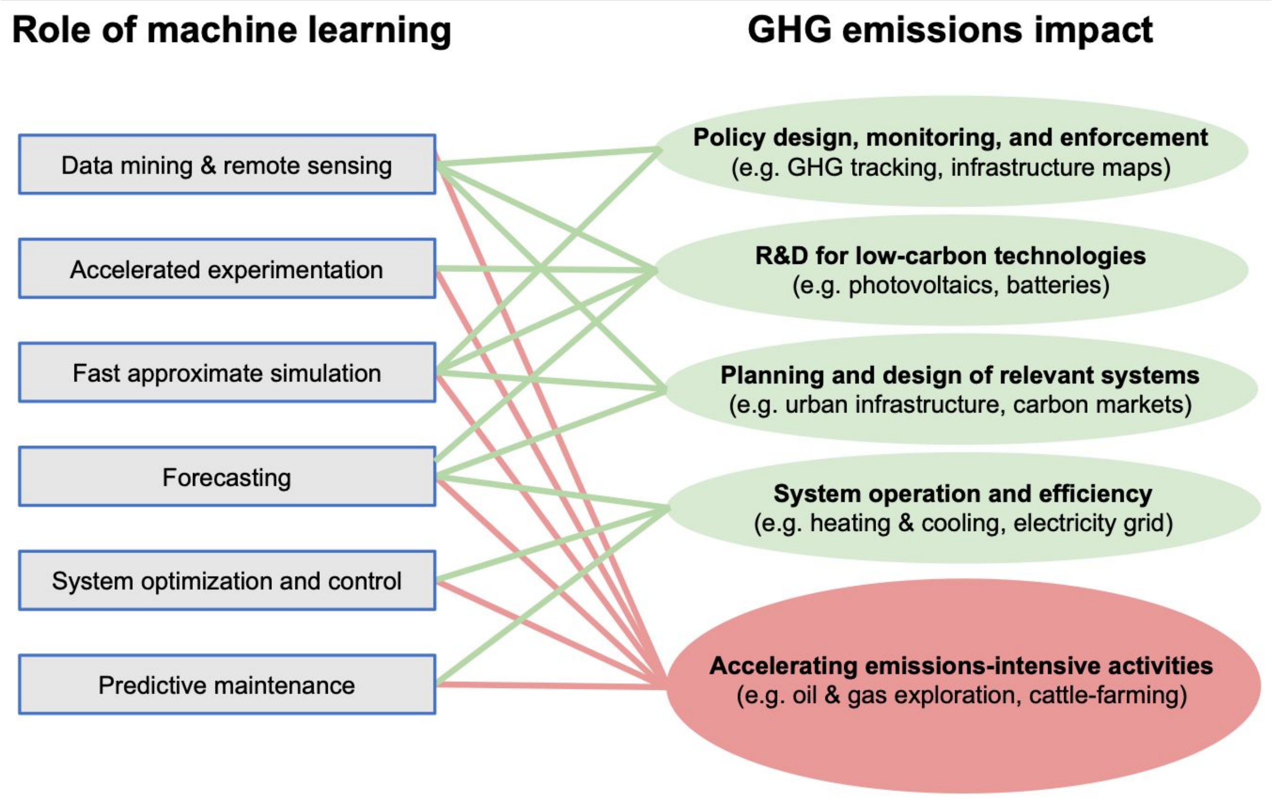
Immediate application impacts

See tutorial section "Opportunities for ML in climate action"



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Broader scope of application impacts

Example: Efficiency improvements in crude oil refining

- Crude oil is turned into lighter hydrocarbons by heat from coker units
- Accurately predicting coke buildup in pipes with ML can help **maintain equipment and reduce energy consumption**
- This application of ML is reducing emissions in the refinery
- The application is also **reducing costs**
- We need to consider how the application affects emissions from the energy and economic system as a whole

ML’s carbon footprint

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System-level impacts of ML

Rebound effects	Reducing energy consumption reduces costs → money saved may be used and cause more emissions *Example: ML for optimizing systems*
Lock-in and path dependency	Technologies compete and dominate → lock-in to suboptimal technologies hampering decarbonization *Example: Autonomous driving and car use*
Consumer behavior	Trends and advertising may change consumption patterns → embodied emissions in those products *Example: ML in advertising and social media*
Communication and education	Societal support for climate action essential *Example: ML on social media*

ML’s carbon footprint

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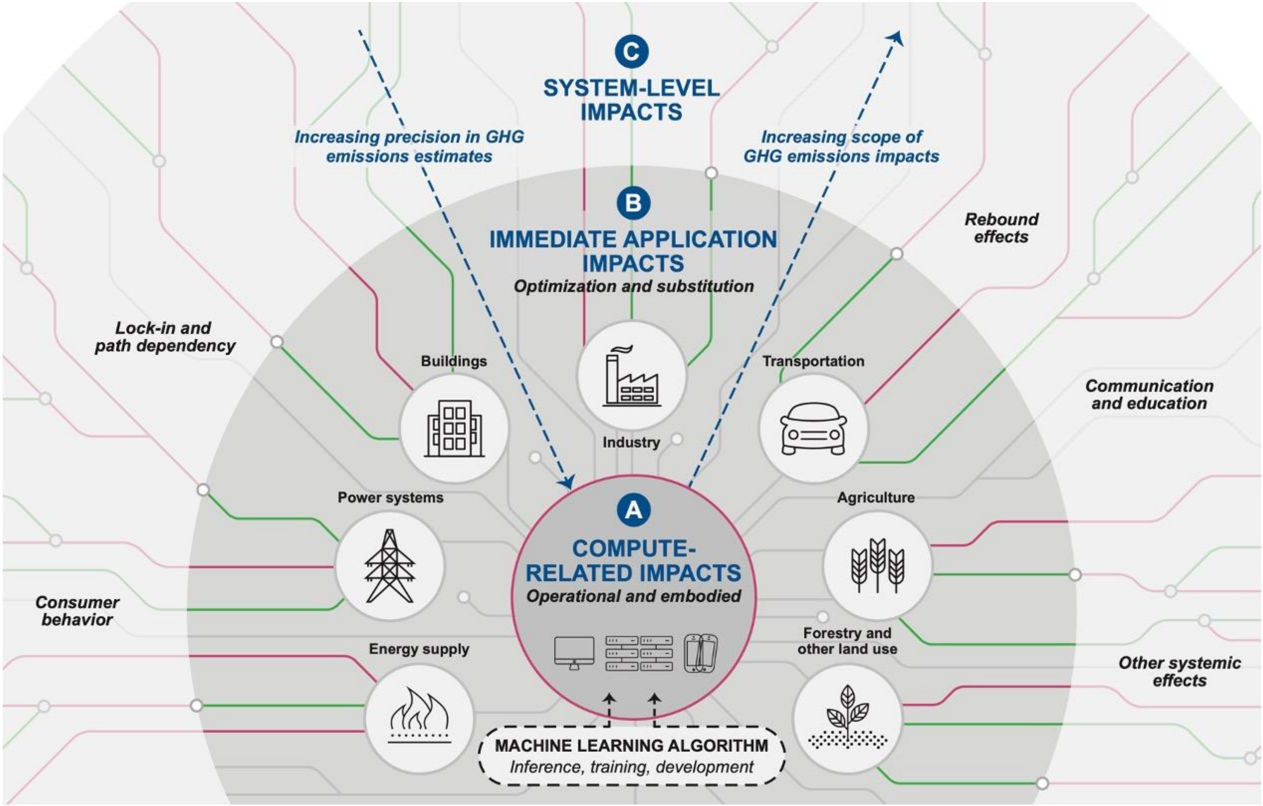
Overall framework



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Takeaways: Climate change impacts of ML

Computing-related:

- **Measure** your footprint with tools such as ML CO2 Impact, Carbontracker, CodeCarbon, or tools specifically for Azure or Hugging Face
- **Reduce** your impacts by choosing more efficient models, and reducing wasteful model retraining and execution

Application-related:

- **Quantify and evaluate** the application impacts where possible
- Be **transparent** about impacts in publications and with stakeholders (quantitatively and qualitatively)
- **Shape** the impacts through your work

Takeaways: Climate change impacts of ML

Consider the system-level impacts of your work:

- All ML applications may potentially have an effect on the climate (e.g. recommender systems)
- Choose **what** you (or the ML community) works on
- Bring climate considerations into **how** you build an application
- Initiate **company-wide policies** such as internal carbon pricing or conditions on the projects or products realized
- Don’t forget about **other social and other environmental** impacts

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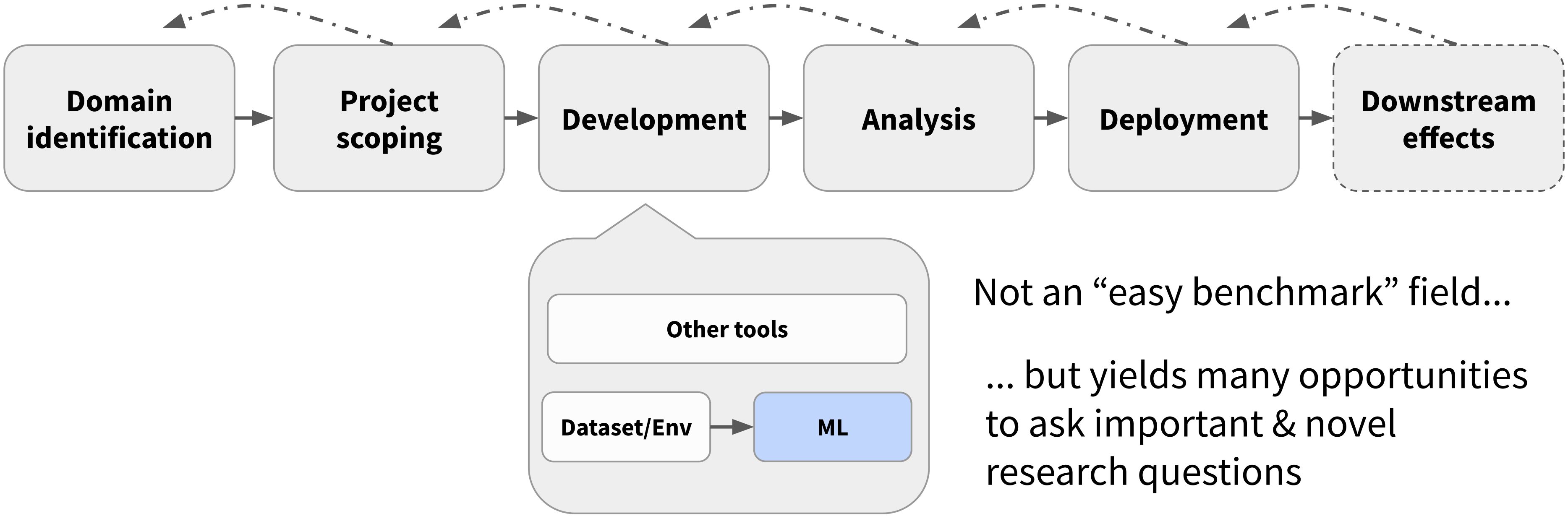
Considerations for research and deployment

Takeaways and how to get involved

Considerations for ML-for-climate

Considerations for ML as a whole

ML-for-climate: Pathway to impact



Not an “easy benchmark” field...

... but yields many opportunities to ask important & novel research questions

Developing data, simulators, and metrics

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 (www.climatechange.ai/dataset-wishlist.pdf)
- Lacuna Fund funding for climate datasets
- NeurIPS Datasets and Benchmarks track

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

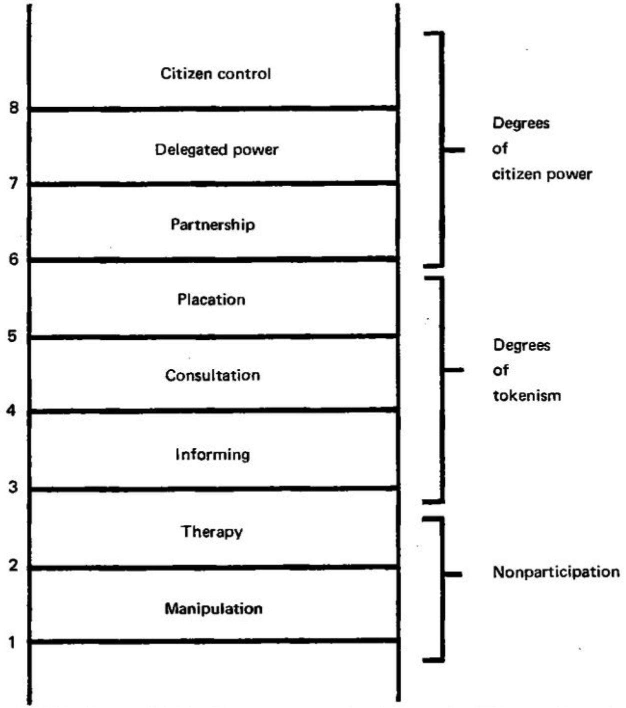
- Centering diverse stakeholders: E.g., industrial ag vs. smallholder farmers
- Avoiding centralization: Democratized capacity and compute, digital divide
- Avoiding digital colonialism: E.g., smart meters, analysis of remote sensing data

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.

Considerations for ML as a whole

If you work on ML, your work probably impacts climate change

Consider emissions impacts from applications and compute
(See tutorial section: “Is ML a help or hindrance for climate action?”)

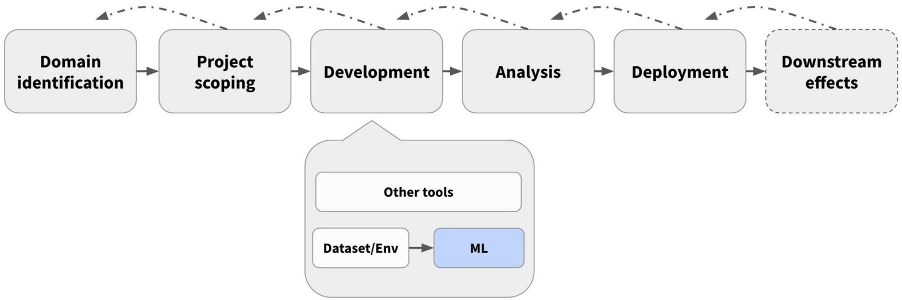
Apply a climate justice lens: ML may concentrate resources and widen the digital divide, affecting mitigation & adaptation capacity

Communicate responsibly about ML’s capabilities, limitations, and alternatives: Risk of misunderstanding, diversion of funding/attention

Takeaways: Considerations for research & deployment

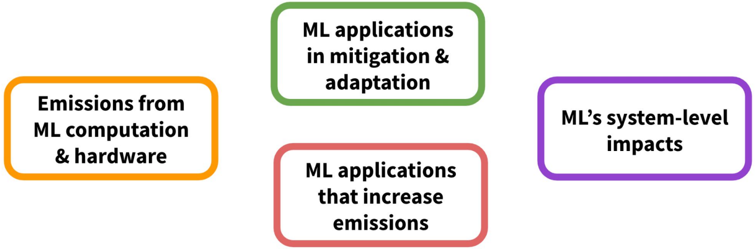
ML-for-climate: Consider the full pathway to impact, including

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



ML overall: Consider climate impacts

- Emissions impacts
- Climate justice
- Implications of communication



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Ways to get involved

Communities and resources

Roadmap for starting out

Ways to get involved

Include climate-relevant applications in the set of problems that motivate your work, and **collaborate with relevant domain experts**

Especially for students: **consider becoming a bridge** between ML and another field, such as energy, agriculture, or Earth sciences

Many job opportunities exist in this space, incl. mainstream CS research, focused institutes, startups, major tech companies, public sector initiatives

Working explicitly on climate problems isn't the only way to help - consider how to better **align your existing projects** w/ climate goals

Every application of ML affects the climate, often in multiple ways

Outside ML, may be able to **advance broader actions** by employer or society

Climate Change AI

Catalyzing impactful work at the intersection of climate change & ML

Digital resources

Reports with opportunities for researchers, practitioners, and policymakers

New community-driven Wiki w/ datasets & additional resources

+ Forecasting supply and demand High Levera

+ Improving scheduling and flexible demand

Conferences & events

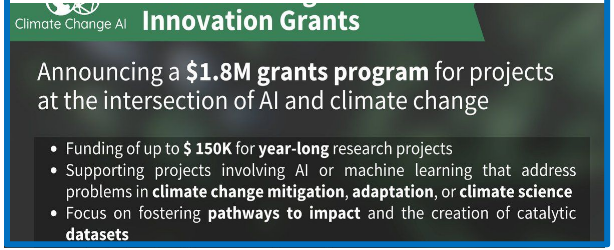
Workshop series

- Submit or attend @ NeurIPS '22
- Mentorship programs
- www.climatechange.ai/papers

Summer school (multiple tracks)

Funding programs

Global research funding for impactful projects



Newsletter, blog, & community

- Calls for Submissions
- Funding
- Projects & Courses
- Readings
- Jobs

Webinars & happy hours

Webinar series (monthly)

Virtual happy hours (biweekly)

Learn more & join in:

www.climatechange.ai

@ClimateChangeAI

Other relevant resources

Selected communities & events

- **Energy:** ACM e-Energy, IEEE Power & Energy, PSCC, BuildSys, AI.EPRI
- **Land use:** GRSS-IEEE, Int'l Soc. of Precision Ag, Restor, Global Forest Watch
- **Climate & Earth science:** Climate Informatics, AGU/EGU, Phi-Week
- **Biodiversity:** AI for Conservation slack, WILDLABS, GEO BON
- **General:** CompSustNet (community & doctoral consortium)

Publication venues: ICML/NeurIPS/CVPR/etc, upcoming special track of JMLR, Environmental Data Science, ACM COMPASS, many domain-specific venues

More info in the **Climate Change AI monthly newsletter**

Datasets and challenges

Energy: CityLearn, OPFLearn, ARPA-E GO, PowerGridworld, L2RPN, BeoBench, Building Data Genome, bbd.labworks.org, COBS, BOPTEST/ACTB, Open Catalyst

Land use: TorchGeo, blutjens/awesome-forests, CropHarvest, Radiant ML Hub, LandCoverNet, Agriculture-Vision, chrieke/awesome-satellite-imagery-datasets

Climate & Earth science: mldata.pangeo.io, ClimateBench, ClimART, CauseMe

Adaptation: wandb/droughtwatch, Global Flood Database, FloodNet, ITU GEOAI

Biodiversity: iNat dataset, LifeCLEF, FGVC, iWildCam, Movebank

More info (or contribute) at **wiki.climatechange.ai**

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CityLearn Challenge 2022

RL algorithms to coordinate energy use of several connected buildings on a micro-grid

Organized by researchers from UT Austin and CU Boulder, sponsored by NREL & EPRI

NeurIPS 2022 challenge - closes Oct 31

Datasets and challenges

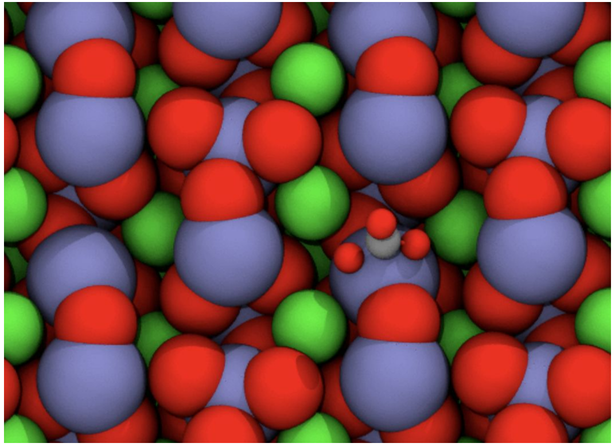
Energy: CityLearn, OPFLearn, ARPA-E GO, PowerGridworld, L2RPN, BeoBench, Building Data Genome, bbd.labworks.org, COBS, BOPTEST/ACTB, Open Catalyst

Open Catalyst Challenge 2022

ML methods (typically GNNs) to approximate quantum chemistry simulations of candidate catalysts for renewable energy storage

Organized by CMU Chem Eng. and Meta AI

Submissions open through Oct 7



Datasets and challenges

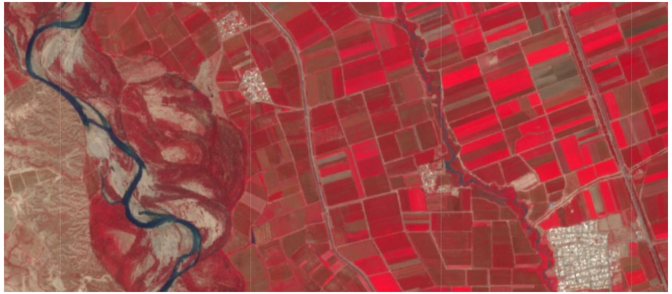
Adaptation: wandb/droughtwatch, Global Flood Database, FloodNet, ITU GEOAI

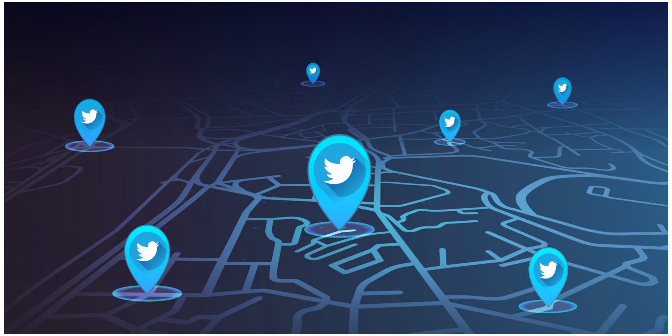
ITU GeoAI Challenge

Two relevant challenges: (1) Cropland mapping with satellite imagery, (2) location mention recognition from social media crisis-related text

Organized by ITU AI for Good

Registration open through Sep 30





Roadmap for working in this space

Identify key areas that you may want to work in

Check out **datasets or challenges** to get hands-on practice

Explore and learn more, including how non-ML techniques are being used

Find (additional) collaborators with complementary domain expertise

Work together to **scope problems** and **data sources** (may not be ML-ready)

Design algorithms to **incorporate domain and deployment constraints**

Work with deployment partners & affected stakeholders to guide impact