

Tackling Climate Change with Machine Learning

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Climate Change AI

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Climate change

Increasingly severe effects

- Storms, droughts, fires, flooding, extreme heat, etc.
- Uneven impacts

Feedbacks (e.g. albedo, permafrost)

Need net-zero greenhouse gas emissions by 2050 (UN Intergovernmental Panel on Climate Change)

- But emissions still increasing each year



What it means to tackle climate change

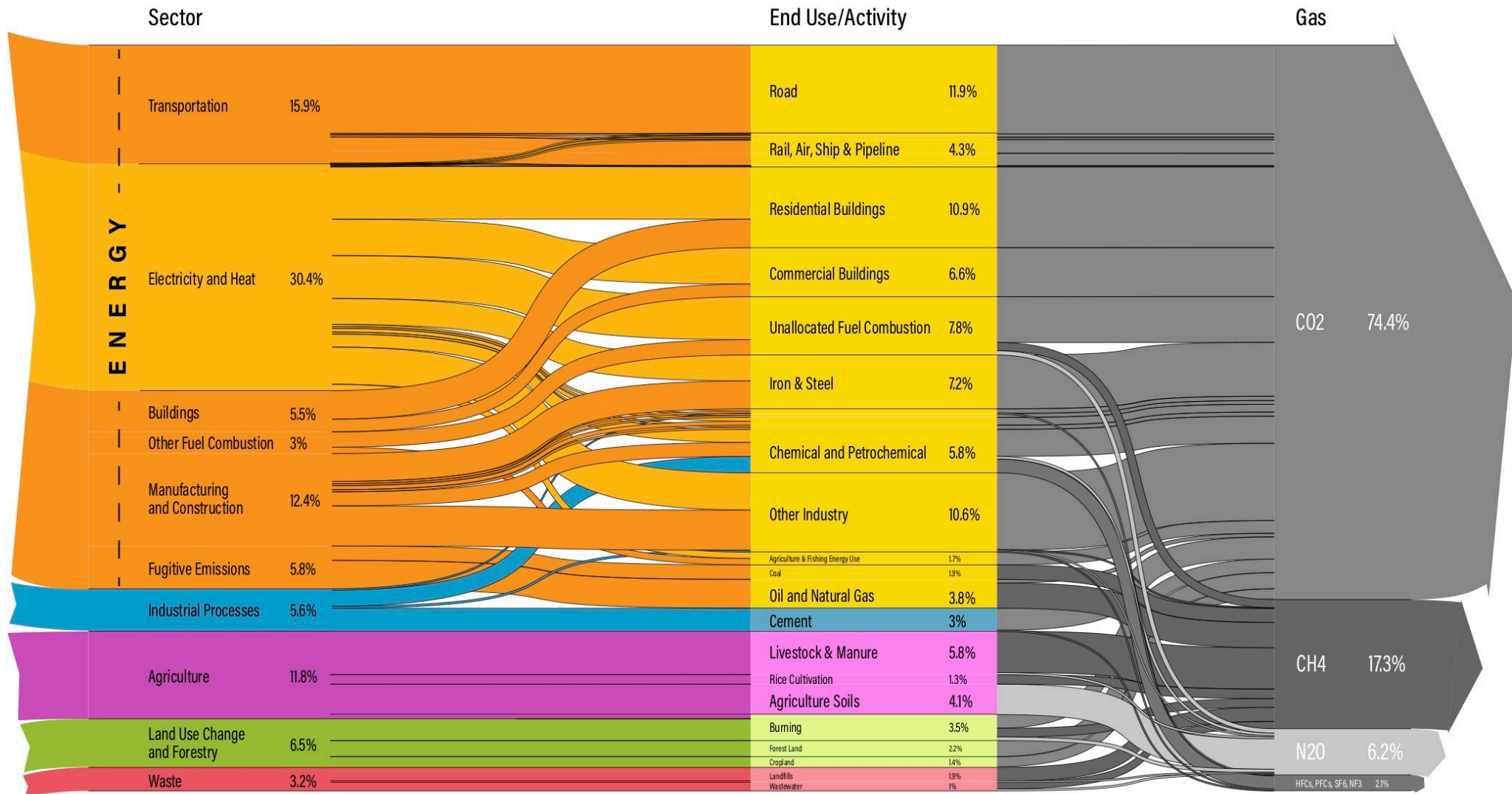
Climate change is not an on/off switch

Mitigation: Reducing greenhouse gas emissions

Adaptation: Resilience to consequences of climate change

World Greenhouse Gas Emissions in 2016

Total: 49.4 GtCO₂e



Tackling Climate Change with Machine Learning

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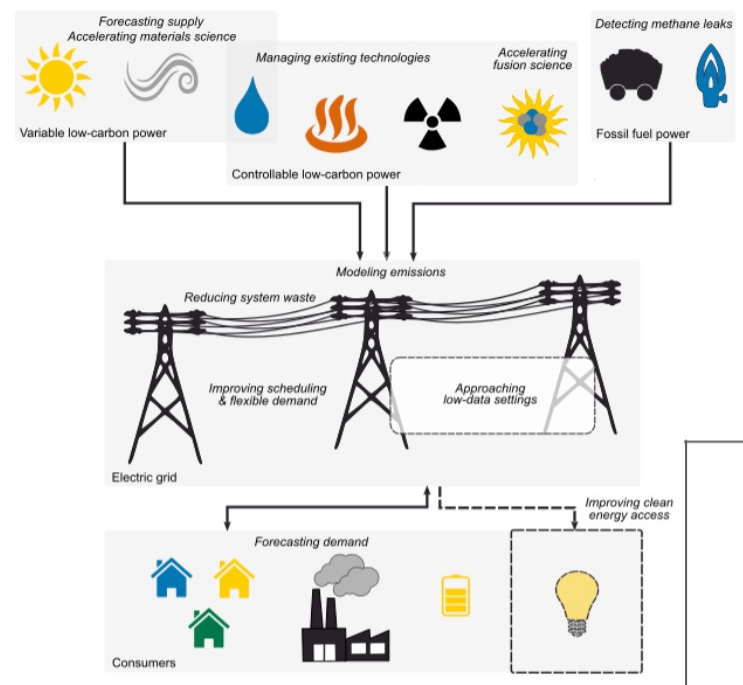
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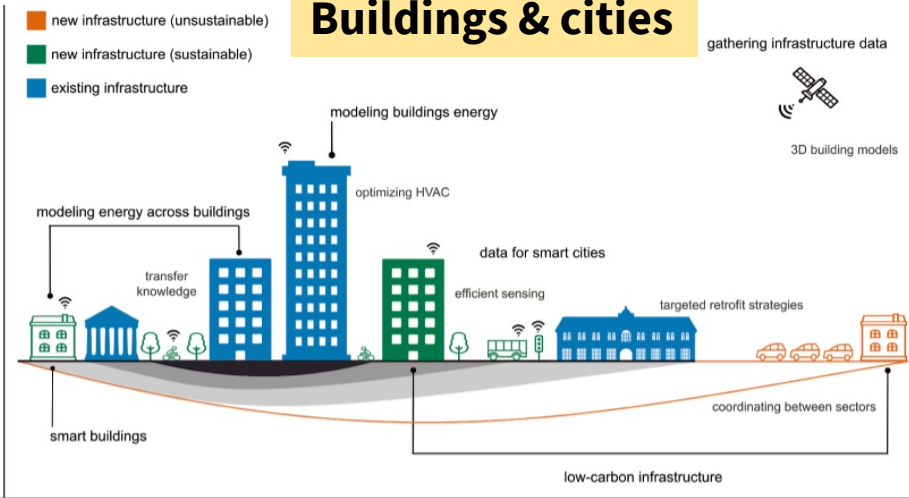
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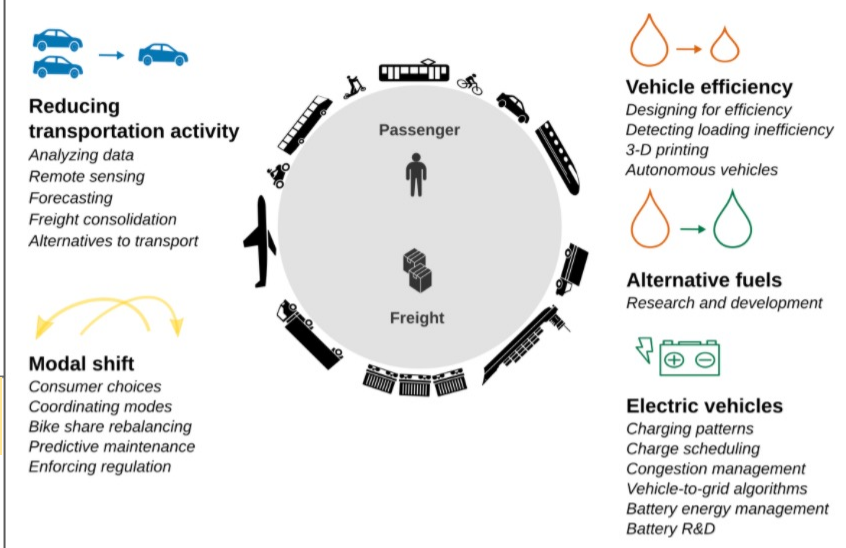
Electricity systems



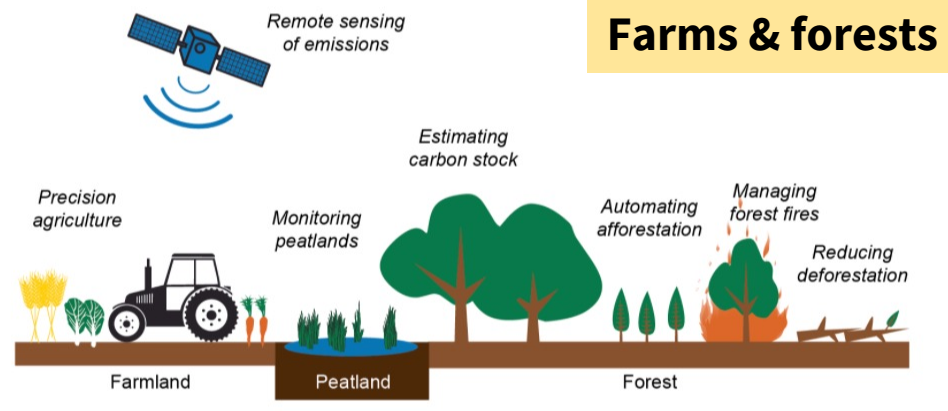
Buildings & cities



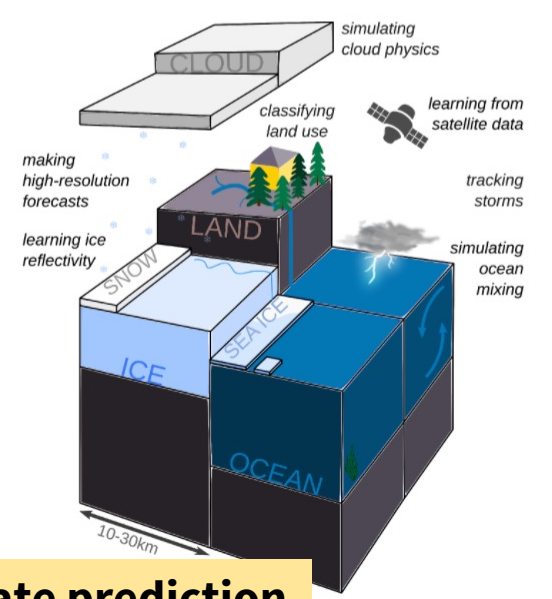
Transportation



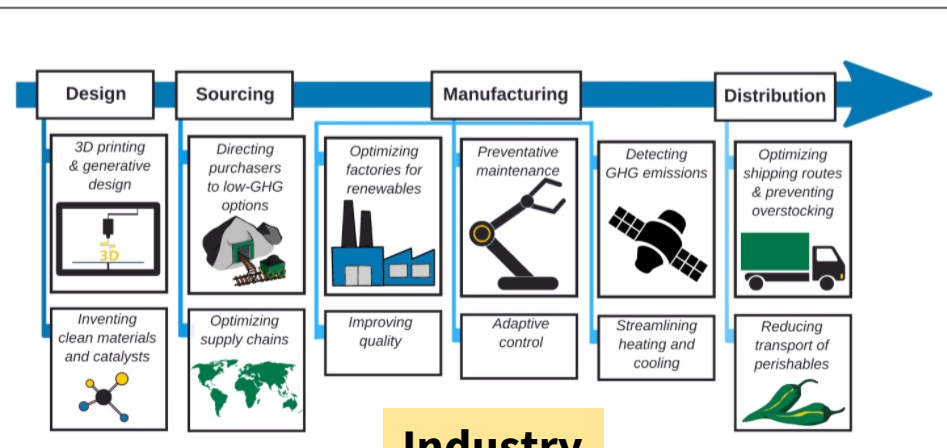
Farms & forests



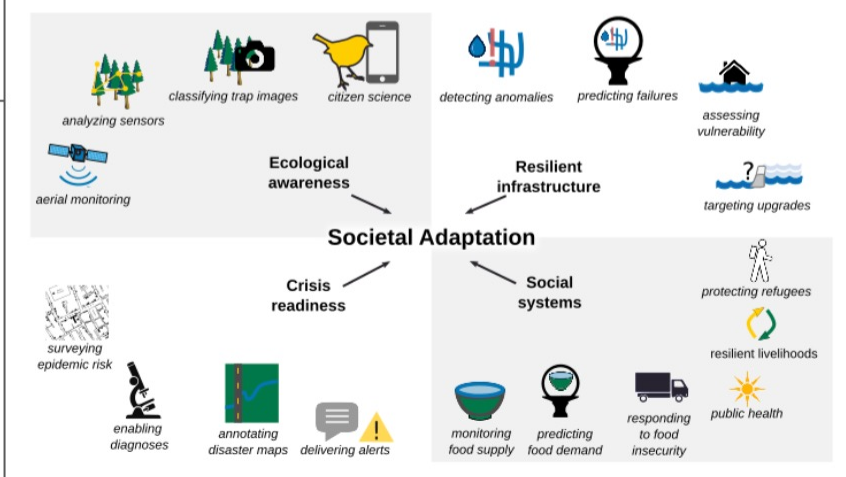
Climate prediction



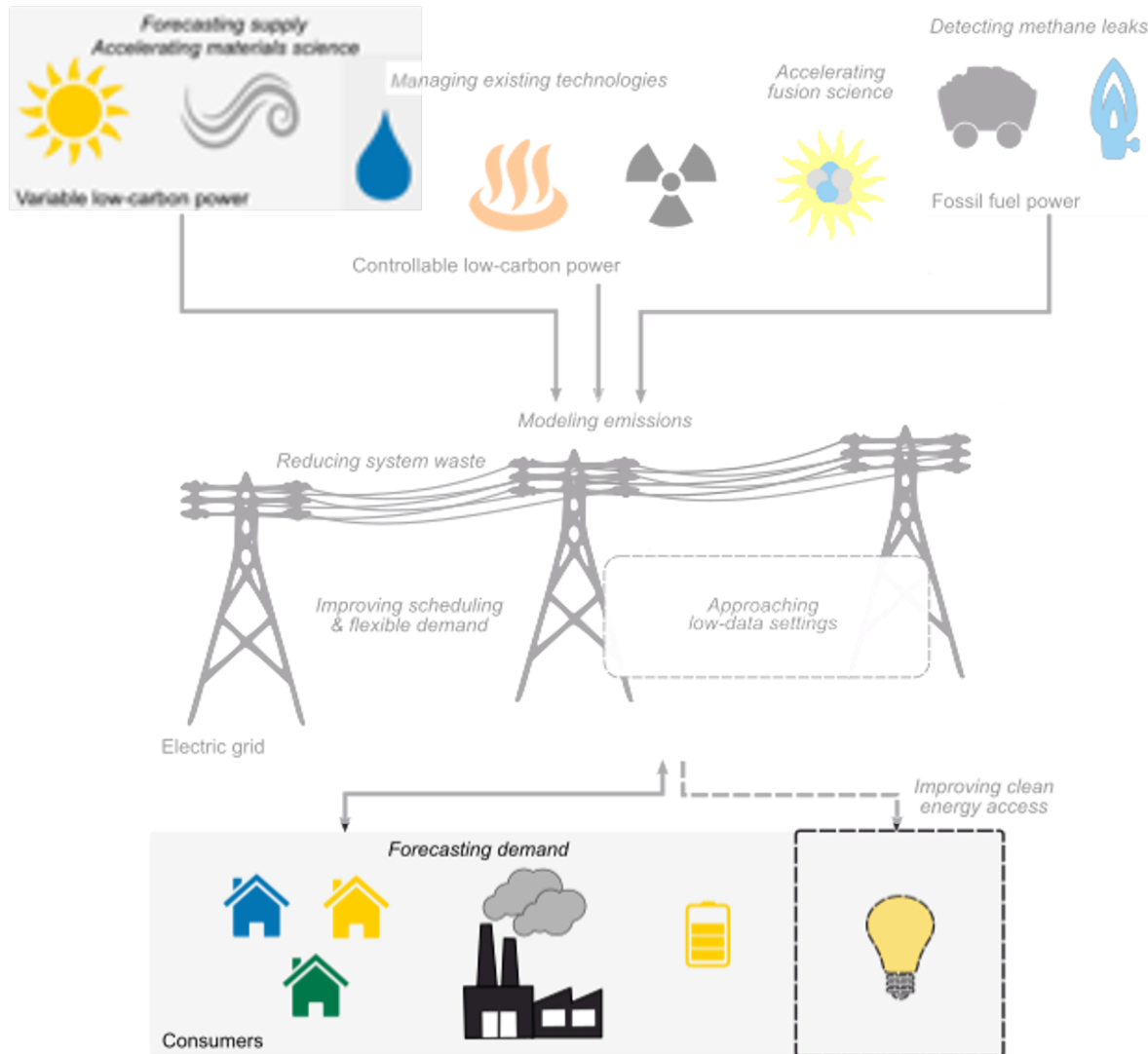
Industry



Societal adaptation



Electricity systems >> Forecasting supply and demand



Need: Scheduling and planning

ML: Short- and medium-term forecasts

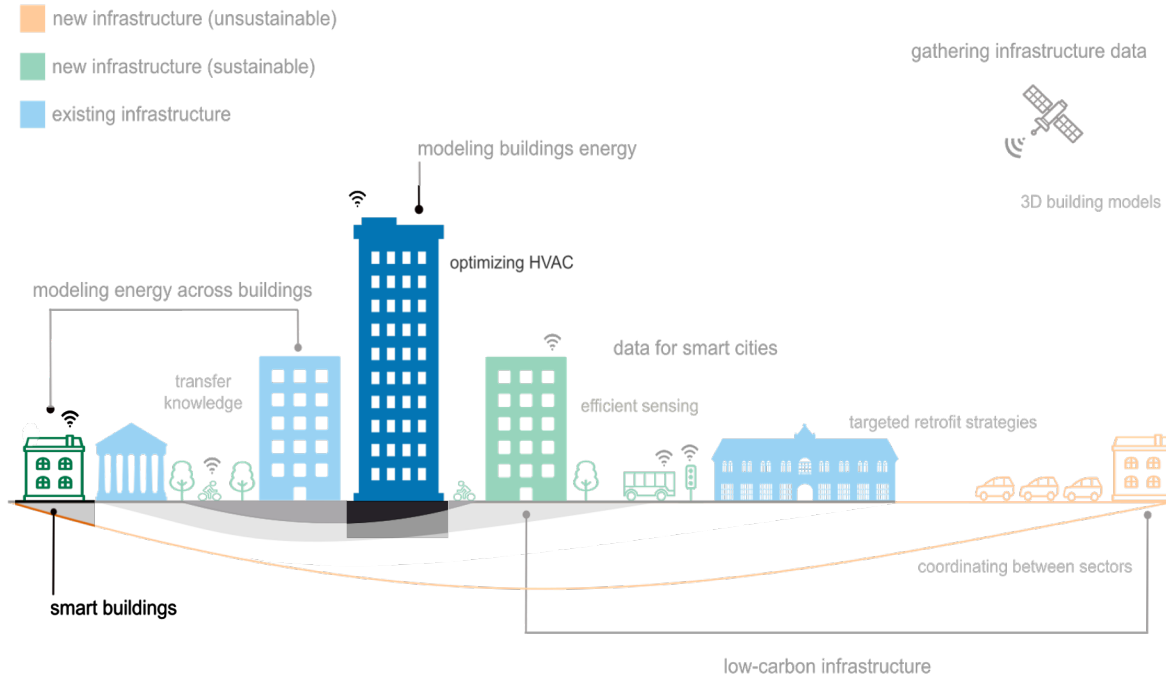
- Historical data, physical model outputs, image/video data

Stakeholders: System operators, power producers, demand aggregators, ...

Important considerations:

- Incorporate system physics & goals
- Characterize uncertainty
- Interpretable forecasts

Buildings and cities >> Building energy use optimization



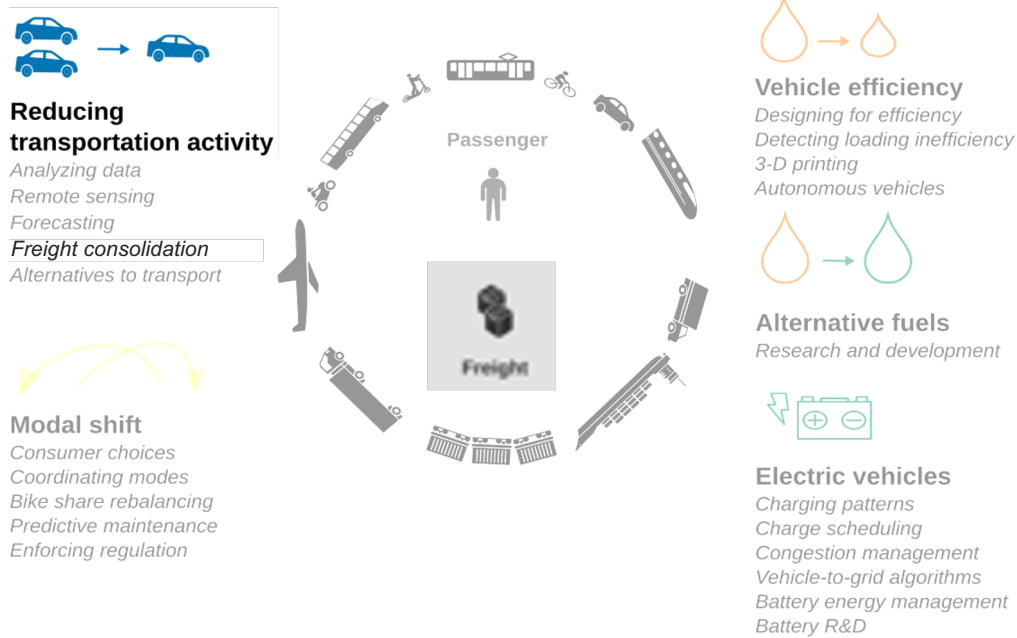
Need: Increased energy efficiency in both existing and new buildings

ML: Smart equipment control (coupled with base measures such as insulation)

- Heating and cooling (HVAC)
- Lighting
- Industrial equipment

Stakeholders: Building managers, city planners, equipment manufacturers, ...

Transportation/Industry >> Optimizing supply chains



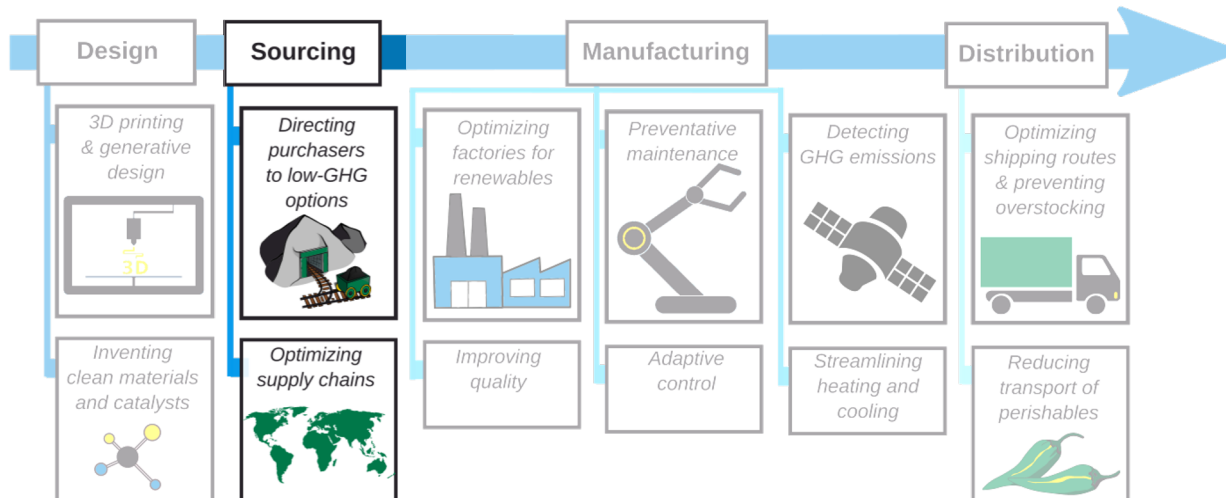
Need: Decrease emissions associated with sourcing of goods

ML:

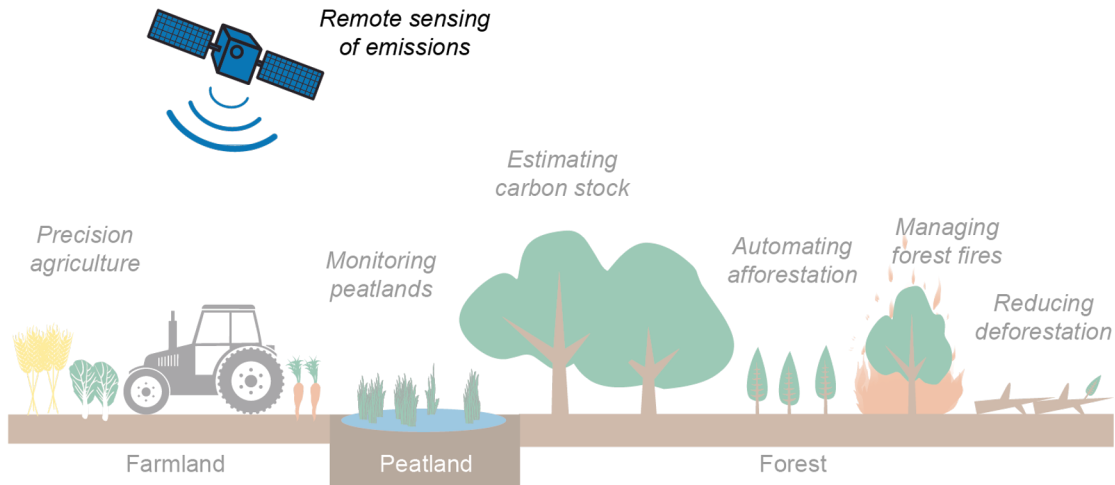
- Cluster suppliers (bundle shipments)
- Improve routing and auctions
- Predict demand (reduce overproduction)

Stakeholders: Logistics management companies, rail/freight companies, ...

Note: Beware the Jevons paradox



Farms and forests >> Gathering land use data



Need: Model emissions and land use for simulation, accounting, policy

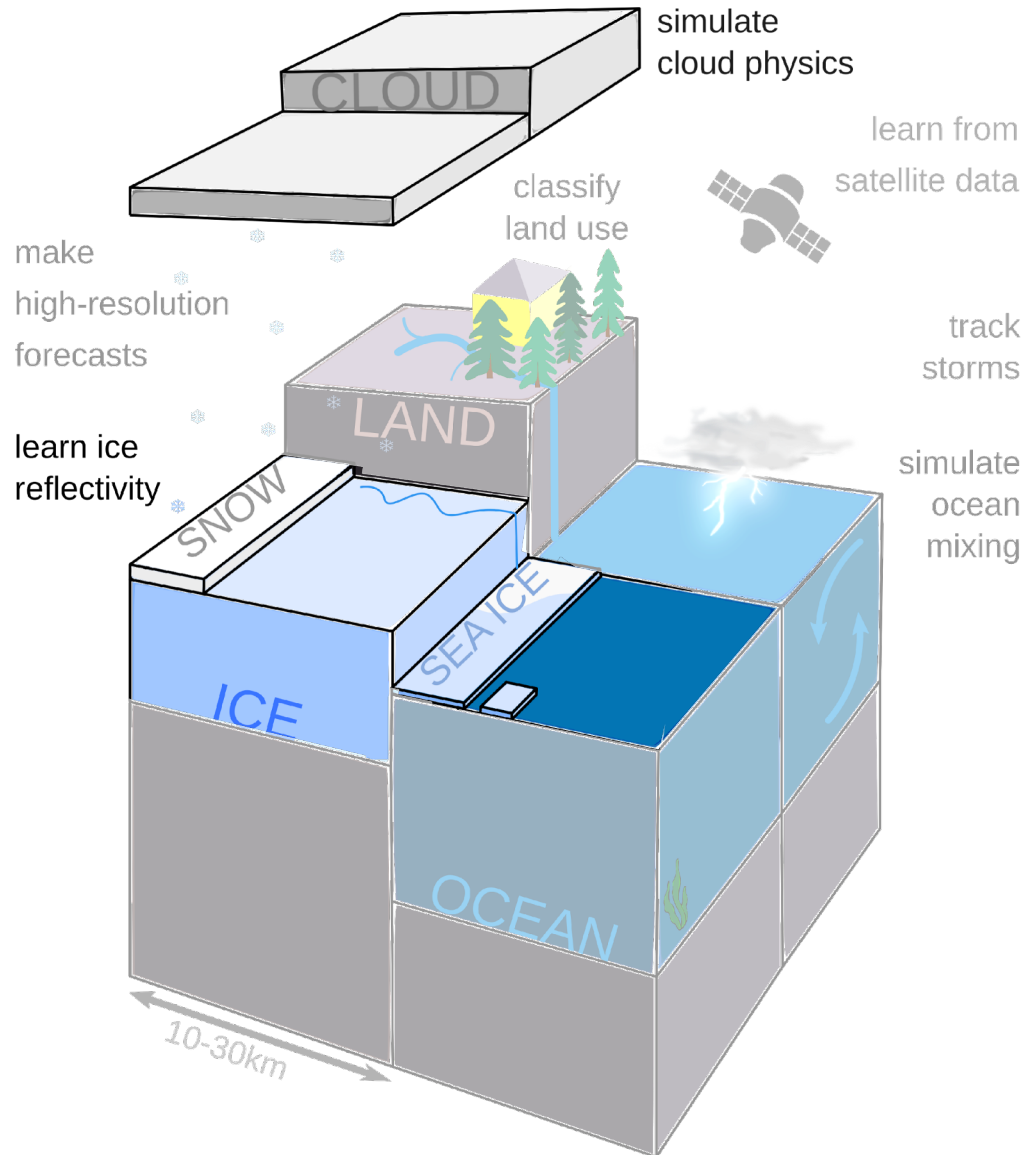
ML: Remote sensing

- Data: Satellite, aerial, or drone imagery (color images, LiDAR, etc.)
- Object detection, semantic segmentation, spatio-temporal forecasting, super-resolution,...



Stakeholders: Farmers, NGOs, gov programs, agriculture startups, ...

Climate prediction >> Accelerating climate simulations



Need: Efficient, accurate climate simulations

ML: Improve portions of simulations

- Approximate cloud physics through reduced-form models
- Gather data about ice sheets and sea level rise from satellite imagery

Stakeholders: Climate scientists, local governments

Collective decisions >> Analyzing policies

Need: Evidence-based decision-making based on analysis of climate-relevant policies

ML: Natural language processing to classify, cluster, and otherwise analyze text corpora

Stakeholders: National and local governments

Table 5. Error analysis.

SENTENCE	LABEL	CONTAINS	BERT	STUDENT	EXPERT
It is envisaged that emission reduction will be achieved through the mitigation actions in the sectors.	MITIGATION	MITIGATION	MITIGATION	MITIGATION	MITIGATION
The Steering Committee is the supreme body for decision making and sectoral implementation .	STRATEGY	MITIGATION	STRATEGY	STRATEGY	STRATEGY
The mitigation actions that enhance afforestation are projected to result in the sequestration of 1 mtCO2e annually.	LAND USE	LAND USE	AGRICULTURE	MITIGATION	LAND USE
In the absence of project activity, fossil fuels could be burned in power plants that are connected to the grid.	STRATEGY	EQUITY	ENERGY	INDUSTRY	ENERGY
Due to the outbreak of the Ebola Virus the development gains made after a 10-year civil war were rudely reversed.	ENVIRONMENT	NO LABEL	MITIGATION	NO LABEL	NO LABEL

Source: Corringham et al., 2021

Recurring themes

Gathering information (GHG emissions, deforestation, infrastructure, crops)

Forecasting (renewable energy, transportation demand, extreme events)

Improving operational efficiency (heating and cooling, freight, food waste)

Predictive maintenance (methane leaks, resilient infrastructure)

Accelerating scientific experimentation (batteries, electrofuels)

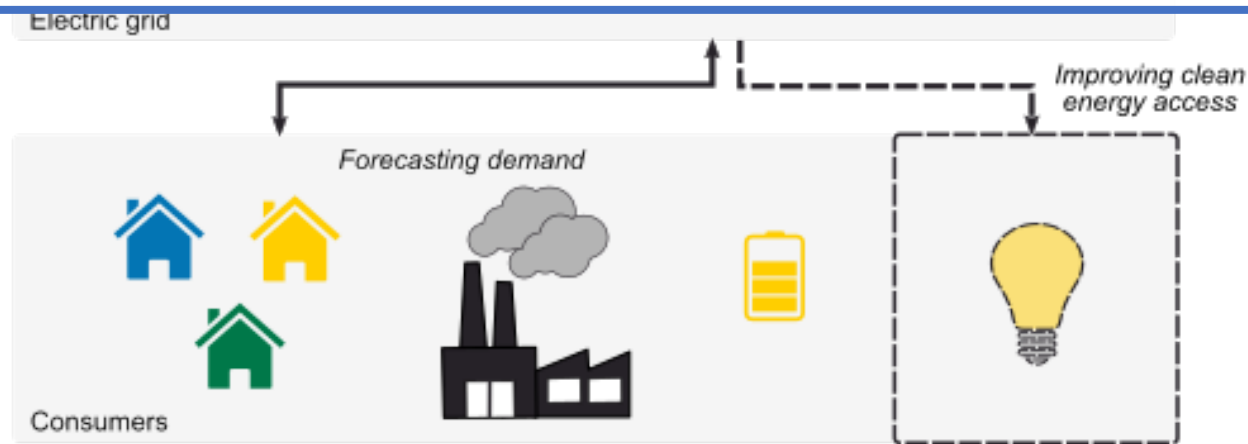
Approximating time-intensive simulations (climate, energy, city planning)

Quick Dive: Electric Power Systems



Many ML applications in the power sector can benefit from the incorporation of **physics, hard constraints, or domain knowledge**

One mechanism: **Implicit layers** in neural networks

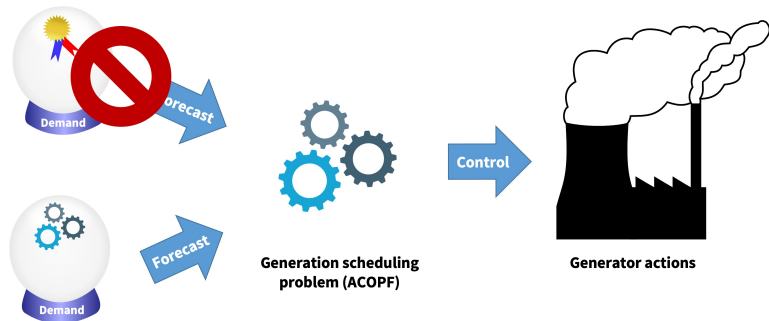


Paradigms for implicit layers in power systems

Enable **decision-driven models** (e.g., demand forecasting)

Provide **inductive biases** (e.g., inverse optimal power flow)

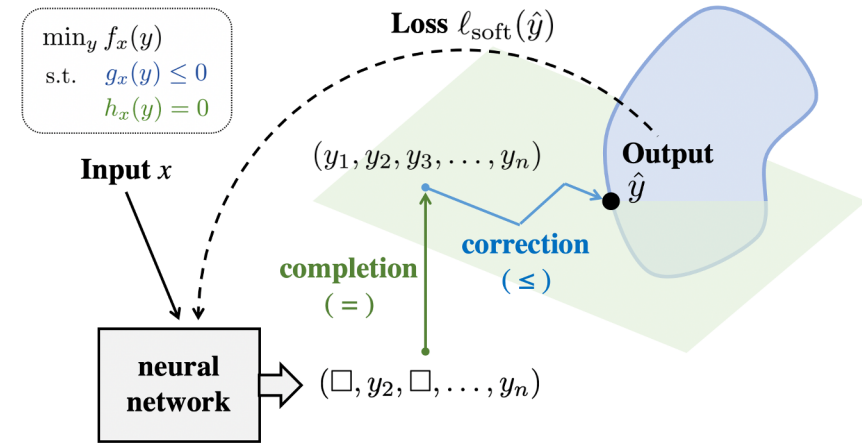
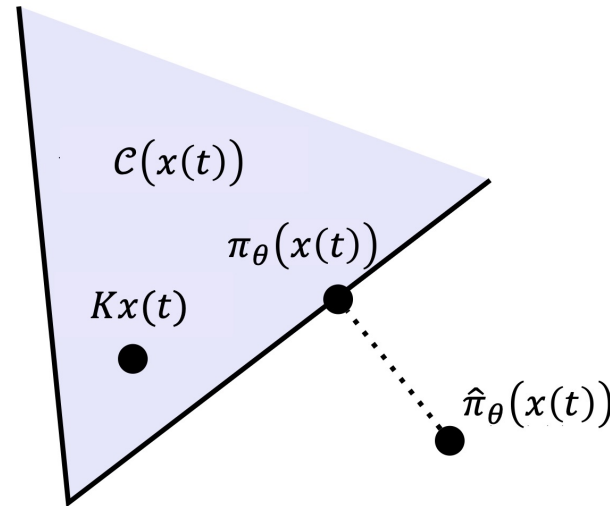
Enforce hard constraints (e.g., robust control via DL; approximating ACOPF)



Inverse optimal power flow

$$\underset{\hat{c}, \hat{Y}}{\text{minimize}} \ell \left((p_g, \lambda), (\hat{p}_g, \hat{\lambda}) \right)$$

$$\text{subject to } \hat{p}_g, \hat{\lambda} = \text{ACOPF}(\hat{c}, \hat{Y}, p_d)$$



Important Considerations

Machine learning: Strengths & limitations

Machine learning (ML): Group of techniques that automatically extract patterns from (large amounts of) data

STRENGTHS

- **Scaling human insight** by analyzing patterns in large amounts of data
- **Optimizing complex systems**
- **Generating “new” (derived) data** from other sources of data
- **Integrating with other methods**, e.g. domain and physical models

LIMITATIONS

- **“Garbage in, garbage out”**
 - Does not work on bad or overly limited data
- **Inherits biases in data/design/use**
 - Not “objective”
- **Assumes patterns are persistent**
 - Difficulty with e.g. long-term forecasts
- Finds **correlation, not causation**

Machine learning is not a silver bullet

- Not applicable everywhere
- Where applicable, only one part of the strategy
 - E.g. insulation more important than smart buildings!
- Impactful applications are often not flashy
- Work needs to be driven by end users

Important considerations for deployment

- Sometimes simple methods work
- Rebound effects: Efficiency does not always translate to climate impact
- Equity in scoping, deployment, and access
- Partnerships are key: researchers, implementing industries, end users, policymakers, other affected parties

ML's multi-faceted impact on climate change

ML applications in mitigation & adaptation

ML applications that increase emissions

ML applications w/ uncertain or systemic impacts

Energy use of ML itself

What you can do

General

- Check out Climate Change AI resources & community: www.climatechange.ai
 - Virtual happy hour (fortnightly) and Circle discussion platform
 - Newsletter, tutorials, Wiki, talk recordings
 - Workshops and webinars

Students

- Contact potential mentors & collaborators in the space
- Take classes in multiple disciplines

Professionals

- Join community meetings
- Leverage your network
- Engage with technology-policy interface



Climate Change AI

Catalyzing impactful work at the intersection of climate change and AI

Digital resources

Foundational report on climate change and AI

Resource Wiki w/ datasets and additional resources

+ Forecasting supply and demand

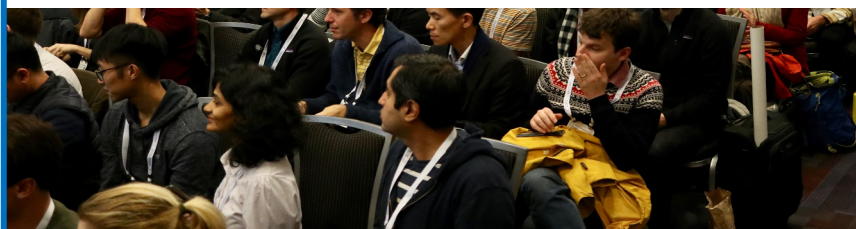
High Leverage

+ Improving scheduling and flexible demand

Conferences and events

Next workshop (virtual) @ NeurIPS

- Attend: Dec 14



Funding programs

Global research funding for impactful projects

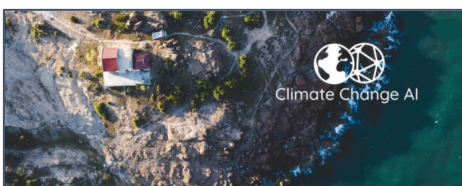
datasets

- Submission **deadline** on **October 15th**

For more info on the grants & submissions, please visit:
climatechange.ai/calls/innovation_grants

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Newsletter and community



Climate Change AI



Calls for Submissions



Funding



Projects & Courses



Readings



Jobs

Welcome to the Climate Change AI community!

We are excited to have you here!

This is a place to *connect, share* and *discuss* all things related to climate change & machine learning 🌍🤖

If this is your first time here, you might want to head over to the  Hello channel and introduce yourself.

Webinars and happy hours

Next webinar: Nov 19

Machine learning for carbon capture and sequestration

Next happy hour: Nov 17

Spatial planning of low-carbon cities with machine learning



Dr. Jason Cao
Professor
Humphrey School of Public Affairs at the University of Minnesota

Cities represent the lion's share of the world's energy...

Learn more:

www.climatechange.ai

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