Berkeley AI + Climate Change Reading Group #1

Presenter: Colorado Reed

Many images/texts taken shamelessly from this fantastic blog series:
https://blog.codecentric.de/en/2019/09/how-to-tackle-climate-change-with-machine-learning-electricity-systems/#post-69396

Reading Group Goals

- Meet people with shared interest [at Berkeley]
- Form a collective interest group
- Find collaborators or form collaborations
- Learn about research at the intersection of AI + Climate Change

Breakout: introduce yourself to a small group =)

(e.g. name, what you work on)

We’re looking for presenters + organizers

- Email Colorado/Medhini (see reading group website for emails)
- Feel free to present your own research or a paper you find interesting
  - Or ask for suggestions =)

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[9], Nikola Milojevic-Dupont[10,11], Natasha Jaques[12], Anna Waldman-Brown[12], Alexandra Luccioni[6,7], Tegan Maharaj[6,8], Evan D. Sherwin[2], S. Karthik Mukkavilli[6,7], Konrad P. Körding[1], Carla Gomes[13], Andrew Y. Ng[14], Demis Hassabis[15], John C. Platt[16], Felix Creutzig[10,11], Jennifer Chayes[17], 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]École Polytechnique de Montréal, [9]Harvard University, [10]Mercator Research Institute on Global Commons and Climate Change, [11]Technische Universität Berlin, [12]Massachusetts Institute of Technology, [13]Cornell University, [14]Stanford University, [15]DeepMind, [16]Google AI, [17]Microsoft Research

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U.C. Berkeley is missing =(

Challenges & key capabilities

	Accelerated experimentation	Control systems	Forecasting	Human interaction	Hybrid physical models	Predictive maintenance	Remote sensing	System optimization
1 Electricity systems								
Enabling low-carbon electricity	•	•	•		•	•	•	•
Reducing current-system impacts			•			•	•	
Ensuring global impact			•		•		•	
2 Transportation								
Reducing transport activity	•	•	•				•	•
Improving vehicle efficiency	•	•						•
Alternative fuels & electrification	•	•	•					•
Modal shift		•	•	•		•	•	•
3 Buildings and cities								
Optimizing buildings		•	•		•	•		•
Urban planning							•	
The future of cities								•
4 Industry								
Optimizing supply chains		•	•					•
Improving materials	•							
Production & energy		•				•		•
5 Farms & forests								
Remote sensing of emissions							•	
Precision agriculture		•	•				•	
Monitoring peatlands							•	
Managing forests		•	•				•	
6 Carbon dioxide removal								
Direct air capture	•				•			
Sequestering CO_2					•			
7 Climate prediction								
Uniting data, ML & climate science			•		•		•	
Forecasting extreme events			•		•		•	
8 Societal impacts								
Ecology							•	
Infrastructure						•		•
Social systems			•	•			•	•
Crisis			•				•	
9 Solar geoengineering								
Understanding & improving aerosols		•			•			
Engineering a planetary control system		•			•			
Modeling impacts					•			
10 Individual action								
Understanding personal footprint			•	•				
Facilitating behavior change				•				
11 Collective decisions								
Modeling social interactions				•				
Informing policy				•				
Designing markets			•					•
12 Education				•				
13 Finance			•	•				

Accelerated experimentation

e.g. materials discovery for fuels, construction materials, fertilizer

Control systems

e.g. electrical power systems, HVA
planetary control systems

Forecasting

e.g. future demand and supply, localized impacts of climate chang

Human interaction

e.g. targeted education, agent-base modelling, mechanism design

Hybrid physical models

e.g. climate & earth simulations, Integrated Assessment Modeling

Predictive maintenance

e.g. increase efficiencies of industr improve infrastructure resilience

Remote sensing

e.g. low-data environments, city planning, measuring emissions

System optimization

e.g. supply chains, transportation, multi-objective decision-making

https://junshern.github.io/paper-reading-group/2021/04/03/tackling-climate-change.html

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Reading Group:
→Briefly overview each area
→Breakout: Which area is most interesting/relevant to you?
→Vote on area to deep dive next time.

https://junshern.github.io/paper-reading-group/2021/04/03/tackling-climate-change.html

Interactive website demo

- https://www.climatechange.ai/summaries

Interactive website demo

- https://www.climatechange.ai/summaries
- **Homework**: use the interactive website to find overlaps with your area of interest + read the short subsection

Paper Emphasis

- Where can ML have impact on real problems?

- Collaborate across fields: **ML Folks: collaborate with domain experts** ***(and vice-versa!)***

Problem Delineation I

- **Mitigation –** Reducing emission
- **Adaptation** – Resilience planning (e.g. disaster management)

Problem Delineation II

High Leverage denotes bottlenecks that domain experts have identified in climate change mitigation or adaptation and that we believe to be particularly well-suited to tools from ML. These areas may be especially fruitful for ML practitioners wishing to have an outsized impact, though applications not marked with this flag are also valuable and should be pursued.

Long-term denotes applications that will have their primary impact after 2040. While extremely important, these may in some cases be less pressing than those which can help act on climate change in the near term.

Uncertain Impact denotes applications where the impact on GHG emissions is uncertain (for example, the *Jevons paradox* may apply[3]) or where there is potential for undesirable side effects (*negative externalities*).

Mitigation Area: Electricity Systems

- Rapidly transition to low-carbon electricity sources (such as solar, wind, hydro, and nuclear) and phase out carbon-emitting sources (such as coal, natural gas, and other fossil fuels).

- Reduce emissions from existing CO_2-emitting power plants, since the transition to low-carbon power will not happen overnight.

- Implement these changes across all countries and contexts, as electricity systems are everywhere.

Electricity Systems

- *forecasting power generation & demand*
- *accelerating materials science*
- *optimizing the capture of ambient energy*
- *increasing the safety of nuclear power plants*
- *advancing research of nuclear fusion*
- *reducing fossil fuel and electricity loss during transport*
- *modeling live emissions of electricity*
- *collecting data in regions with scarce information about the local grid*

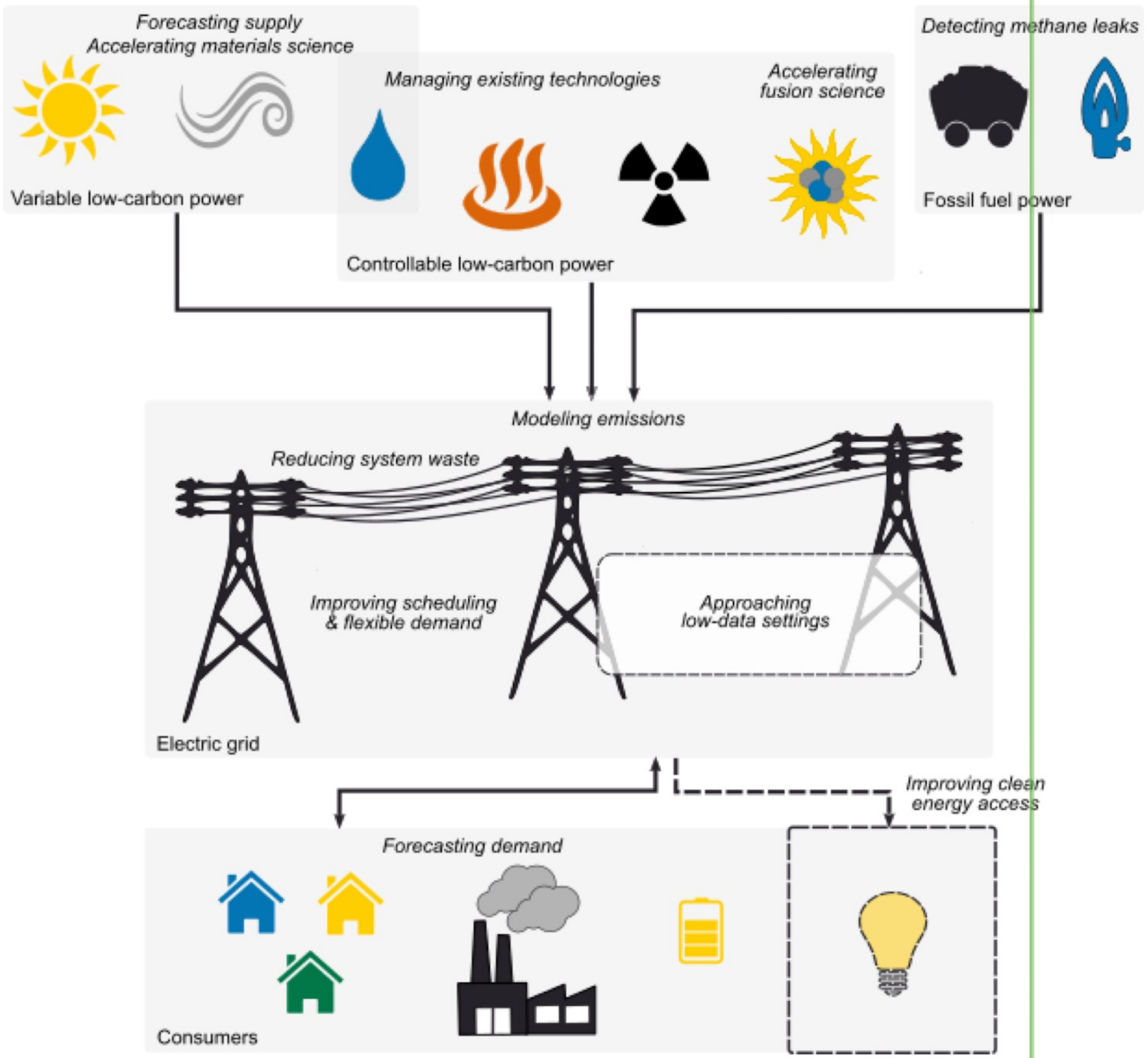
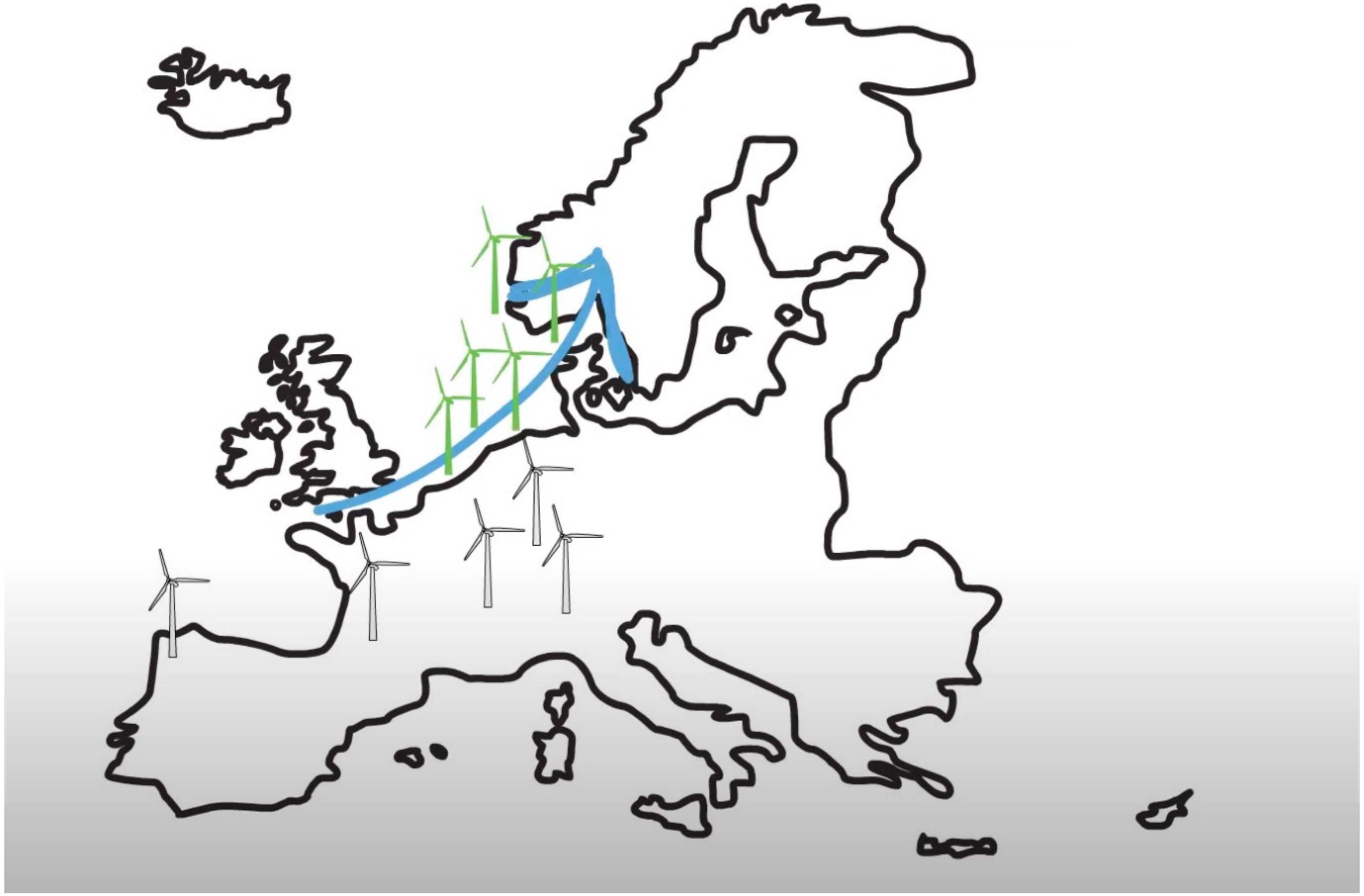


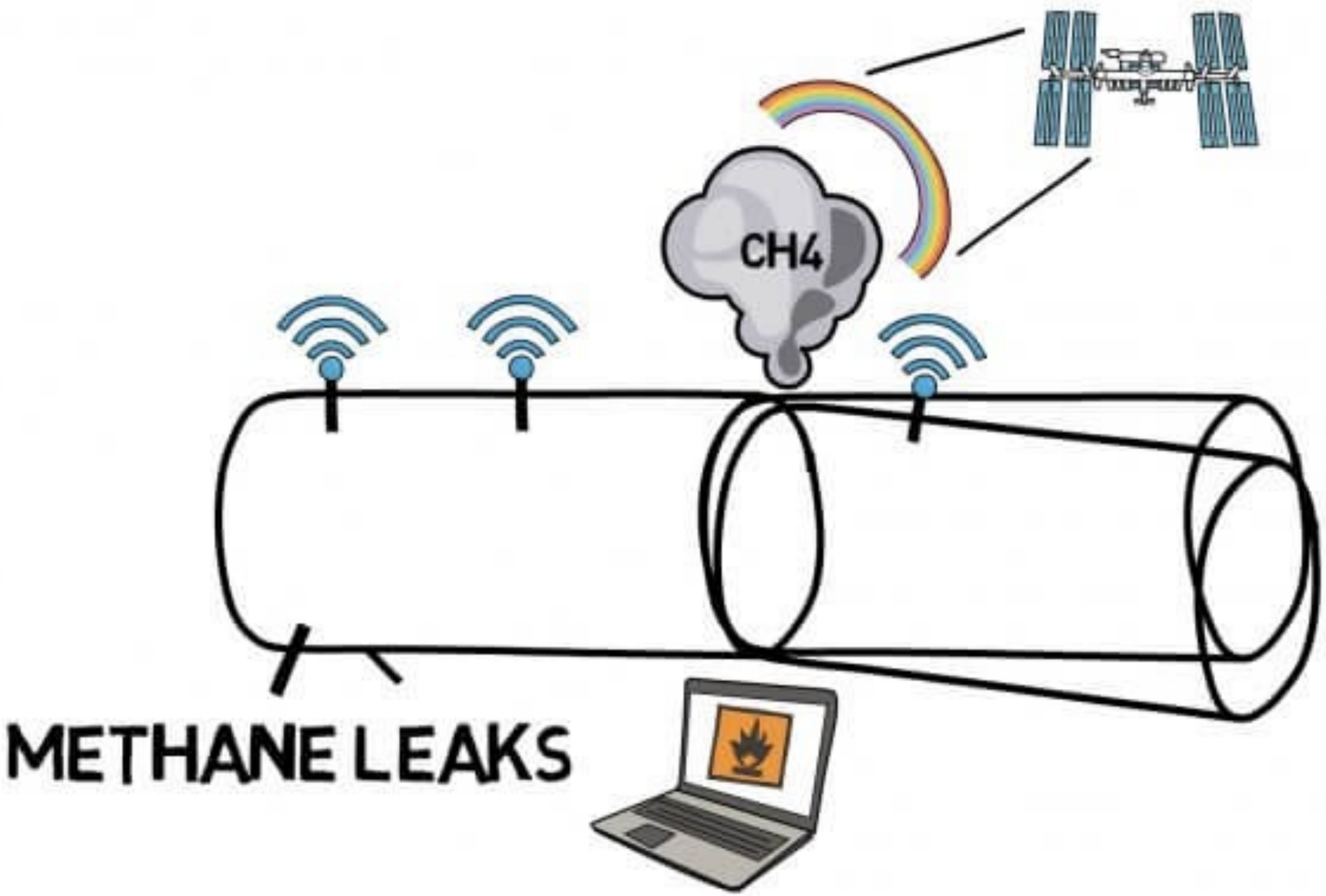
Figure 1: Selected opportunities to reduce GHG emissions from electricity systems using machine learning.

https://www.youtube.com/watch?v=pHdv4o0mfd0

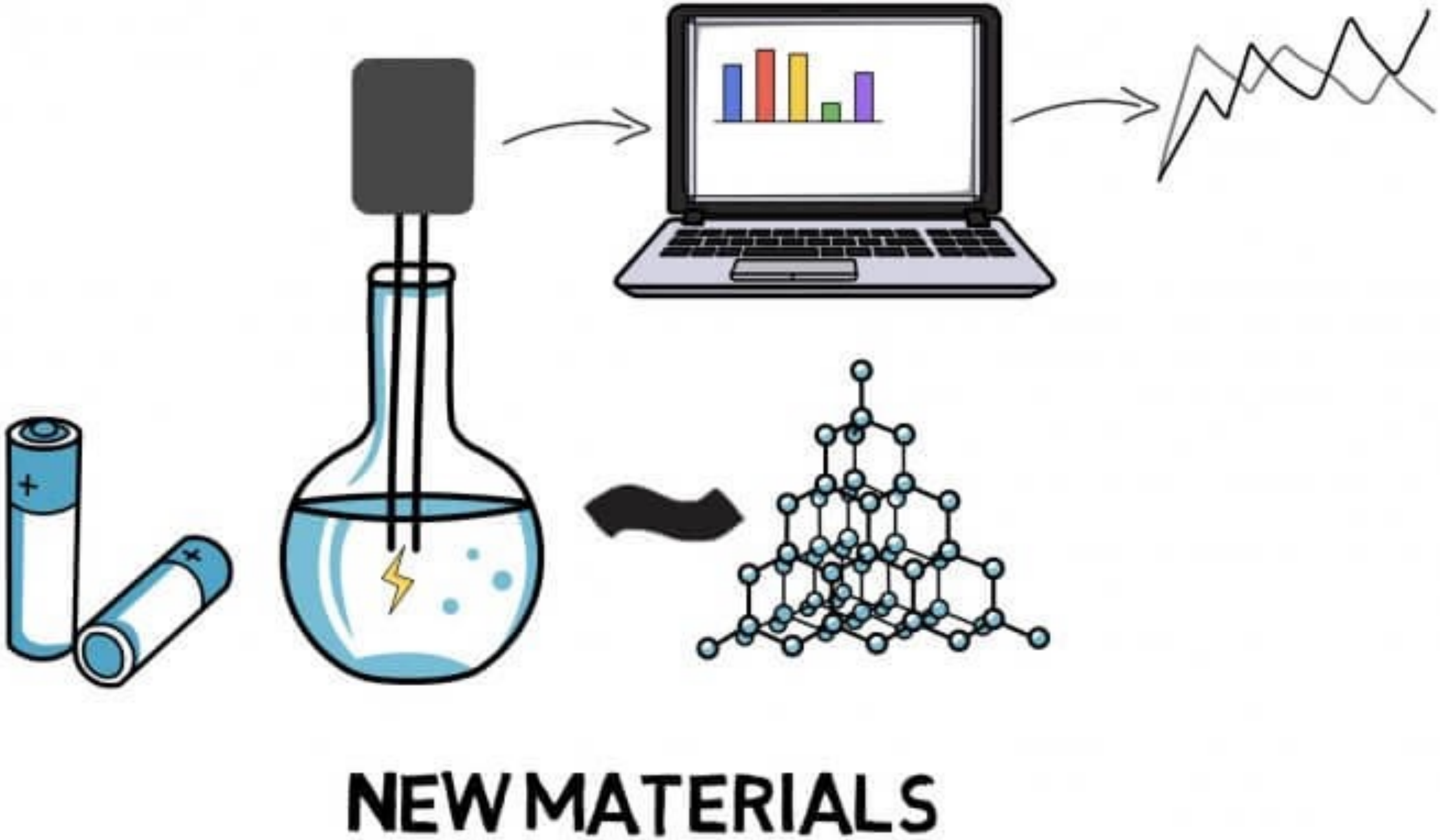
E.g. long term forecasts indicate where to build new wind farms.



E.g. detecting fossil fuel loss during transport

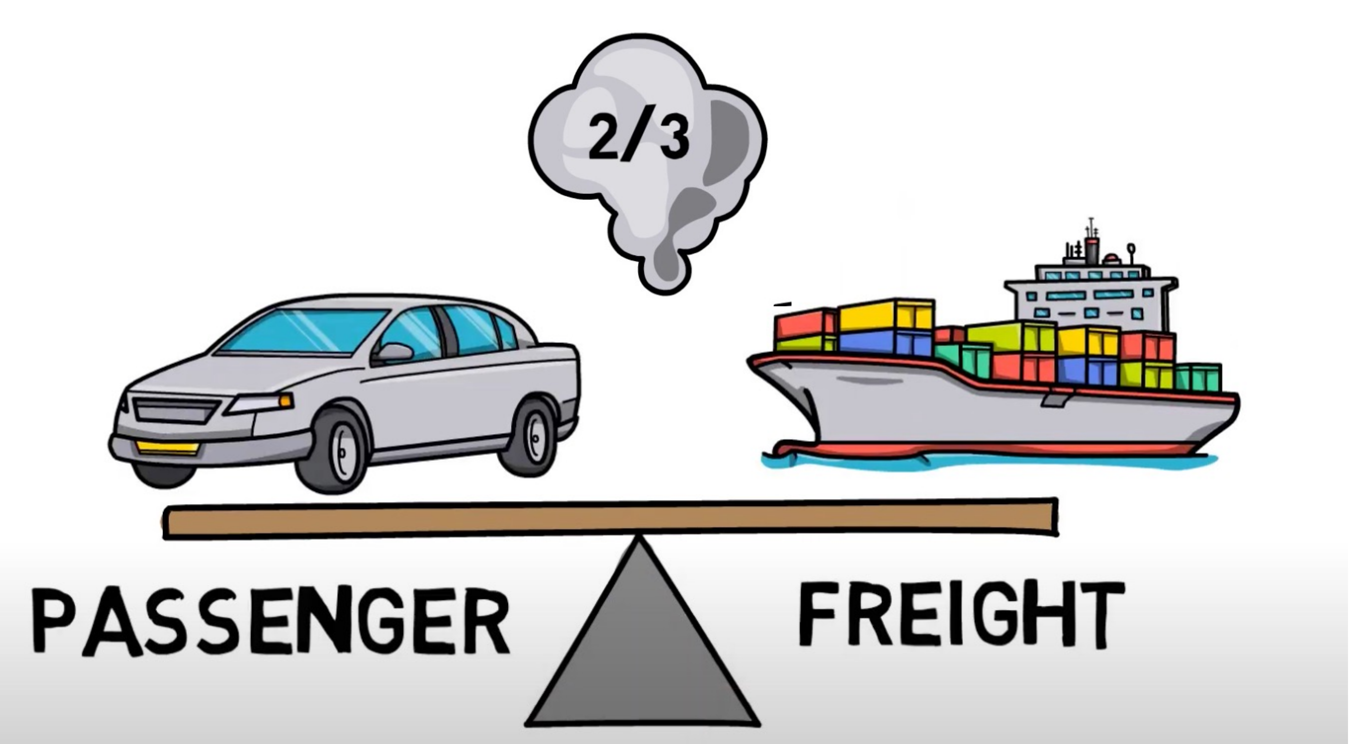


E.g. ML to improve new materials development



Mitigation Area: Transportation

- Accounts for about 1/4 Global CO2 emissions



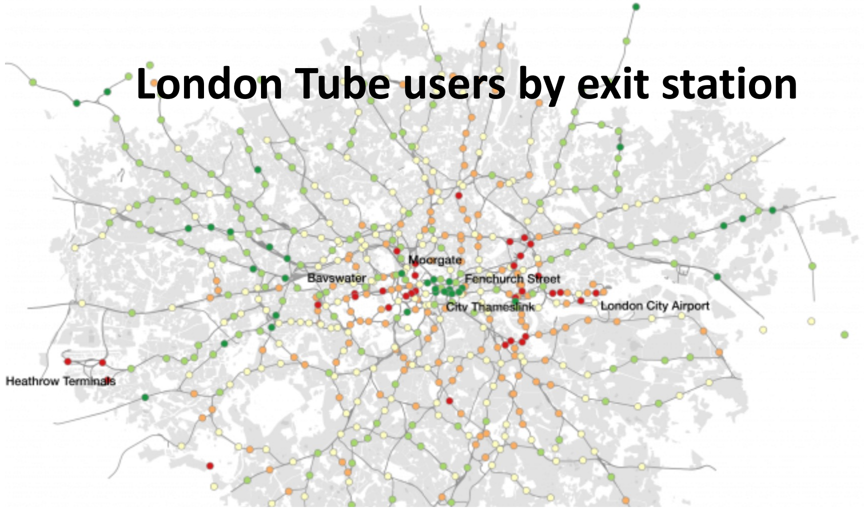
Mitigation Area: Transportation

- ↓ understanding transportation patterns
- ↓ modeling transportation demand
- ↓ estimating the impact of shared mobility concepts
- ↓ optimizing freight routing and bundling
- ↓ boosting alternatives to transport
- ↓ designing for vehicle efficiency
- ↓ enabling autonomous vehicles
- ↓ improving electric vehicles
- ↓ improving low-carbon transportation

e.g. ML for Transportation demand

- Learning about the behavior of public transit users from smart card data or online booking data [Paper]

- model bikeshare station usage [Paper]

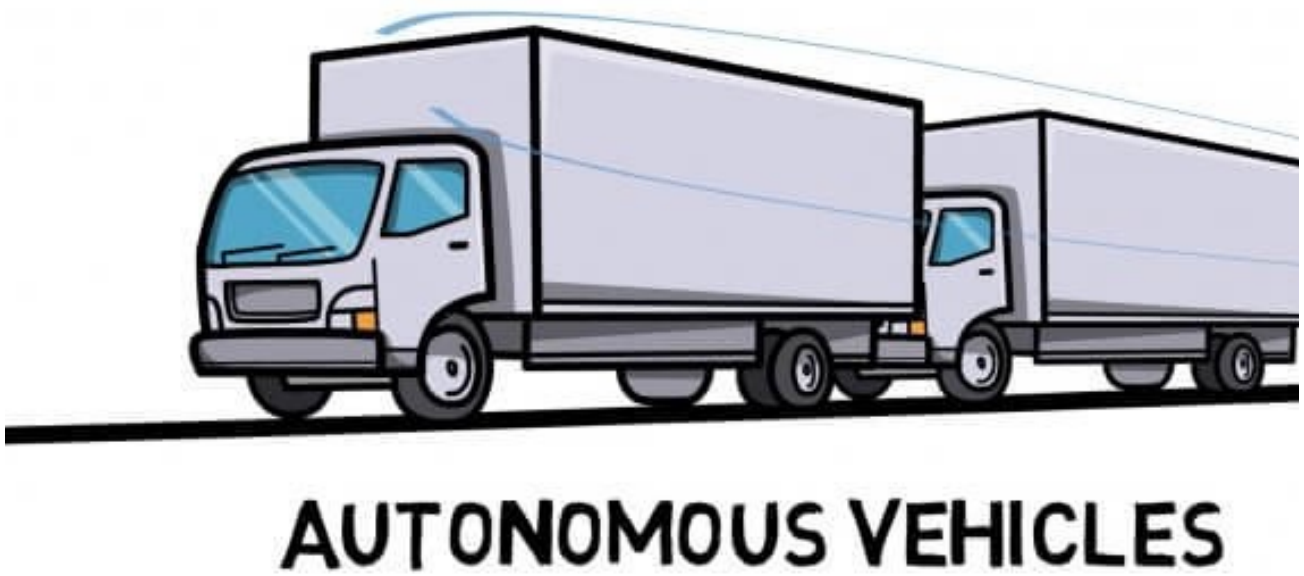


(a) Demand in 8 a.m.-9 a.m. (b) Demand in 6 p.m.-7 p.m.

Bike sharing demand *Pan et al., 2018*

e.g. Autonomous vehicles

- enabling trucks to drive very close together (platooning) [Paper]
- smoothing out traffic [Paper]
- reducing emissions of last-mile delivery with small & light autonomous vehicles, such as delivery robots and drones could [Paper]



Possible Jevons paradox – where increased efficiency leads to higher demand

https://blog.codecentric.de/en/2019/09/tackling-climate-change-with-machine-learning-buildings-cities/#post-69738

Machine Learning can help reduce the carbon footprint of buildings and cities by

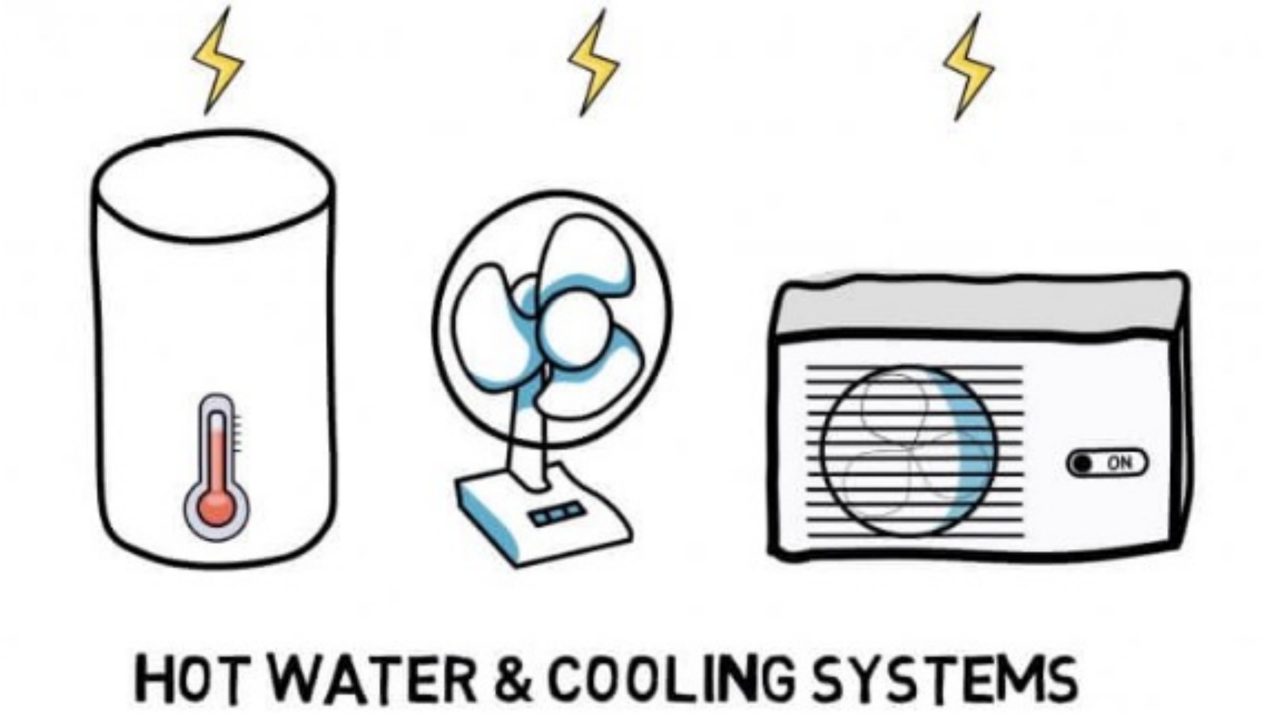
- ↓ modelling the energy consumption of buildings
- ↓ enabling smart buildings
- ↓ understanding the energy consumption of cities
- ↓ gathering infrastructure data
- ↓ collecting data for smart cities
- ↓ improving low-emission infrastructure

e.g. Modelling the energy consumption of buildings

- forecast energy demand for individual buildings from data produced by meters and home energy monitors;
  - use this data to evaluating building design and operation, and can also inform grid operators [Paper]
- predict energy consumption of building concepts and generate more efficient building concepts, also **transfer knowledge from commercial to residential buildings**, from gas- to electricity-heated buildings [Paper]

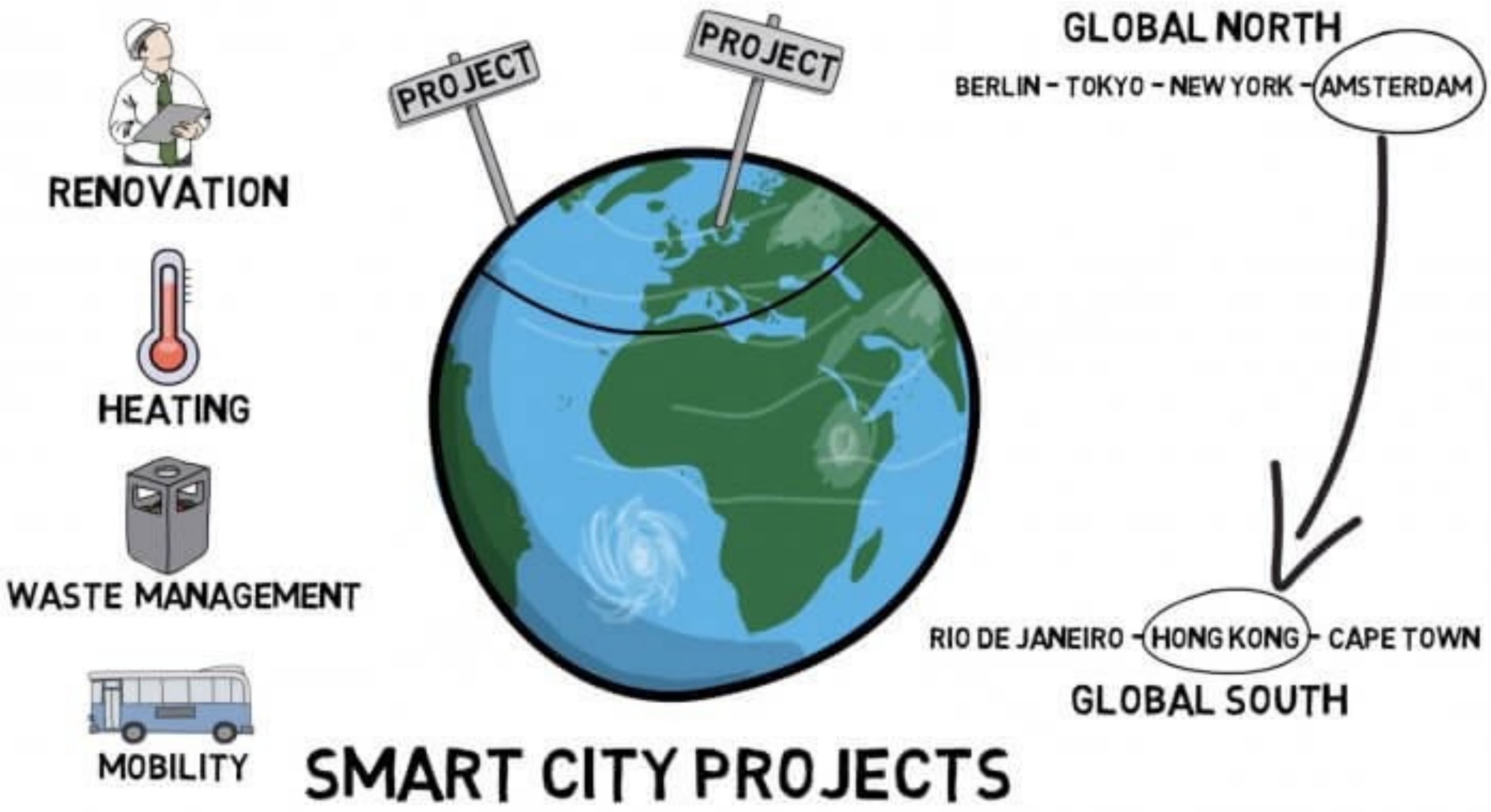
https://blog.codecentric.de/en/2019/09/tackling-climate-change-with-machine-learning-buildings-cities/#post-69738 e.g. The majority of energy consumed by buildings is caused by heating, ventilation and air conditioning (HVAC). Smart buildings try to reduce HVAC energy consumption

- forecast what temperatures are needed and thereby improve control. ML could also help detecting faults [Paper]
- improving efficiency of cooling systems by identifying faults such as refrigerant leakage [Paper]
- schedule efficient energy use based on data from sensors / IoT devices [Paper]
- adapt devices which consume energy to usage patterns, such as occupancy patterns [Paper]



Side note

- *Smart sensors use energy, energy savings have to be higher than the consumption of energy consumed by all sensors. One has to be aware of security and privacy risks as well.* ← ***potentially interest research area***



e.g. transfer climate solutions across cities (from Global North to Global South) by clustering cities based on climate-relevant factors. [Paper

Farms & Forests

- Land use responsible for ~1/4 of greenhouse gas emissions
- Machine Learning can help reduce the carbon footprint by:
  - ↓ enhancing precision agriculture
  - ↓ protecting peatlands
  - ↓ estimating forest carbon stock
  - ↓ enabling automated afforestation
  - ↓ helping with forest fire management
  - ↓ tracking deforestation

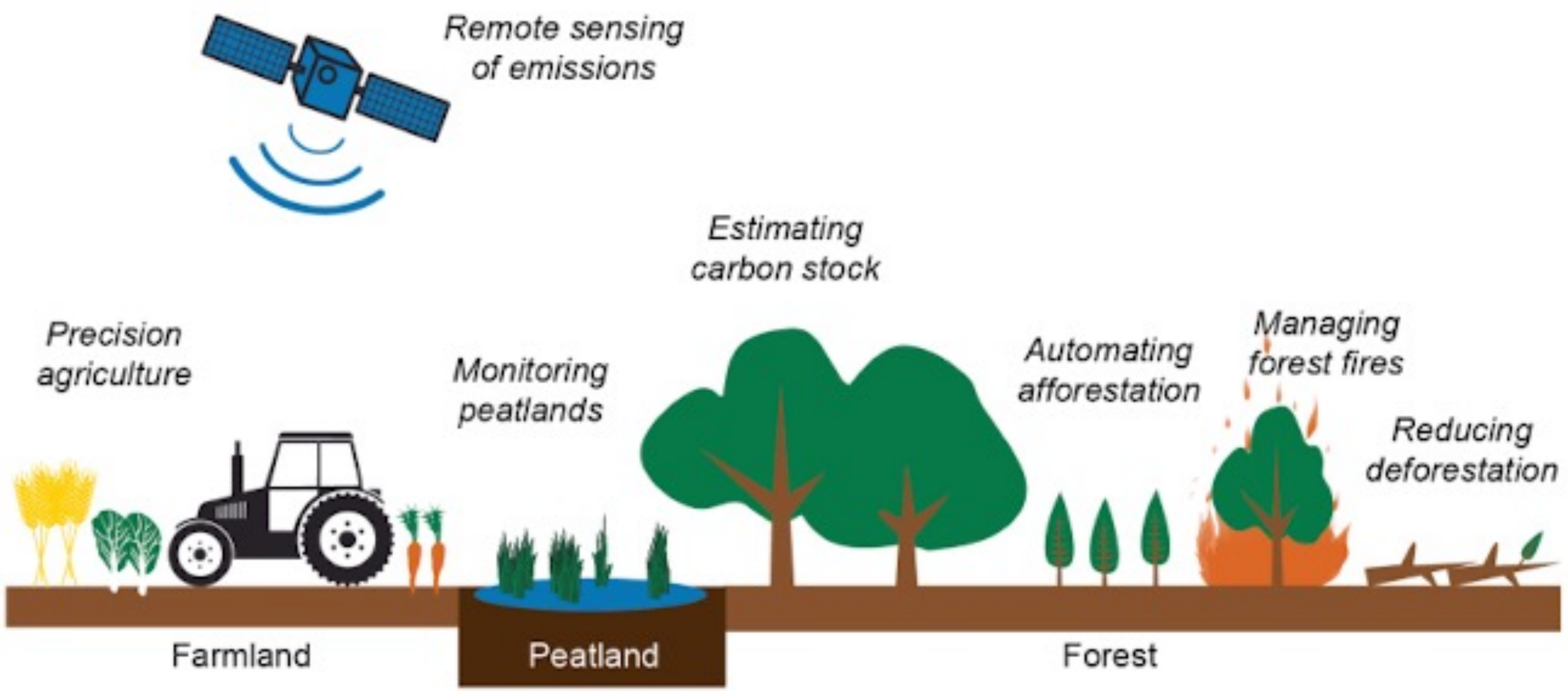
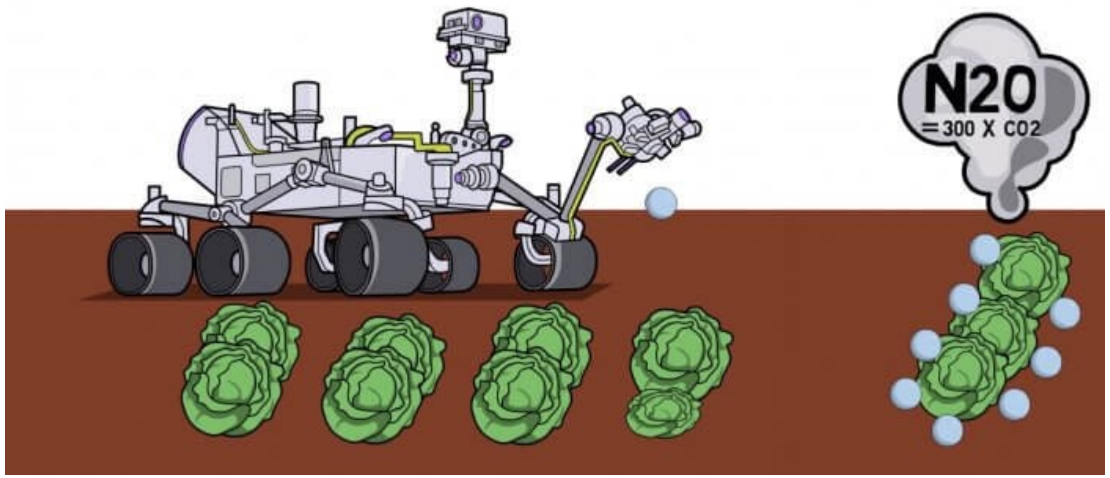


Figure 5: Selected strategies to mitigate GHG emissions from land use using machine learning.

e.g. Enhancing precision agriculture

ML can help:

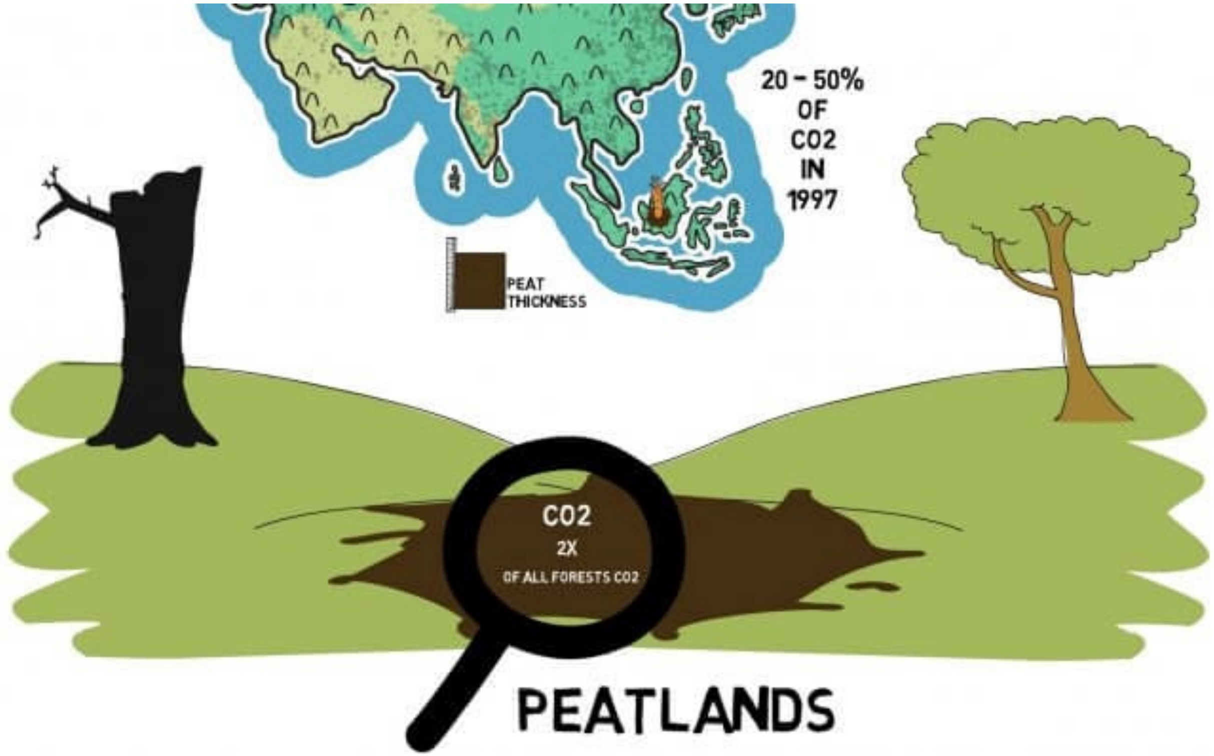
- predict crop yield [Paper] [Paper]
- detect plant diseases [Paper]
- sense soil
  - e.g. for levels of nitrogen, water, carbon, texture and mineralogy [Paper]
- Only apply fertilizers to plants that need it [*Paper*]



e.g. Protecting peatlands

- Peatlands cover only 3% of Earth's land area, yet they hold twice as much carbon as all the world's forests combined (which cover ~30%).
  - A single peat fire in Indonesia in 1997 caused between 20% and 50% of all emissions of that year.

- **E.g.** ML can help protect peatlands by monitoring them, estimating peat thickness and predicting risks of fire [Paper techniques]



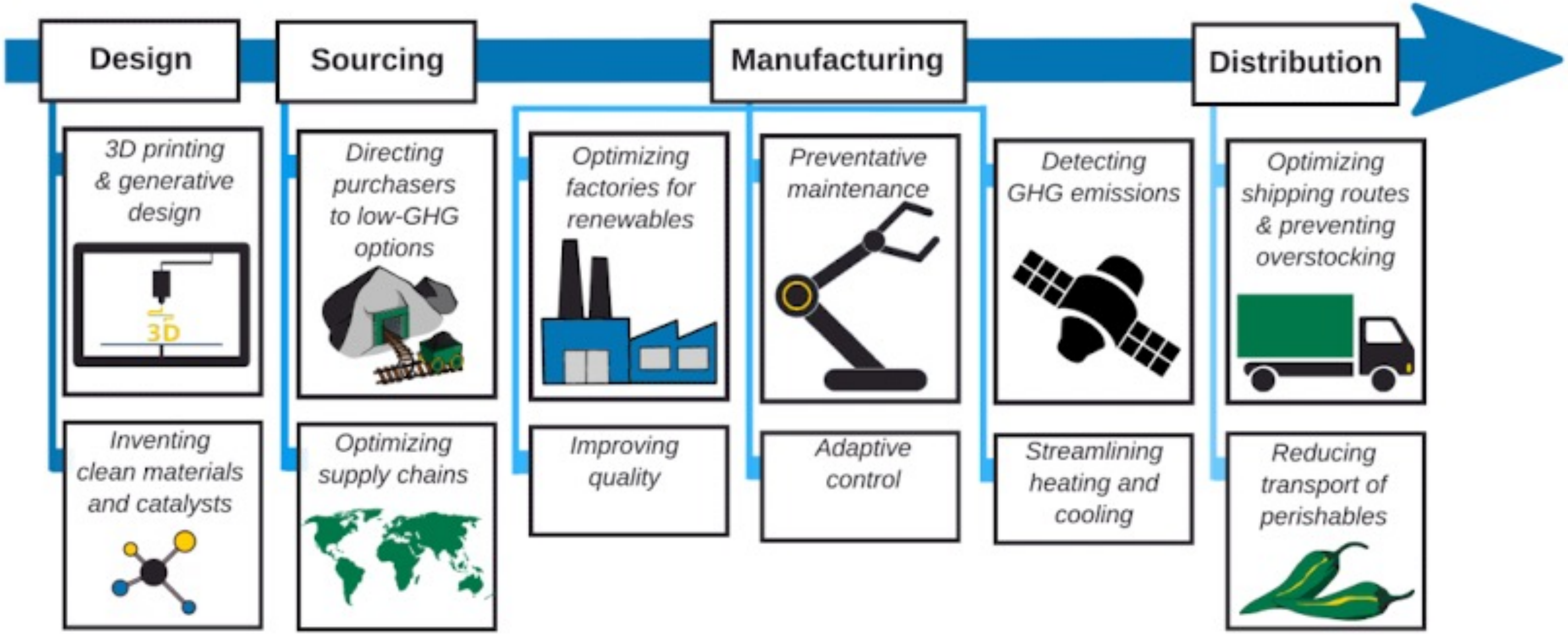
e.g. Helping with forest fire management

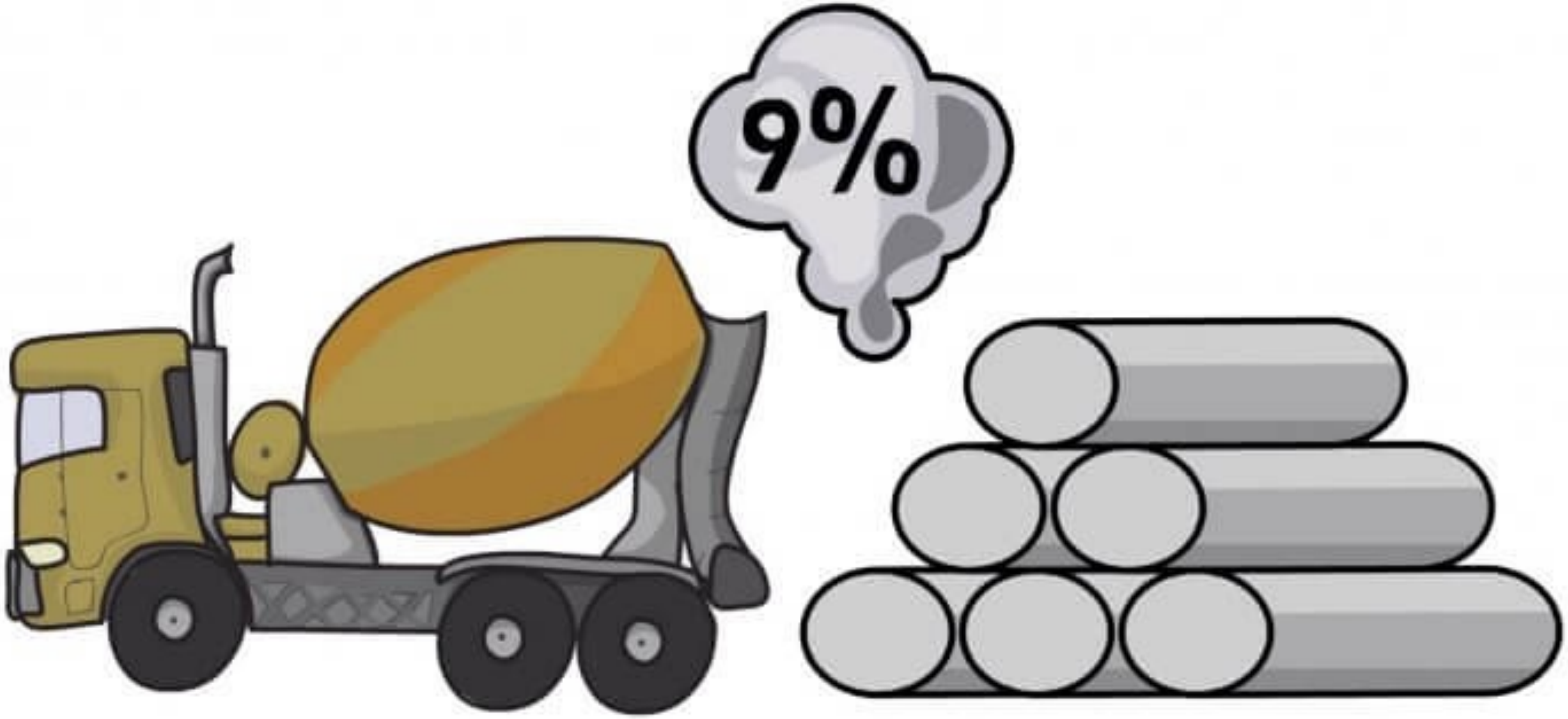
ML can help:

- forecast droughts which helps to locate forests at risk [Paper]
- predict spatial progression of fires [Paper]

Industry & carbon dioxide removal

- Machine Learning can help reduce the carbon footprint by:
  - ↓ reducing waste in supply chains
  - ↓ reducing material by inventing new constructions
  - ↓ reducing factory energy consumption





CEMENT & STEEL PRODUCTION

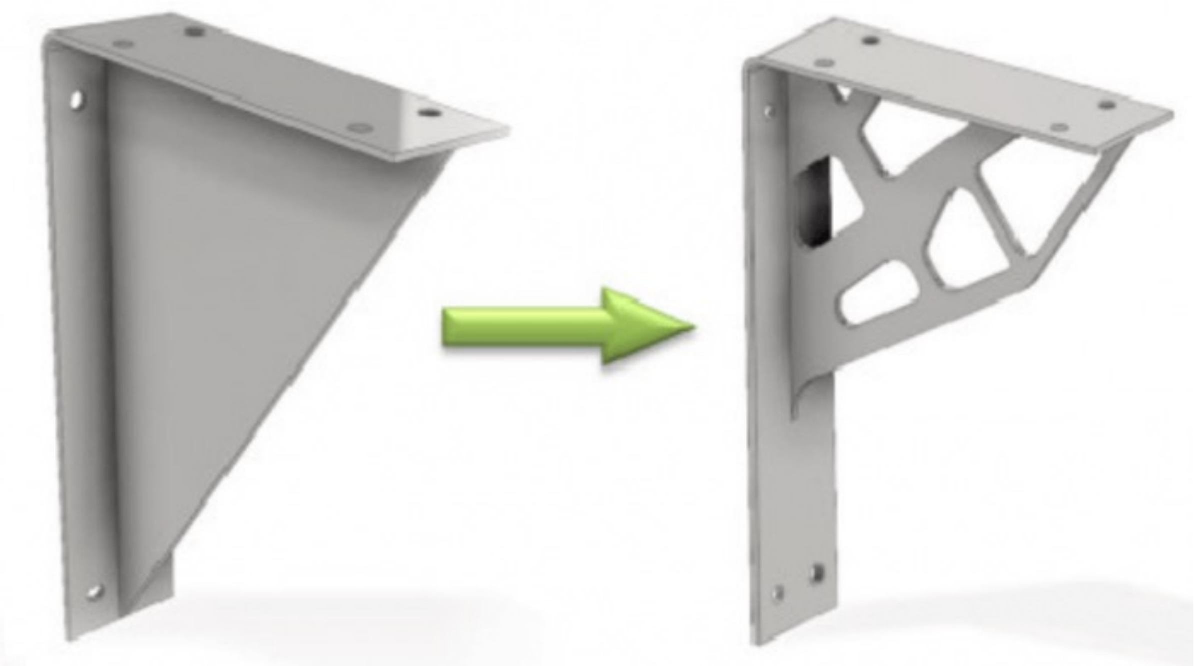
e.g. Reducing material by inventing new constructions

ML can help

- develop structural products that require less raw material [Paper – Generative Design]

- improve simulation of the physical processes of 3D printing [Paper]

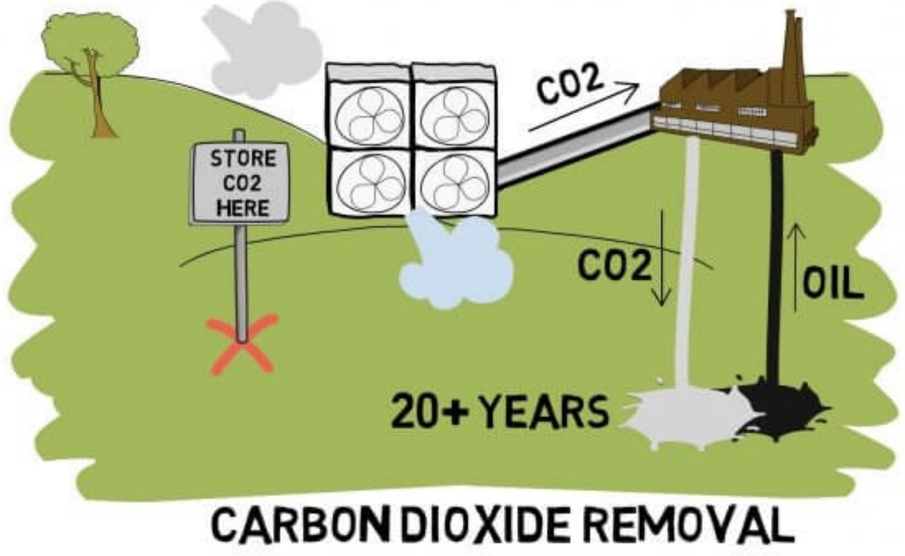
- push materials science for low-carbon concrete / steel,



Carbon Dioxide Removal

ML can help

- identify and characterize potential storage locations [Paper]
- monitor and maintain active sequestration sites and help with simulations [Paper]
- monitor potential CO2 leaks from wells [Paper]

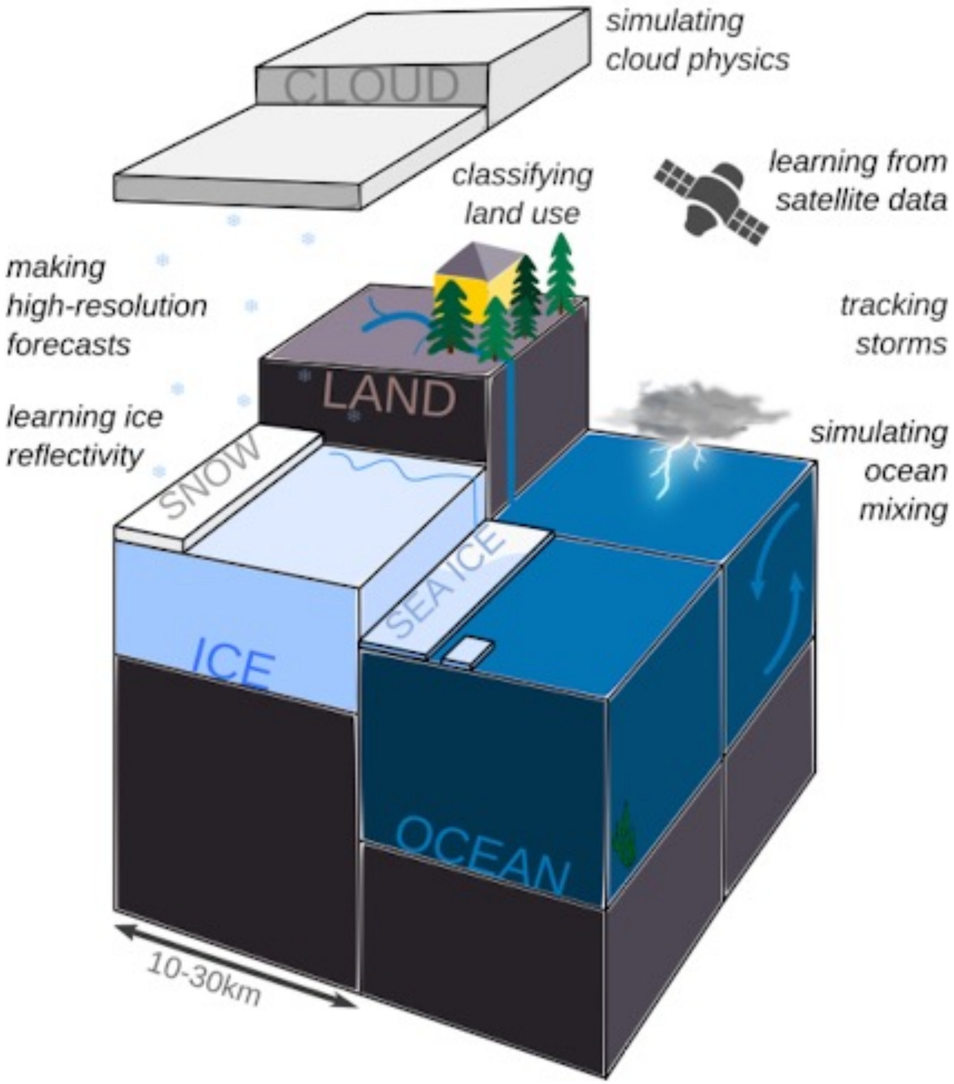


e.g. Norwegian oil company has successfully sequestered CO2 from an offshore natural gas field underground for more than twenty years.

Climate Modeling

ML can help:

- Extract relevant info from satellite data
- Speed up climate models
  - Especially for clouds
- Forecast extreme events



Roadmap for ML for climate change

For those who want to apply ML to climate change, we provide a roadmap:

- **Learn.** Identify how your skills may be useful – we hope this paper is a starting point.
- **Collaborate.** Find collaborators, who may be researchers, entrepreneurs, established companies, or policy makers. Every domain discussed here has experts who understand its opportunities and pitfalls, even if they do not necessarily understand ML.
- **Listen.** Listen to what your collaborators and other stakeholders say is needed. Groundbreaking technologies have an impact, but so do well-constructed solutions to mundane problems.
- **Deploy.** Ensure that your work is deployed where its impact can be realized.

Note! This is a very comprehensive paper, but there are many areas not discussed.

- E.g. ocean floors are one of the most carbon rich ecosystems
  - Recent research indicates that certain fishing practices (bottom trawling) emit between 0.52-1.47 billion metric tons of CO_2 each year.
    - As a reference point, global air travel—responsible for ~2 percent of the global CO_2 emissions—releases 0.9 billion tons of CO_2

Discussion break out

- Which areas from https://www.climatechange.ai/summaries are you interested in?
  - Do you have any ongoing projects in this area?
  - Would you be willing to present in this area in the future? ;)

Poll – which area for a deeper dive at the next meeting?

1. Electricity systems
2. Transportation
3. Buildings/Cities
4. Industry / Carbon Removal
5. Climate Prediction
6. Other, e.g:
   - Geoengineering
   - Societal impacts
   - etc

Awesome AI + Climate Change Papers

- **Meta project**: curate a Github repo of AI + Climate Change publications (contact Colorado if interested - cjrd@berkeley.edu)

ICML 2021 Workshop
Tackling Climate Change with Machine Learning

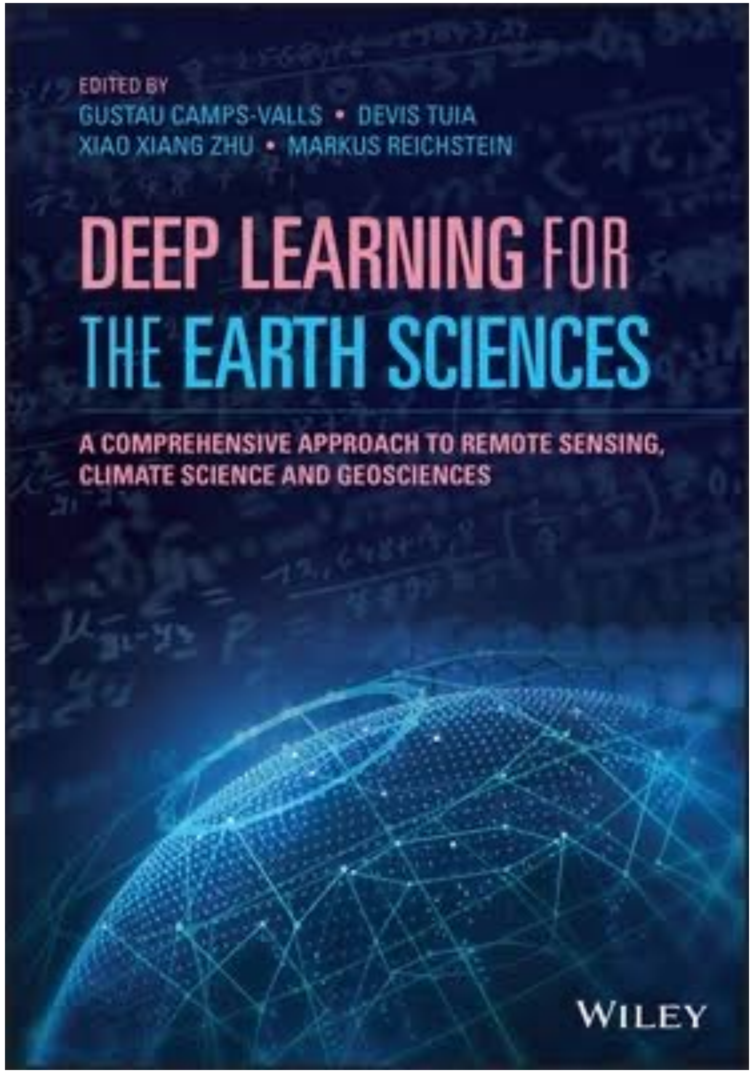
Announcements

- Applications for the mentorship program are now open! Mentors and mentees may apply until **April 28**. More information here.
- Access the recordings for our informational webinar here, where we answer questions about the mentorship program and how to prepare a successful submission for the workshop. More information here.
- The call for submissions of Papers or Proposals is available here. Submissions can be made here by **May 31**.

A few readings:

- Tackling climate change with machine learning
  (excellent blog post – many images and texts taken from here)
- Bret Victor's blog: What can a technologist do about climate change – 2015

Interesting book (end-of-year?)



Deep learning for the Earth Sciences: A comprehensive approach to remote sensing, climate science and geosciences
Camps-Valls

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