

Machine Learning and Climate

Reading Schedule (Tentative)

Template for each session:

Week	Topic	Readings
X	Session Title Climate topic(s). ▷ ML topics that pertain to climate topic(s) above.	<ul style="list-style-type: none">○ Climate-related reading○ ML-related reading○ (Additional readings, if necessary)

Last updated: November 1, 2023. Subject to change.

Please see the next page.

Week	Topic	Readings
1	Introduction The scale of the problem. ▷ Context and background.	<ul style="list-style-type: none"> ○ Kaack et al. [2022]
2	Biodiversity Forecasting biodiversity using regression. ▷ Predictive vs. causal models.	<ul style="list-style-type: none"> ○ Sirén et al. [2022] ○ Reference: [Pearl et al., 2016, Ch. 1,2]
3	Climate event attribution What causes heatwaves? ▷ Counterfactual analysis using data.	<ul style="list-style-type: none"> ○ Hannart et al. [2016] ○ Reference: [Pearl et al., 2016, Ch. 3]
4	Time series effects Earth system applications. ▷ Granger causality, structural causal discovery.	<ul style="list-style-type: none"> ○ Runge et al. [2019]
5	Monitoring emissions Tracking emissions from photographic imagery. ▷ Image processing, convolutional neural networks.	<ul style="list-style-type: none"> ○ Wang et al. [2020] ○ Vedaldi [2019]
6	Energy systems Power flow optimization ▷ Non-convex optimization with constraints.	<ul style="list-style-type: none"> ○ Donti and Kolter [2021] ○ Donti et al. [2021]
7	Policy Tackling climate change doubt; analyzing text-based patterns ▷ Topic modeling.	<ul style="list-style-type: none"> ○ Boussalis and Coan [2016] ○ Grimmer and Stewart [2013]
8	Urban planning Energy usage prediction, design for large systems. ▷ Gaussian process regression.	<ul style="list-style-type: none"> ○ Kolter and Ferreira [2011] ○ [Stan Development Team, 2021, Ch. 10]
9	Accelerating science Material science discovery, optimizing wind farm layouts. ▷ Bayesian optimization.	<ul style="list-style-type: none"> ○ Hellan et al. [2023] ○ Shahriari et al. [2015]
10	Manufacturing Data-driven manufacturing; optimization during production. ▷ Bayesian optimization.	<ul style="list-style-type: none"> ○ Attia et al. [2020] ○ Shahriari et al. [2015]
11	Computational material science New materials for climate change mitigation applications. ▷ Diffusion models	<ul style="list-style-type: none"> ○ Düreth et al. [2023] ○ Luo [2022]
12	Aligning ML and Climate ML's own carbon footprint; how to quantify and mitigate.	<ul style="list-style-type: none"> ○ Strubell et al. [2020] ○ Lacoste et al. [2019] ○ Henderson et al. [2020] ○ Luccioni and Hernandez-Garcia [2023]
13	Final presentations Projects.	

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