Machine learning for geographically differentiated climate change mitigation

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Abstract

Artificial intelligence (AI) and Machine learning (ML) promise to transform climate change research. However, climate change academics are only slowly taking up methods and insights from ML. Here, we perform a systematic bibliographic review of applied ML studies that are of relevance for climate change mitigation, focusing on spatial data and specifically on the fields of remote sensing, transport, and buildings. We find a rich body of twenty years of literature that is exponentially growing. Our review identifies crucial avenues for upscaling solution-oriented research at a high spatial resolution, and for delivering globally consistent comparative policy solutions that respect local differences. In the outlook, we suggest a meta-algorithmic architecture and framework that uses ML to optimize urban planning for accelerating, improving and transforming urban infrastructure provisioning.

1. Introduction

Climate change mitigation research provides a refined set of methods to serve as a reference for governments, for instance by simulating multiple socially optimal decarbonization pathways consistent both with global average temperature stabilization targets and stylized societal or environmental constraints (IPCC, 2018). Yet, important disagreements remain when quantifying mitigation potential, especially for energy end-use and for spatially explicit settings and geographies (Creutzig et al., 2016). The emergence of big data and artificial intelligence methods offers climate solution research to overcome generic recommendations and provide policy solutions at urban, street, building and household scale, adapted to specific contexts, but scalable to global mitigation potentials.

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Based on research queries in Web of Science and following reporting standards in evidence syntheses (Haddaway & Macura, 2018), we find few research papers relying on ML methods to explicitly tackle climate change mitigation. However, there are more than 10 times more sector-specific studies that either address greenhouse gas emissions or energy use directly, or offer important intermediary material while not making the link to relevant metrics explicit. Specifically, we identified 121 publications for climate change mitigation, 1,120 for buildings, 1,705 for transportation and 8,824 for remote sensing. An overview of the most prevalence classes of applications and algorithms retrieved is presented on Fig. 1.

2. Review: Towards generating mitigation-relevant digital twins

We argue that ML methods have the potential to transforming climate mitigation research by generating highly accurate digital twins of humans systems. A digital twin is a virtual replication of physical entities that enables to simulate their behaviors, e.g. for real-time optimization or predictive maintenance. Originally developed for manufacturing applications, digital twins have been a disruptive technology in various sectors and could address the lack of spatial context in mitigation studies. We take here the example of urban systems, mitigation-relevant digital twins of cities could build on the following components.

Human infrastructures observed from big data Infrastructures are the physical basis of human societies and are a first-order component to analyse their metabolism. Here, remote sensing enables the geometric (2D to 3D) and semantic (usage, physical properties) reconstruction of infrastructures e.g. the building stock (Esch et al., 2017; Blaha et al., 2016); it helps identify spatial patterns of CO_2 emissions (Tao et al., 2014) and deploy mitigation technologies (Yu et al., 2018). Making sense of mobility flows provides fundamental information on the structure of cities (Zhao et al., 2016).

Individual efficiency Individual infrastructural components determine the efficiency of the urban system (Gershenfeld et al., 2010) and have been subject to more precise modelling at small scale. ML enable to make sense of the complex electricity use data in buildings (Kelly & Knottenbelt, 2015) and to optimize devices (Wang et al., 2017). Reducing inefficacies in driving offers marginal emissions reduction (Magaña & Muñoz-Organero, 2015). To upscale studies' spatial relevance, transfers of knowledge from data-rich to data-scarce contexts are key (Mocanu et al., 2016).

Human behaviors and perceptions Dwellers' choices ultimately determine activity levels and resulting emissions (Creutzig et al., 2018). ML helps investigate how psychological features, e.g. acceptance of novelty (Carr-Cornish et al., 2011), are relevant to target interventions. Other studies develop heuristic models of behavioral triggers and resistances to more energy-efficient lifestyles (Gabe-Thomas et al., 2016). To understand mode choices and foster modal shifts, ML has been applied in discrete choice models (Yang et al., 2018), for instance for modelling car ownership.

Planning & management A last holistic layer with strong potential is to re-plan the infrastructure in order to frame future behaviors. ML can also support the reduction of carbon intensity in land transport by support the development of low carbon modes, for example the deployment of electric vehicles (Longo et al., 2017) or shared bicycles (Xu et al., 2018). A handful of studies have targeted urban planning, investigating the effect of urban form and built-in on travel behavior (Monajem & Nosratian, 2015).

3. Outlook: Machine Learning for urban planning

We see three main limitations for applying the surveyed literature for geographically-differentiated climate change mitigation: (*i*) a predominant focus on behavioral models and business applications congruent with social risks of surveillance; (*ii*) a counterfactual lack of public policy analysis; (*iii*) a resulting large dominance of utilizing ML for efficient use of existing infrastructure compared to other mitigation levers.

In turn, we claim there is a need for more studies where robust and long-term mitigation potential is found: in urban spatial configurations. Spatial settings can offer low-carbon transport systems, with reduced distance, and more energy efficient transport modes, if connectivity is high, land-use is mixed, and structures are compact.

High resolution scenario prediction for sustainability outcomes An AI Infrastructure for low-carbon Urban Planning (AI-UP) could address two of the main challenges towards providing planning scenarios at high spatial and contextual resolution: (*1*) mining high-resolution energy or emission data to generate digital twins of cities metabolism, (*2*) pinpointing from data and models concrete solutions to simulate mitigation pathways. The workflow and an example application are depicted on Fig. 2.

(*1*) *Digital twin of cities' metabolism.* A central hypothesis is that mitigation semantics can be extracted from features of urban activities and form[1]. One route is then to train spatial data (remote sensing, mobility patterns, etc) with spatialized energy use (Silva et al., 2017). An alternative route is to predict intermediate metrics and use back-end modelling (Feygin & Pozdnoukhov, 2018).

(*2*) *Climate solutions informed by data*. Urban environments are unstable and policy responses differ with context, which requires to account dynamically for changes in relevant interacting dimensions. A third block of AI-UP focuses on action-oriented prospective predictions, making use of scenario techniques (Silva et al., 2018) and advances in causal inference research (Burlig et al., 2017).

Governance implications The outlined AI infrastructure for low-carbon urban planning can enable more agile and rapid deployment of effective solution strategies in all human settlements.

Restructuring the global solution space. Generating models of climate mitigation solutions at high spatial resolution will transform global environmental assessments, such as those of the IPCC. Instead of providing long-term scenarios, and abstract policy suggestions, place-specific solution strategies can be compared and evaluated.

Empowering urban policy makers. With data and learning across municipal jurisdiction, the AI-UP empowers policy makers also of smaller and mid-sized cities to advance data-science supported strategies. AI-assisted typologies and synthesis of cases studies together could greatly help answer this challenge (Lamb et al., 2019; Creutzig et al., 2015).

Focusing on developing countries. AI-UP will have the highest value in developing countries and small resources for bottom-up policy modelling. Cities in developing countries with rapid population growth and urbanization are a priority for mitigation strategies. AI-UP could partially level the playing field between rich and poor jurisdiction by predicting key missing socio-economic data (Jean et al., 2016).

4. Conclusion

AI can profoundly transform climate change mitigation by transcending the generic output of global mitigation scenarios, and breaking down solutions strategies building by building, and street by street worldwide. All main classes of ML algorithms have been explored already on relevant spatial issues, from micro to macro scale, and on various problems (behaviors, stocks...)—there is a strong potential from a further integration in 'digital twins of cities'.

[1]Urban form include density, land use mix, connectivity and accessibility; they have been related to the energy use from transportation and buildings (Silva et al., 2018).

	Deep Learning	Shallow neural networks	Decision trees	Support Vector Learning	Others Clas./Reg.	Recurrent neural networks	Reinforcement learning	Clustering	Dimensionality reduction	ML not defined
Climate change mitigation *n=121*										
Agriculture	0	1	5	0	0	0	0	1	1	0
Soil	0	2	10	2	0	0	0	2	1	2
Cities	0	8	1	3	1	0	0	0	1	1
Forest and Biomass	0	6	21	4	1	0	1	1	4	4
Energy	0	8	2	4	0	0	1	3	2	1
Human behavior	0	0	1	0	0	0	0	1	3	1
Macro-scale	0	6	0	3	1	0	0	4	0	2
Remote sensing *n=8824*										
Air	35	228	146	114	40	5	6	51	94	21
Biomass	118	1069	1778	1076	202	17	39	233	696	82
Carbon	2	103	171	62	16	2	5	18	60	16
Earth surface	16	388	304	231	35	2	5	54	204	23
Impervious/Built-up	120	395	410	471	126	7	17	120	195	52
Water	37	797	483	403	62	6	23	116	354	51
Others	394	707	38	784	362	28	36	321	730	92
Buildings *n=1120*										
Building sub-system	10	189	23	38	13	3	47	17	37	42
Whole building	10	247	33	60	27	7	7	12	26	9
Environmental factors	1	43	5	12	1	0	1	3	3	2
Medium scale	2	70	25	17	8	1	8	15	10	8
Large scale	2	57	18	12	3	1	3	9	3	6
Human factor	1	35	10	17	8	3	15	11	10	15
Urban transportation *n=1705*										
Mobility patterns	8	28	27	13	13	7	30	45	20	17
Road traffic optimization	45	228	35	62	40	27	86	42	25	46
Public transport opt.	8	77	21	30	11	0	13	21	17	9
Travel behavior	1	35	30	9	3	1	21	4	5	7
Low carbon mobility	2	17	5	1	2	2	13	12	4	7
Planning	0	28	9	5	1	0	2	16	13	3
Others	60	203	61	102	48	7	41	57	71	50

Artificial intelligence method class

Figure 1. Summary of machine learning methods reviewed. AI has not been widely applied to explicit climate change mitigation studiesbut other relevant fields, especially remote sensing, display a considerable literature already. Supervised learning tasks (columns 1 to 6) are the most frequent applications in all fields. The information was extracted from the publicly available metadata of the records; Machine Learning not defined corresponds to no specific method available from the metadata. When several groups of methods are used in a record (e.g. dimensionality reduction and supervised learning), the record is counted in both categories.

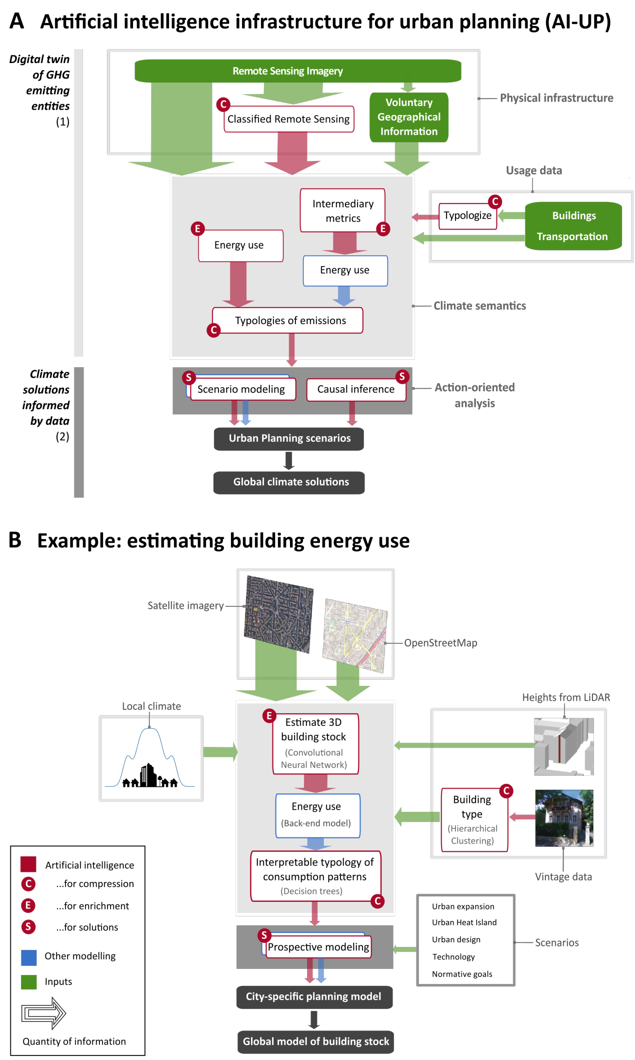

Figure 2. An architecture of Artificial Intelligence for Urban Planning (AI-UP). (**A**) depicts an information flow from big data to semantically relevant data for climate change mitigation-oriented urban planning. The data can be processed by a succession of different phases including AI and other media. (**B**) shows an example workflow for estimating energy use of individual buildings at large scale. Spatial data available at large scale are trained with precisely metered building data.

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