Low-carbon urban planning with machine learning

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Abstract

Widespread climate action is urgently needed, but current solutions do not account enough for local differences. Here, we take the example of cities to point to the potential of machine learning (ML) for generating at scale high-resolution information on energy use and greenhouse gas (GHG) emissions, and make this information actionable for concrete solutions. We map the existing relevant ML literature and articulate ML methods that can make sense of spatial data for climate solutions in cities. Machine learning has the potential to find solutions that are tailored for each settlement, and transfer solutions across the world.

1. Introduction

Climate change mitigation research provides a refined set of methods whose outcomes serve as a reference for governments and individuals for climate action, e.g. by simulating portfolios of decarbonization pathways consistent both with global average temperature stabilization targets and stylized societal or environmental constraints (IPCC, 2018). Yet, large disagreements remain about mitigation potentials, e.g. for energy end-uses (Creutzig et al., 2019). The emergence of big data and ML methods offers climate solution research to overcome generic recommendations and provide options at urban, street, building scale, adapted to specific contexts, but scalable to global mitigation potentials.

We conduct a systematic review of applied ML studies that use on spatial data for mitigating climate change in cities. Specifically, we survey the fields of remote sensing, transport, and buildings. Based on research queries in Web of Science, and following reporting standards for 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 ten times more sector-specific studies that either address GHG emissions or energy use directly, or offer important intermediary material while not making the link to energy use and emissions explicit. For an overview of the most prevalent topics and methods retrieved, see Fig. 2.

2. Digital twins of cities' metabolism

We argue that ML methods have the potential to transform climate mitigation research by generating digital twins[1] of cities' metabolism[2]. Such models would connect together urban structure and activities influencing energy use and GHG emissions (see Fig. 1). A central hypothesis is that city metabolism can be predicted from the former city characteristics, if high resolution data is integrated (Silva et al., 2018; 2017; Creutzig et al., 2016; Zheng et al., 2014). We first detail current ML methods that can generate knowledge on urban structures and activities relevant to city metabolism.

Infrastructures observed from big data. Infrastructures are the physical basis of cities. They are a first-order component to analyse city metabolism, and predict localized energy or emissions patterns. Many data sources are available, from remote sensing to city sensors; but this data is often incomplete and the link with cities' metabolism is rarely made. ML can retrieve information to model infrastructures (Esch et al., 2017; Blaha et al., 2016) or mobility flows (Zhao et al., 2016) at fine grain. This knowledge enables the determination of spatial patterns of CO_2 emissions (Tao et al., 2014) and deployment strategies for mitigation technologies (Yu et al., 2018).

Technological efficiency. Individual technological components determine the efficiency of the urban metabolism (Gershenfeld et al., 2010). Technologies have been subject to more precise modelling at small scale using ML. In

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[1]*Digital twins* are virtual replications 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 could address the lack of spatial context in mitigation studies. Note that highly simplified twins may be sufficient here, while reducing storage and computation needs.

[2]*City metabolism* refers to energy use and GHG emissions in cities, but can also include other flows like materials and wastes.

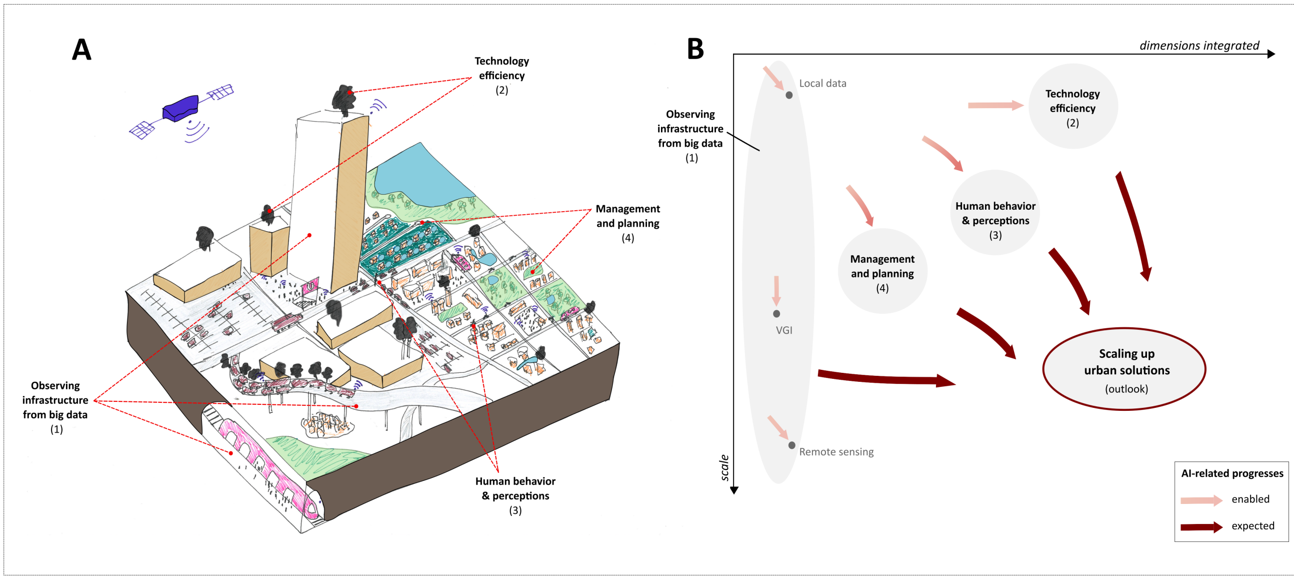

Figure 1. Towards digital twins of cities' metabolism. (**A**) Main components of machine learning research on urban spaces relevant to climate change mitigation. Data sensed in the physical world and processed by ML enables to model and predict cities infrastructures and activities, assess at fine-grain their metabolism, and model different future pathways towards low-carbon societies. (**B**) Integrating ML studies on cities has the potential to scale up of urban solutions. (VGI: Voluntary Geographical Information)

buildings, ML helps understand load signals (Kelly & Knottenbelt, 2015) and optimize devices or system, e.g. cooling (Wang et al., 2017). For efficient mobility, ML can identify ineffecacies in driving (Magaña & Muñoz-Organero, 2015). However, these studies are often idiosyncratic. Transfer learning can upscale their spatial relevance (Mocanu et al., 2016). Linking these methods with infrastructure models could improve district-scale efficiency projects.

Human behaviors and perceptions. Dwellers' choices ultimately determine activity levels and resulting emissions (Creutzig et al., 2018). ML helps target interventions through behavioral models of: acceptance of novelty (Carr-Cornish et al., 2011), triggers and resistances to more energy-efficient lifestyles (Gabe-Thomas et al., 2016), or mobility mode choices and shifts (Yang et al., 2018). Within digital twins, modelling human behaviors can help identify dynamic feedbacks: for example, infrastructure provision (such as bike lanes) can foster changes in mobility choices.

Planning & management. A last holistic layer is to modify the infrastructure in order to frame future usages. For example, 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. A handful of studies have targeted urban planning, e.g. linking urban form and travel behavior (Ding et al., 2018). ML also supports the deployment of low carbon modes, e.g electric vehicles (Longo et al., 2017) or shared bikes (Xu et al., 2018).

3. Climate solutions from spatial settings

We find that a main limitation of the surveyed literature is the dominance of utilizing ML for optimizing current usages, which can lead to substantial rebound effects (Azevedo, 2014). In turn, we argue for greater focus on where robust and long-term mitigation potential is found: in spatial configurations and policy options that can shape them.

Our proposed architecture of ML for low-carbon Urban Planning could help progress towards planning scenarios at high spatial and contextual resolution. Our workflow is two-fold (see Fig. 3). First, it would aim at integrating high-resolution data to generate climate semantics. Relevant ML here includes supervised learning for inferring missing data, and typology methods that identify informative patterns (Creutzig et al., 2015). This stage would provide the base of the digital twin. Second, an action-oriented block would focus on making sense of this data to find policy options. Methods include scenario techniques to simulate development pathways, reinforcement learning to model local interactions and causal inference can assess the success of policies.

Such an architecture could stimulate more agile and rapid deployment of effective solution strategies in human settlements. First, it could transform environmental assessments like the IPCC. Second, it would help policy makers implement municipal climate action. Third, it could have the highest value in developing countries with low resources.

	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

Classes of machine learning methods

Figure 2. Summary of machine learning methods reviewed. Remote sensing, and to lesser degree, spatial studies in mobility and buildings, rely on ML methods, while climate change mitigation studies only scarcely build on ML methods. 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 is reported when there is 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.

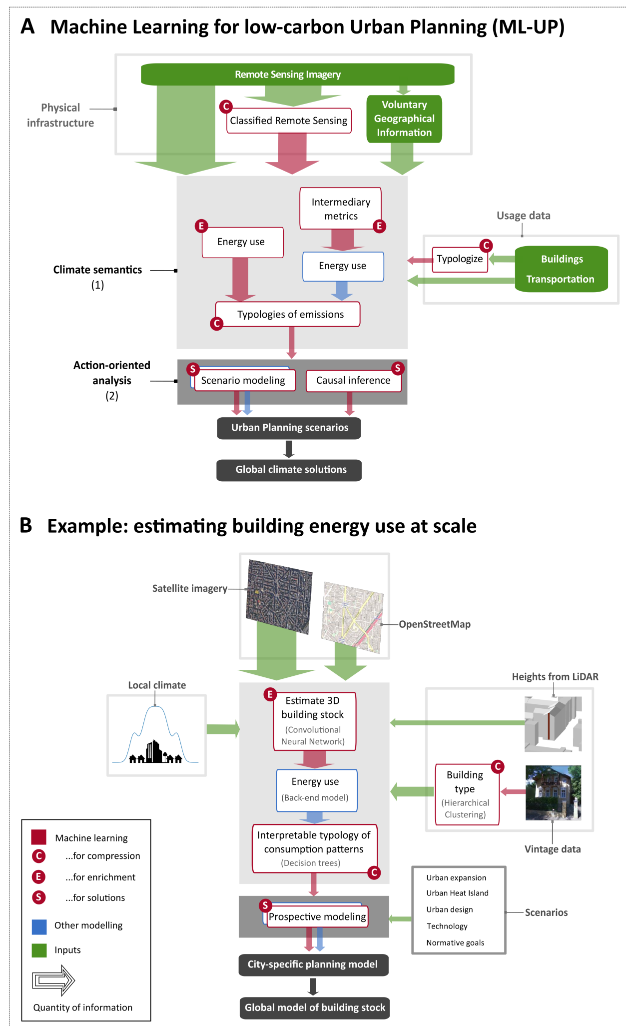

Figure 3. An architecture of machine learning for low-carbon urban planning. (**A**) The architecture is an information flow from big data to semantically relevant data for climate change mitigation-oriented urban planning. The data can be processed by a succession of different phases including ML and other media. (**B**) 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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