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A machine-learning model for the prediction of aggregated building heating demand from pan-European land-use maps

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Abstract. Aggregated building energy demand is a useful indicator for urban energy planning. It can be used by planners and decision-makers to identify clusters of high energy demand in a given urban area and efficiently plan, for example, district heating networks. Various data sources exist at the pan-European level describing land use and built areas. Combined with statistical data, such maps have been used in previous research for estimating building energy performance aggregated at the hectare level, using engineering assumptions. In this paper, we show that large-scale land-use maps alone can be used for predicting annual building energy demand with an accuracy comparable to the one of previous engineering models. We hence present a preliminary method based on Convolutional Neural Networks at different spatial resolutions. The resulting model was trained and tested in an area of about 170 km² in Geneva (Switzerland) using a local annual heating demand dataset comprising 16239 buildings. On a 300-m aggregation tile, the obtained mean error (14.3%) is significantly reduced compared to the one of a simple linear model (37.2%). Using solely land-use data, we also achieve similar results for a 100-m tile as those of an engineering model from the literature.

1. Introduction

The building sector accounted in 2018 for about 36% of the final energy use, which is the largest share among all end-use sectors [1]. Despite a global slight decrease in the latest years [1], in 2018 the demand for space heating still represented more than 50% of the residential energy consumption in selected IEA countries [2].

District energy planning is considered a key solution to provide neighborhoods with adequate low-carbon energy solutions [3], among which we can cite combined heat and power (CHP) plants, waste-to-energy plants and district heating and cooling networks (DHCNs).

In particular, Möller et al. [4] estimated that 71% of the heat demand in 14 EU Countries can be provided by District Heating Networks (DHN). Previous works have investigated the viability of such installations with regard to the heat density in urban areas. Urban areas are considered suitable for DHN with a heating density starting at 5 GWh/km² (50 MWh/ha) in the US, [5], 7 GWh/km² (70 MWh/ha) in selected EU countries, and 50 MJ/m² (14 MWh/ha) in the EU [6]. Even considering the expected decrease of heating demand in future scenarios, DHN are expected to remain competitive in high heat density areas [7].

Previous research focusing on district heating potential has applied different methods. Geiß et al. [8] used high-resolution remote sensing and GIS data for a case-study city in Germany



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to assess a number of suitability indicators for DHN to finally derive a energy-return-to-investment metric, while Gils [9] and Gils et al. [5] used a GIS-based model based on statistical data for continent-wide evaluations. However, these methods are based on country-specific features and/or a wide range of statistical datasets. Moreover, validation with measured data is conducted on closed-access data [8].

This work explores instead the application of machine learning with a single Europe-wide dataset, in a region of Switzerland where a reliable heating demand dataset is openly available. Convolutional Neural Networks (CNN) are deep-learning techniques widely used in computer-vision tasks such as image classification, detection, segmentation and super-resolution reconstruction [10], which are common problems in remote-sensing applications [11]. On this basis, the application of CNNs seems a novel, yet promising application for the mapping of aggregated building heating demand based on land-use maps.

2. Methodology

The work is conducted in the canton of Geneva (Switzerland). The area has been chosen for the presence of high-quality open data of the building heating demand, which are needed to train and test the model. Moreover, this area is particularly interesting due to its varied building morphology comprising both historical urban fabric and modern settlements.

2.1. Input datasets

Two main datasets have been used in this work:

a) the *European Settlement Map* (ESM) which is a set of georeferenced raster images mapping human settlements in Europe, mainly based on SPOT5 and SPOT6 satellite imagery [12]. The raster maps are composed of 8 classes at a 2.5-m resolution, with each class representing one land use, including Water, Railways, Green Areas and Built-Up areas. For full land-use classes description and methodology please refer to [12].

b) the *Geneva building performance* database (IDC) (*Indice de dépense de chaleur*, in French) which provides the weather-normalized annual heating demand at the building level granularity (expressed in MJ/m²), as well as other building attributes [13, *scane_indice_moyennes_3_ans*, 19.12.2020] for multiple years. All tabular attributes are provided as a georeferenced vector dataset, where the geometry attribute is the footprint of the building. In this work, we used the heating demand indicator for 2016, as it contained the most records.

ESM provides the model input, i.e., the images used as the model features, while IDC the labeled dataset with the output variable, i.e., the ground truth used to train, validate and test the model.

Another dataset has been used to prepare an additional layer (mask) for the ESM images, that is a raster Boolean mask indicating building footprints that are in BLD but not in IDC:

the *Geneva Building Footprint* dataset (BLD), which contains the vector geometry of the building footprints (as well as other information from the cadaster) [13, *cad_batiment_horsol*, 19.12.2020]. A shared key allows for join operations with IDC. Figure 2 shows a sample of ESM, IDC and BLD datasets.

For the comparison with the reference engineering model, we used the following datasets:

Hotmaps Heating Density (HD_{Hotmaps}) and *Heated Floor Area* (FloorArea_{Hotmaps}), which contain 100-m resolution rasters representing respectively the heating density (MWh/ha) [14, *heat_tot_curr_density*] and the heated floor area (m²/ha) [14, *gfa_tot_curr_density*] in 2015.

All datasets are available as open data, from the respective data providers. Instructions on how to retrieve them and reproduce the experiments are provided in the repository of the project (<http://github.com/enermaps/heatlearn>).

2.2. Data preparation

All datasets have been tiled to a reference grid, i.e., split into squared images of a fixed size where the center of each image is the center of each tile. Two main grids have been used in this work:

a) a regular fishnet grid of 50-m-wide tiles covering the extents of the Geneva Canton. This grid has been used to train the model with different tile resolutions including 100, 300 and 500-m-wide tiles. At all resolutions, the tiles are centered on the 50-m-wide tiles. This means that all tiles with a resolution higher than 50 m, as it is the case for all experiments presented here, are overlapped. Despite parts of the urban fabric being repeated in neighboring tiles, we consider that each tile is still substantially unique, as the prediction is conducted on the spatially-aggregated heating demand.

b) A sparse grid where the tile centers correspond to the non-null pixels in the HD_{Hotmaps} datasets [14]. This is used for the comparison with the Hotmaps model.

For the purposes of the model building, we split the samples into training, validation and testing sets using a 60-20-20% repartition. The training set has been augmented by flipping the original tiles both vertically and horizontally, hence increasing the dataset by a factor of 4, and shuffled. All input raster images were normalized to a $[0, 1]$ range.

Since the main datasets (ESM on the one side, and IDC and BLD on the other one) present several discrepancies notably due to different sources, methods and years of production, the samples have been filtered to exclude tiles (about 30%) not meeting the following conditions:

- $n_{IDC} \geq 0.40 \cdot n_{BLD}$
- $(CR_{ESM} - CR_{BLD})/CR_{BLD} \geq 2$
- $CR_{IDC} \geq 0.05$

where n_{IDC} is the number of buildings in IDC, n_{BLD} is the number of buildings in BLD and CR is the coverage ratio calculated as the n of pixels for the built-up class divided by the total number of pixels in the image.

An analysis of the tiles' building coverage ratio after the filtering shows that the diversity is substantially preserved, with the median value only slightly increasing from 42% to 47%.

2.3. Machine learning models

Some simple linear models are tested, using either directly the ESM images or the number of pixels of each ESM class as input features. The best performing model (a fifth-degree polynomial regression with Lasso) is then used as one of the two benchmarks model (the other being presented in 2.4).

We then implemented a Convolutional Neural Network (CNN) that takes images with two channels (ESM and the mask) as input, pass them through 4 convolutional blocks (with 16, 32, 64 and 64 filters respectively), two hidden layers with 64 neurons each, and a final linear activation layer to predict a single continuous value. Each convolutional block contains a 2D convolutional layer, a 2D maxpooling layer and a batch normalization layer. Three models were trained with this architecture, for 100-m, 300-m and 500-m tiles respectively. In all cases, the predicted value is the absolute heating demand (from IDC) of the whole input tile.

We finally implemented another CNN (called CNN_{context-aware}) with two parallel convolution sequences, one passing only the central part of the tile (100-m-wide) and another one passing the entire input tile (300-m-wide). This is meant to predict the heating demand on the 100-m-wide tile, while using a larger context as input.

For all models, we used the absolute percentage error as the loss function.

2.4. Comparison with the engineering model

In order to be able to compare the results of the models with Hotmaps, the $HD_{Hotmaps_{adjusted}}$ is calculated for each tile t_{100} :

$$HD_{Hotmaps_{adjusted}} = HD_{Hotmaps} \cdot HDDcoeff_{2015} \cdot \frac{FloorArea_{IDC}}{FloorArea_{Hotmaps}} \quad (1)$$

where $HD_{Hotmaps}$ is the aggregated building heating demand taken from the Hotmaps dataset for 2015, $HDDcoeff_{2015}$ is the heating degree day coefficient for 2015 and $FloorArea_{IDC}$ is the sum of the heated floor area.

This corresponds to adjusting the original $HD_{Hotmaps}$ dataset for the weather in 2015, i.e., obtaining a weather-independent values, and for the building floor area that is actually in IDC, which is usually smaller because of the missing buildings.

It should be noted that the Hotmaps model [14] is produced with different data sources (including ESM), unlike our approach solely based on ESM data.

3. Results

Table 1 and Figure 1 summarize the results of all experiments.

The application of the CNN model largely reduces the error compared to the baseline linear model, with the mean absolute error decreasing from 37% to 13% and a substantial reduction of the variance.

The study conducted at different tile resolutions shows an improvement with increasing tile size, with a mean error of 6.6% for a 500-m resolution. This is intuitively due to the larger context provided to the model that allows for better estimations and to the lower impact of high errors on single buildings in a larger tile.

The context-aware model shows an improvement over the standard CNN of about 9 percentage points (mean error). Errors up to +581% are still present (see also Figure 2), which are in line, though, with the ones of the Hotmaps model.

A sample application can be seen in Figure 2, where results intuitively confirm the potential of a district heating network in dense urban areas such as the one of Geneva.

Table 1: Absolute Percentage Error of the different models and resolutions. The proposed CNN-based models show significant improvements over the linear model and comparable results with the Hotmaps model, while with less inputs that the latter. Note that the comparison between $CNN_{context-aware}$ and Hotmaps is conducted on a different test set than the other experiments.

	Linear	CNN	CNN	CNN	$CNN_{context-aware}$	Hotmaps
	300 m	100 m	300 m	500 m	100 m	100 m
Median	14.3%	34.7%	9.4%	5.2%	28.1%	15.8%
Mean	37.2%	42.4%	13.4%	6.6%	33.7%	28.4%
STD	122.4%	49.3%	16.1%	6.6%	30.5%	50.9%

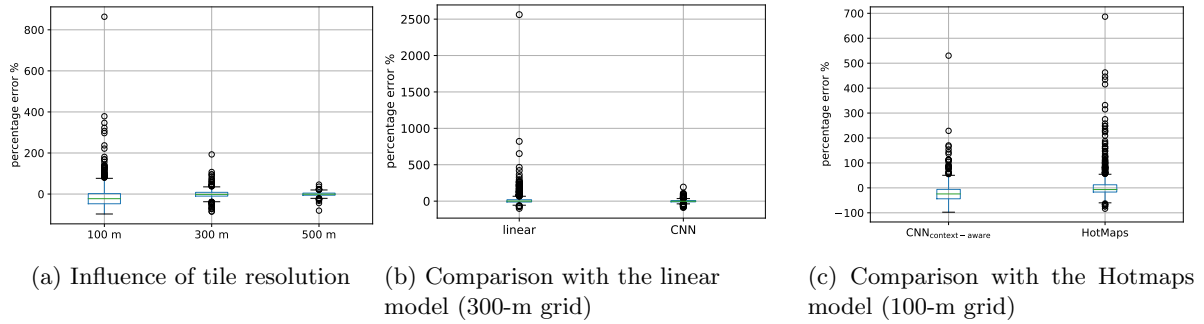


Figure 1: Relative percentage error of the proposed CNN models at various resolutions (a) and comparison with the reference models (b, c). See note on Table 1.

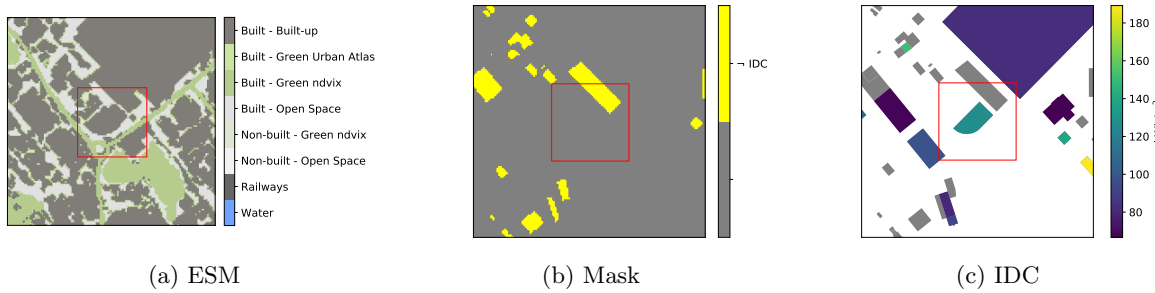


Figure 2: Case of the max error (+581%) for the $\text{CNN}_{\text{context-aware}}$ model. In red, the target 100-m tile. The specific industrial depot end-use, difference between raster (a) and vector-based datasets (b, c) are likely to cause over-prediction.

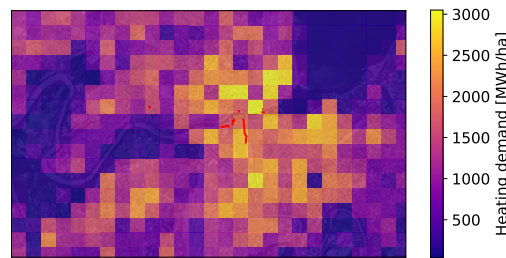


Figure 3: Results of prediction on a 300-m grid over in the Canton of Geneva. In red, current DHNs [13, *ctss_chauffage_conduite*, 03.04.2021], background image: SWISSIMAGE25.

4. Discussion

The present work is only a preliminary study on the development of a predictive model for aggregated building heating demand. Future work should focus on the context-aware model, which is required to have better performance on 100-m-wide tiles, i.e., the standard resolution of equivalent models.

Alternative models might be developed based on remote-sensing imagery. However, such

high-resolution datasets are usually available with restricted access, whereas we wanted the model to be accessible via an open-data platform. The integration in a web mapping platform is in fact currently under development for the EU-funded EnerMaps project, which will allow for an intuitive large-scale application of the model.

A model trained on additional datasets similar to IDC would be a valuable resource to promote the use of the model in other urban contexts and climates.

5. Conclusions

This paper presented a machine-learning method for the prediction of aggregated building heating demand using solely land-use open-data provided by the European Settlement Map (ESM). Compared to the reference engineering model, the proposed context-aware CNN has a comparable level of accuracy in determining the building performance without relying on statistical data. We have also seen that CNN significantly improves the performance of the baseline linear model and achieves error rates of about 6% for a 500-m resolution.

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