Mercator Research Institute on
Global Commons and Climate Change gGmbH

Estimating energy demand of buildings…
by learning their heights

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1. Infrastructure data in OSM are of high relevance for the sustainability science community.

2. Currently, OSM offers limited coverage of the features that most influence a building’s energy use – e.g. the height.

3. Machine learning could predict these features at scale.

Infrastructure frames energy demand in cities

Mobility

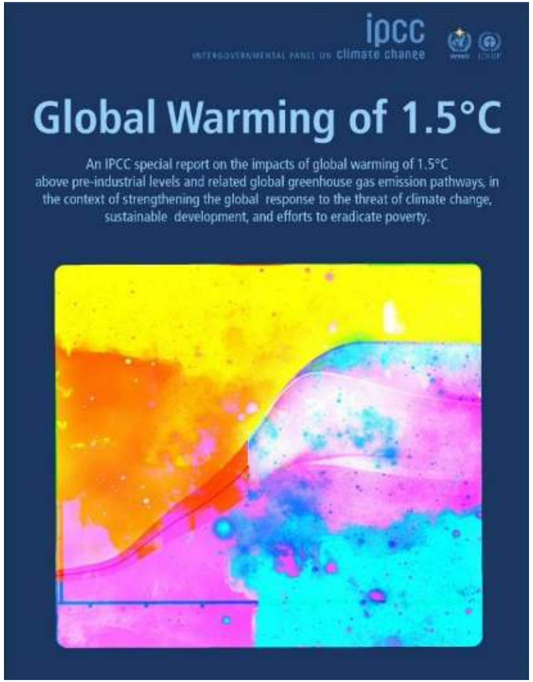
Left: Vikas Taank via Pinterest; Right: http://www.dw.dk/xiamen-bicycle-skyway

Space heating and cooling

Left: Zillow (Southern Living); Right: Elle Interior via Pinterest

Climate emergency

- Buildings and transportation ≈ 60% of our energy demand.
- Without action, energy demand is expected to keep growing.
- We need zero net emissions in 2050 to have good chance to limit global warming to 1.5C.



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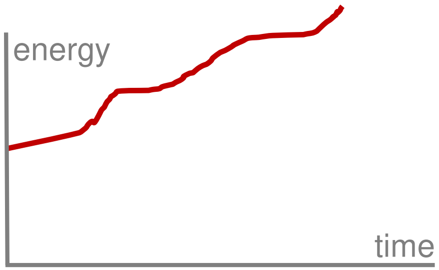
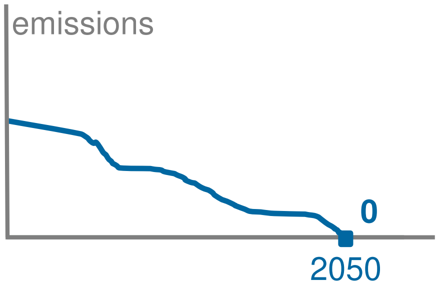




City solutions

- Infrastructure planning can **reframe** energy demand in cities.
- Infrastructure models are the basis for urban planners to design climate mitigation policies.
- Common model framework applicable to different cities would enable comparisons.

Our model

- Gap in literature: building-level energy models at the city scale
- Two main blocks: **3D building model + energy use model**
- Modular framework: simple, increasing complexity as more data gets available

OSM data to develop climate solutions

3D models and height data

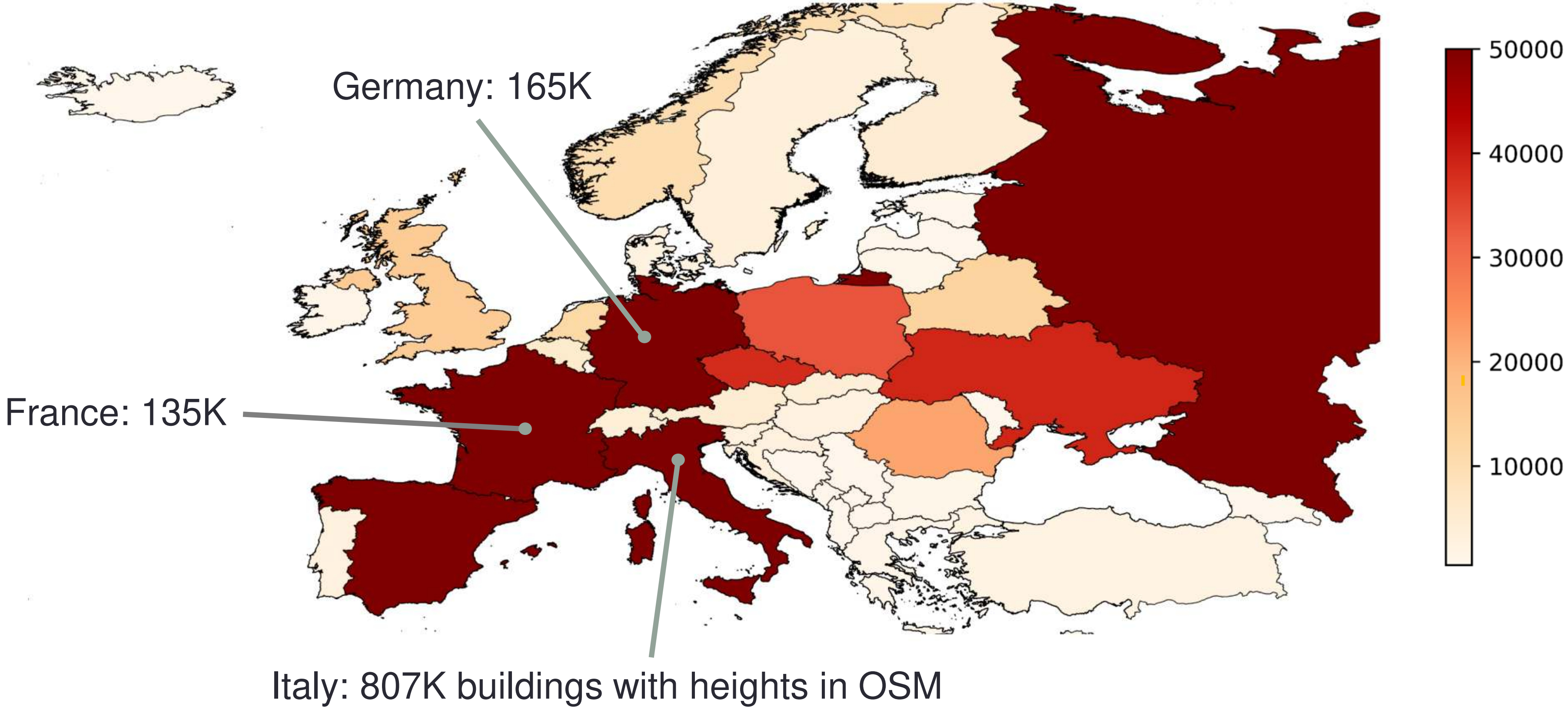
- Level of detail: LOD1 used here

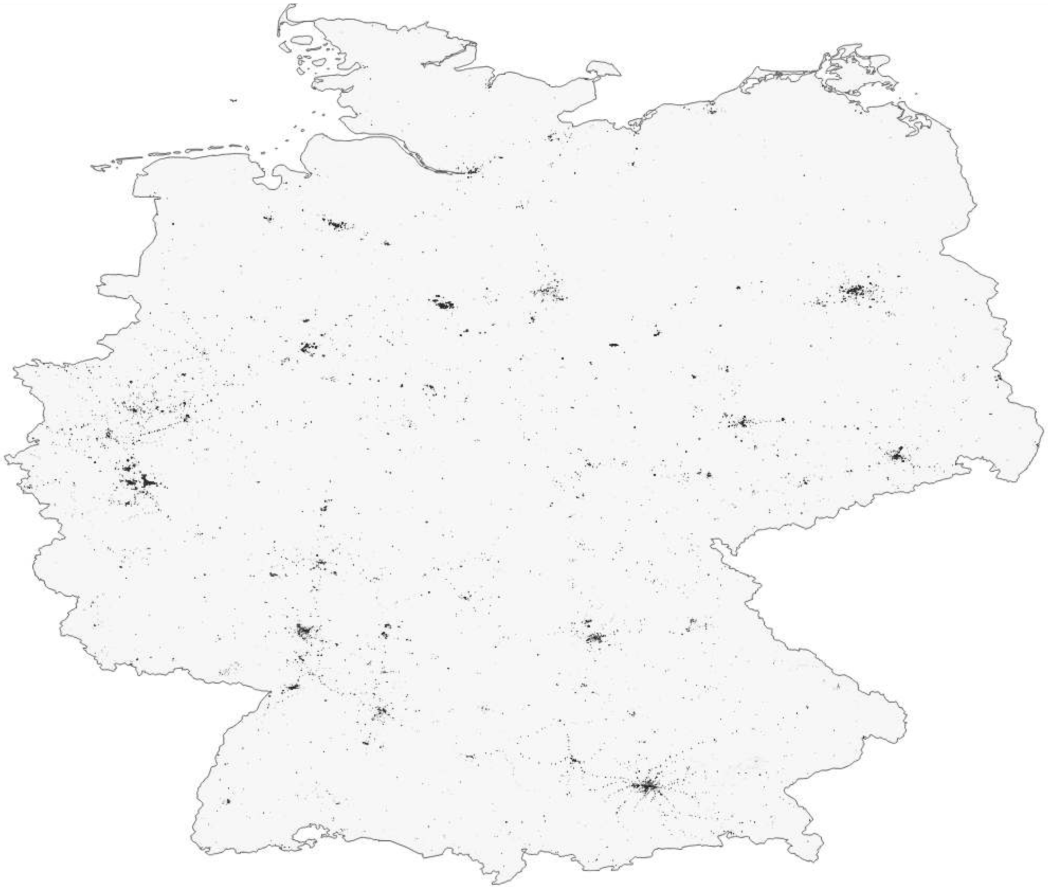
- Sources of height data:
  cadaster, LiDAR, satellite, …

- In OSM, `key:height` ≈ **12M** worldwide ≈ **25** x **Berlin**.

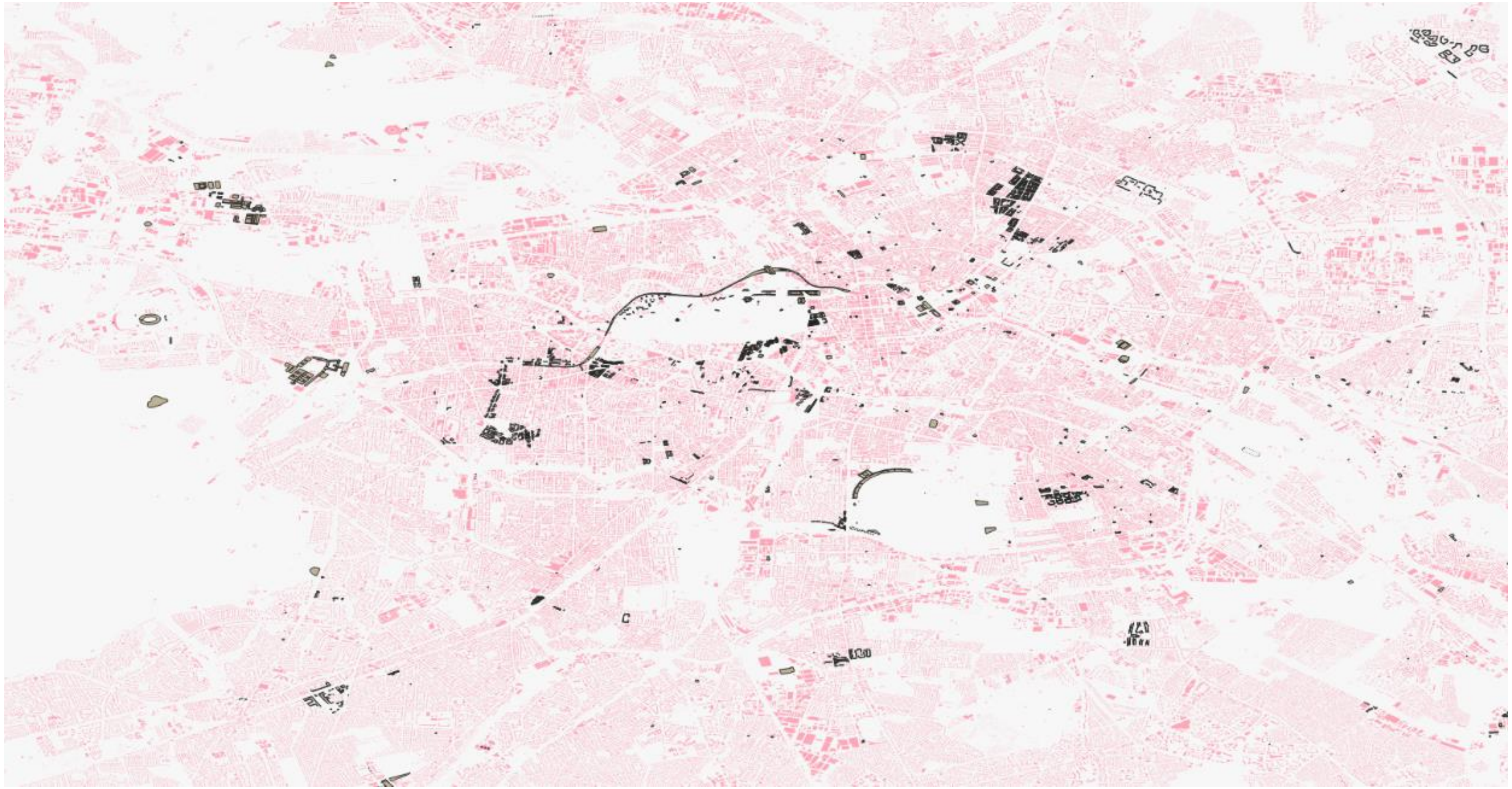
  → Could we predict others?

Europe overall: **1.5M**





Buildings with heights can be fairly well distributed within countries.

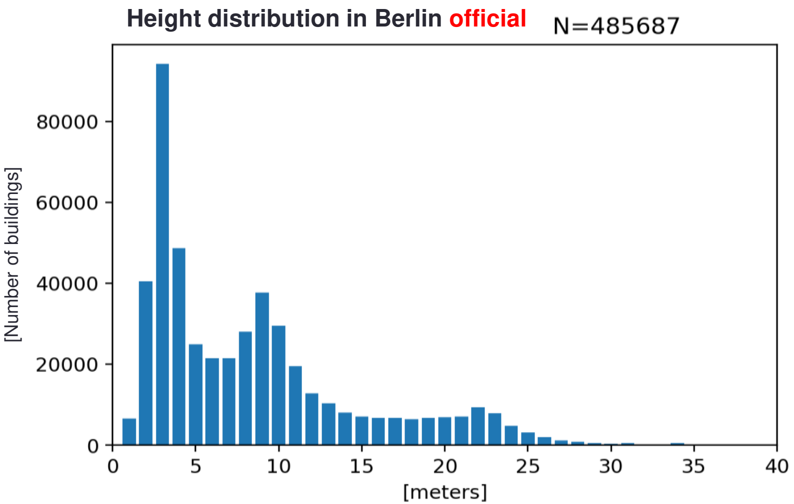


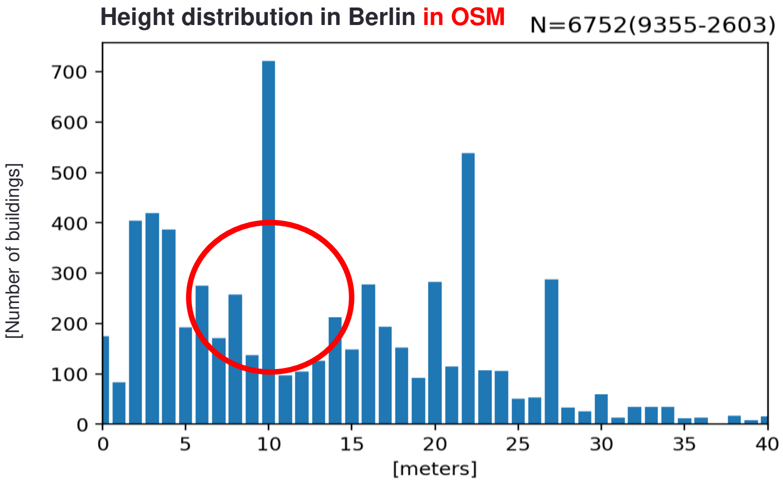
Berlin: ~**1.5**% mapped (6~7K out of ~470K buildings)

Across Europe and
in various contexts,
cities have 100s to 1000s
buildings with heights.

Data management

- Dealing with selection bias
- Merging building parts and removing non-building artefacts
- Wrong entries, level of precision e.g. [5m,10m,15m,…] vs continuous





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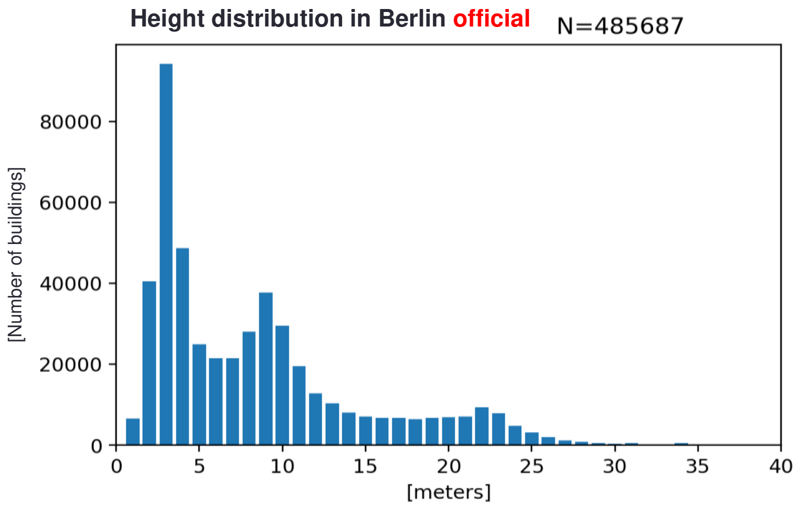

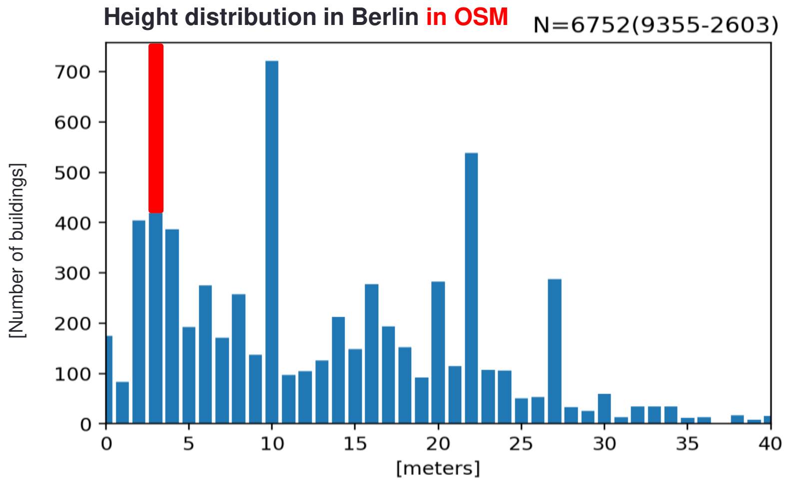

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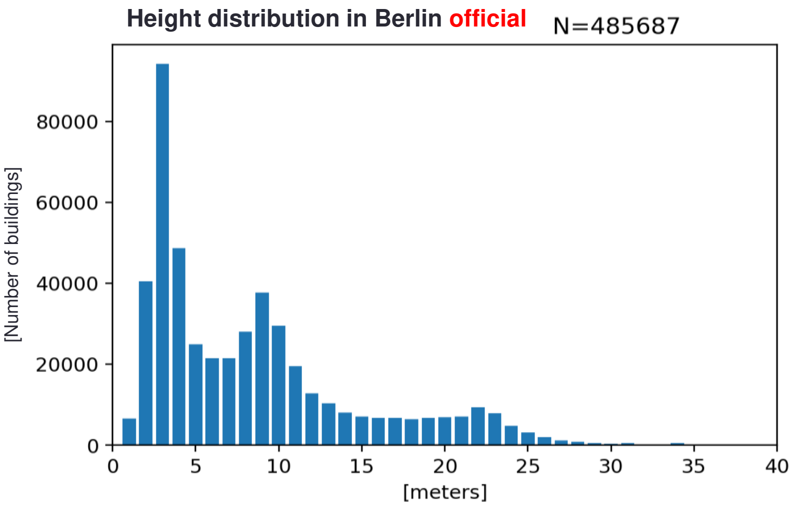
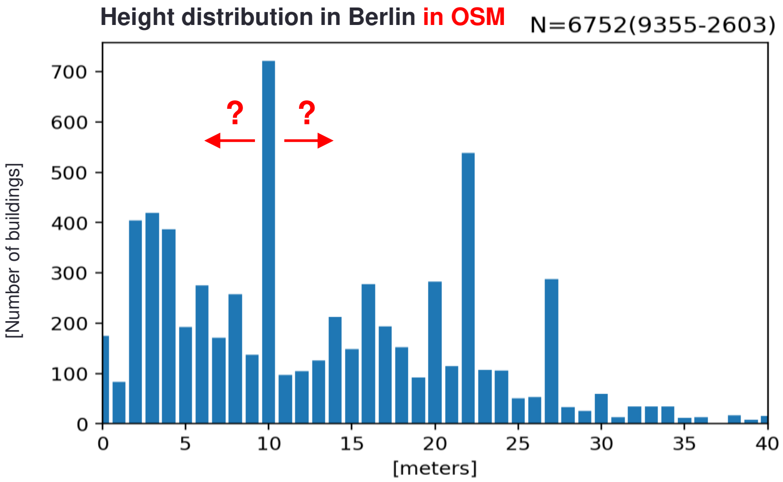




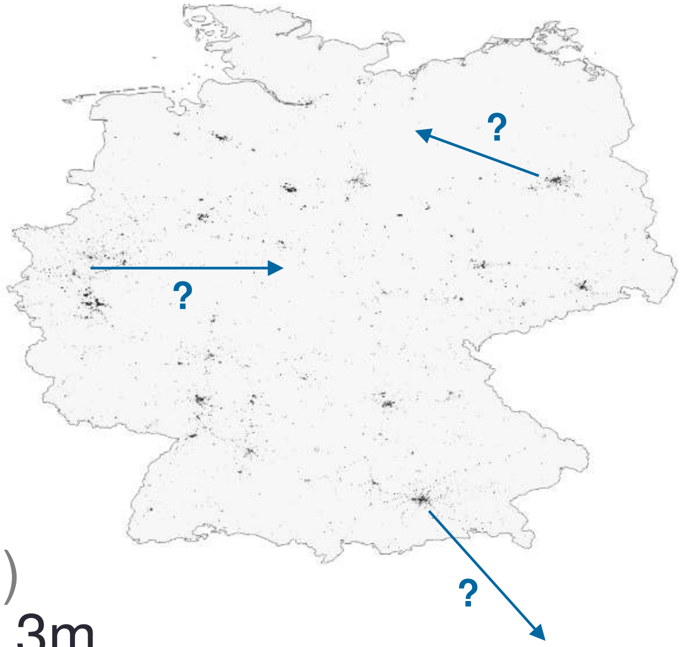
Upscaling building heights in OSM

Height prediction

Goal: Predicting building heights across Europe, using **only** OSM features, and training on **all** available height data

Similar work:

- Whole USA by 'Open City Model' but no accuracy reported
- Two Dutch cities by Biljecki et al. (2017) with MAE = 0.8~3.1m; RMSE = 1.8~4.3m



Features that can be computed for any building in OpenStreetMap

Building

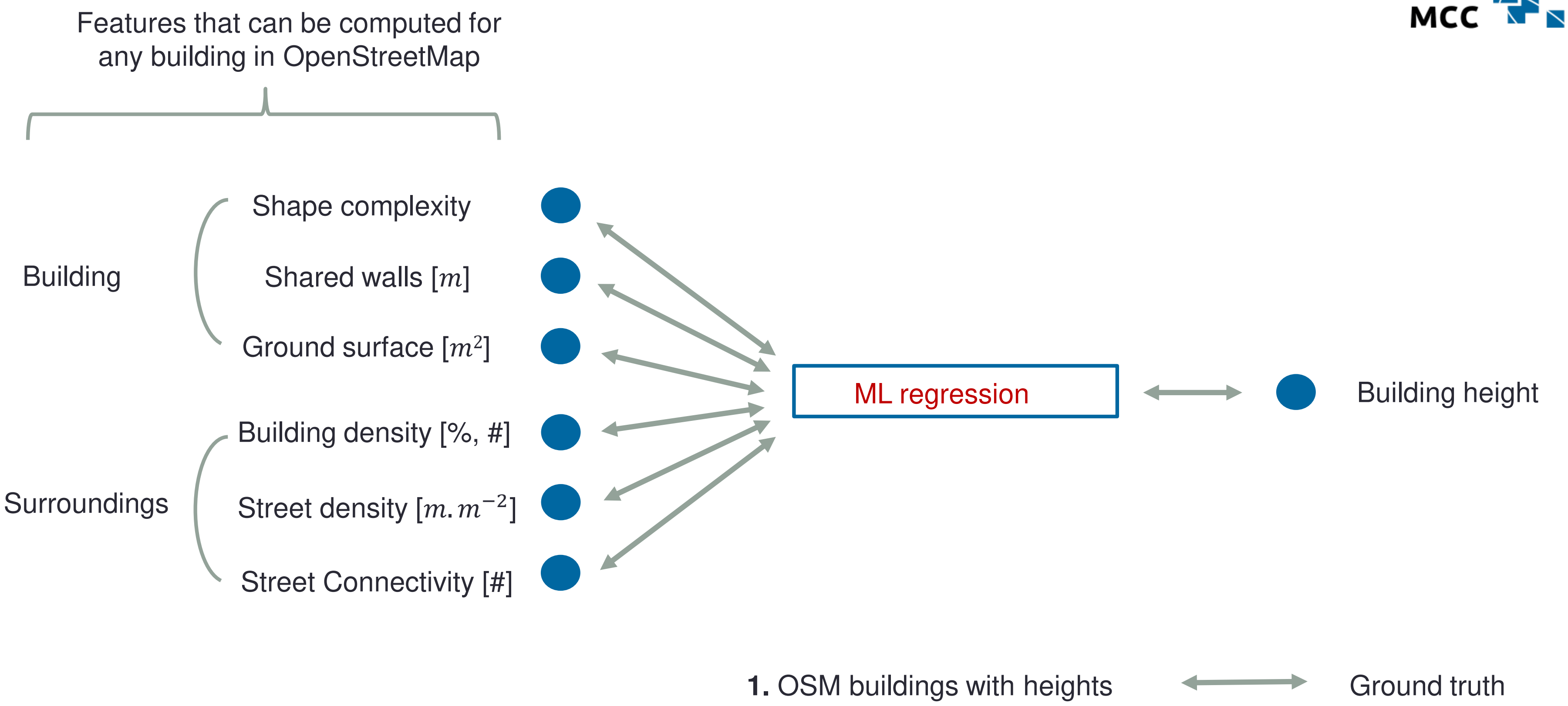
- Shape complexity
- Shared walls $[m]$
- Ground surface $[m^2]$

Surroundings

- Building density [%, #]
- Street density $[m.m^{-2}]$
- Street Connectivity [#]

ML regression

Building height



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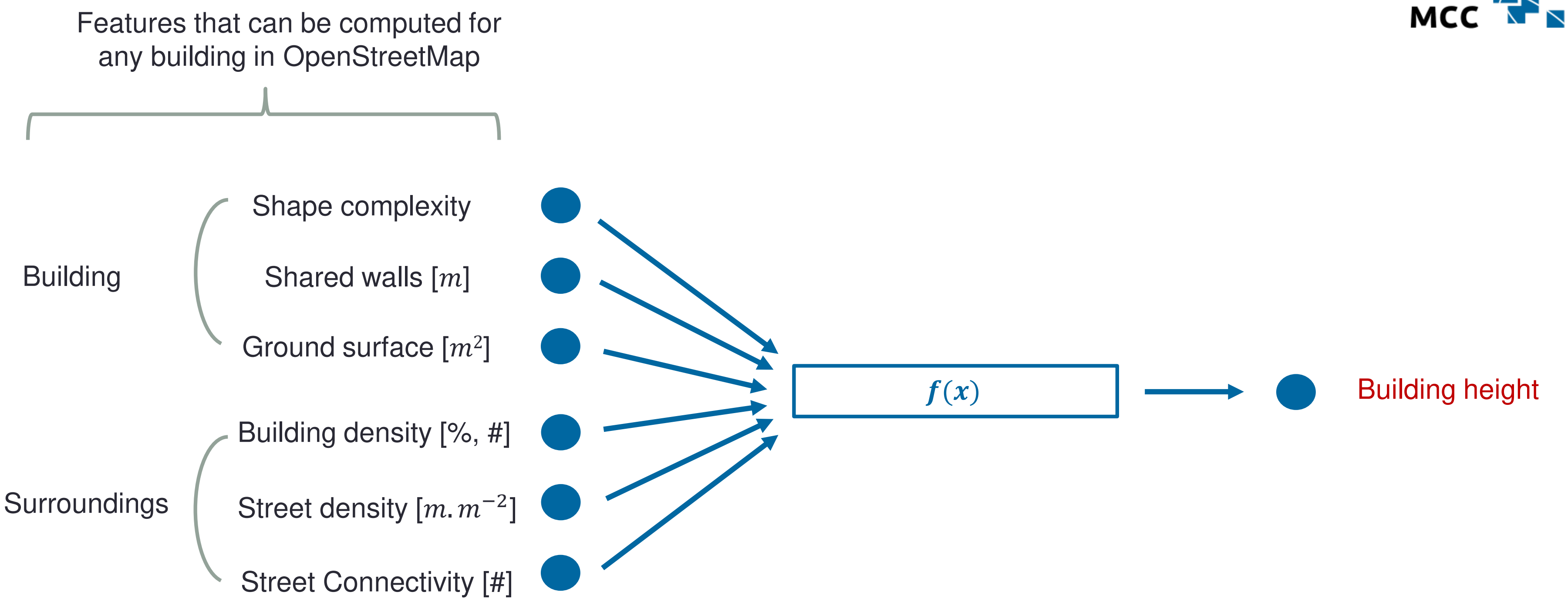
ML regression
Building height
1. OSM buildings with heights
Ground truth



1. OSM buildings with heights $\longleftrightarrow$ Ground truth

2. OSM buildings without heights $\longrightarrow$ Predicted heights

Example

- Random forest,

within and across cities

- Hradec Kralove

$n = 29\text{K}$, $st = 4.6\text{m}$

- Udine

$n = 23\text{K}$, $st = 4.3\text{m}$

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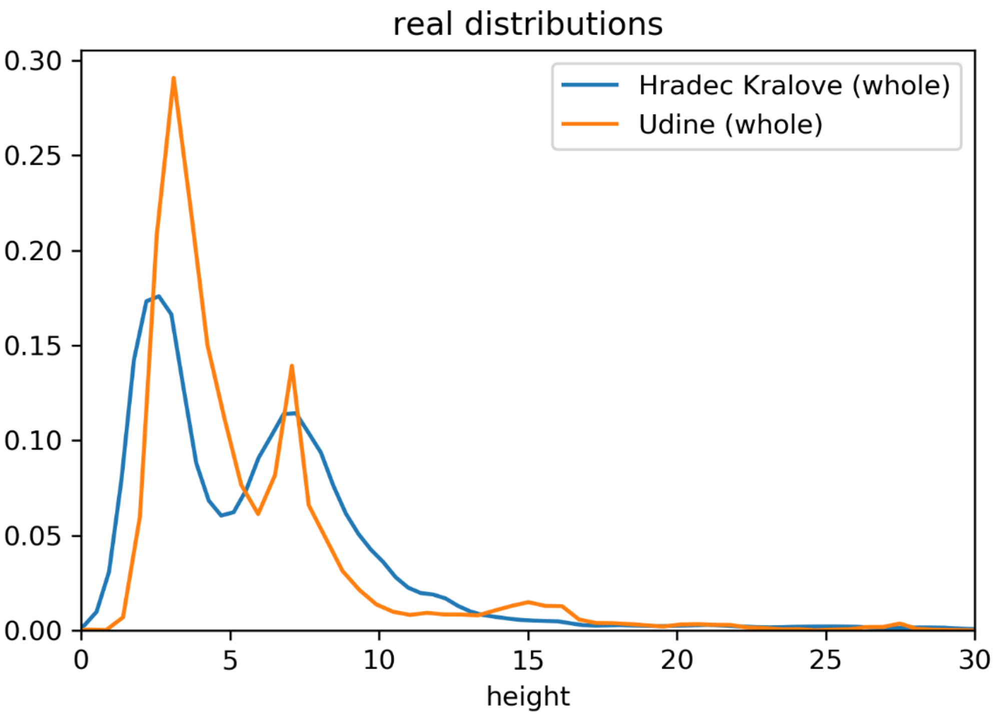
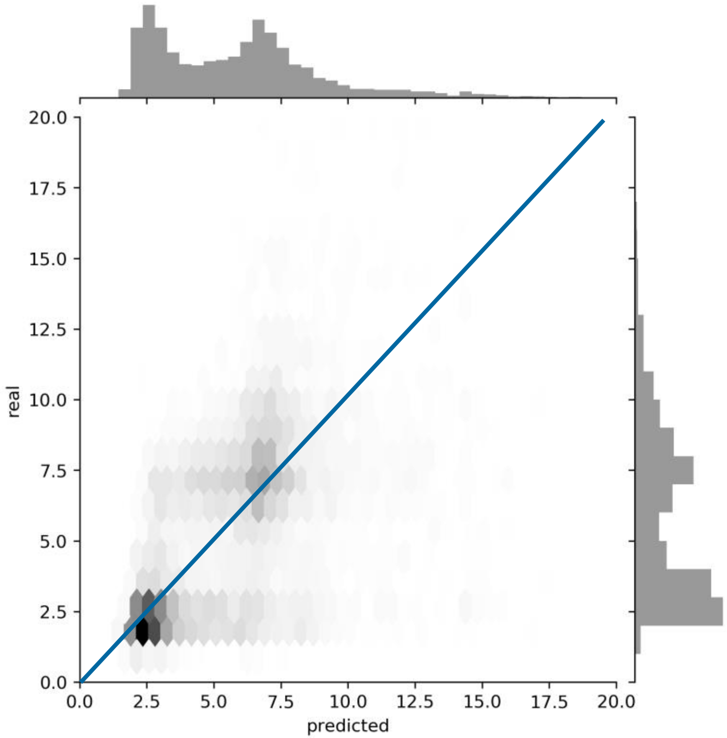
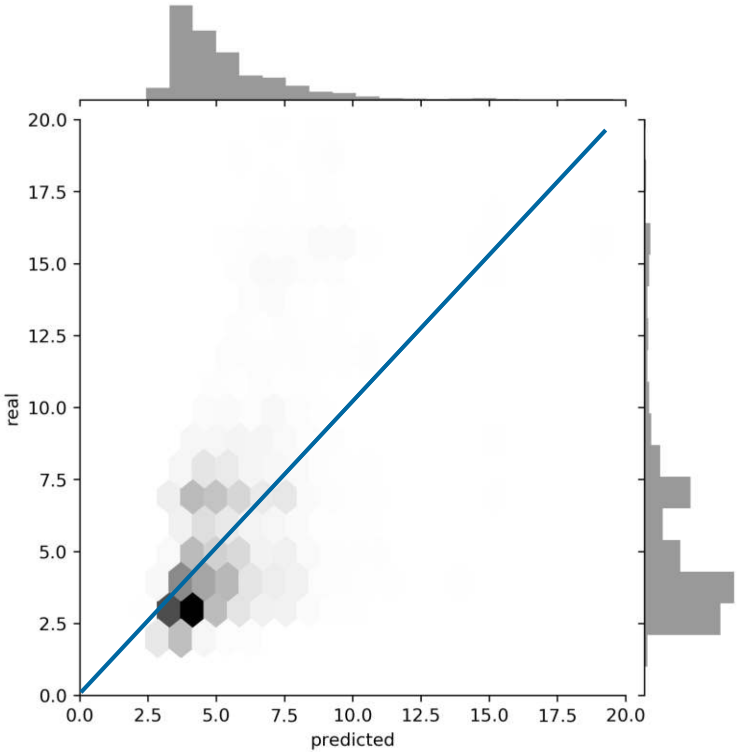




Hradec Kralove

$MAE = 2.46$, $RMSE = 3.79$



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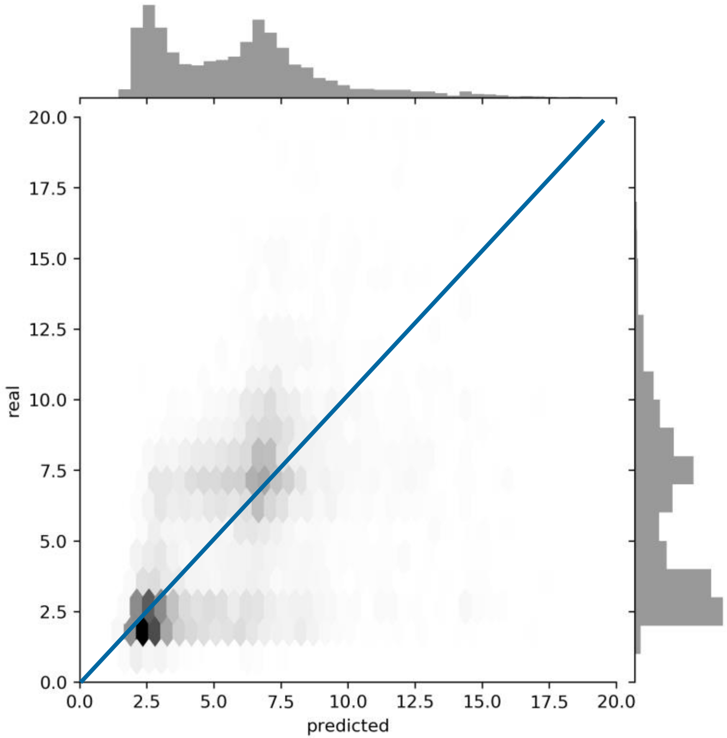

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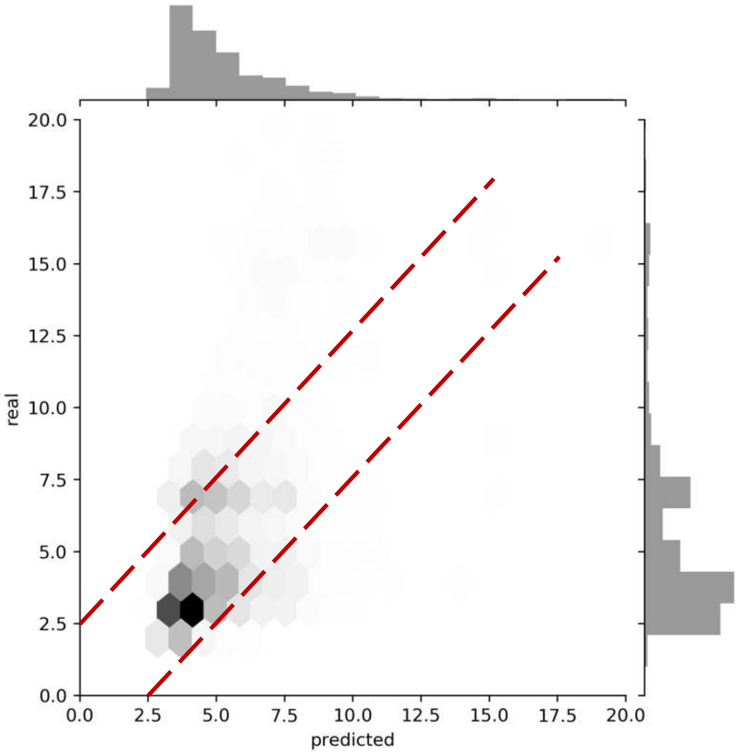

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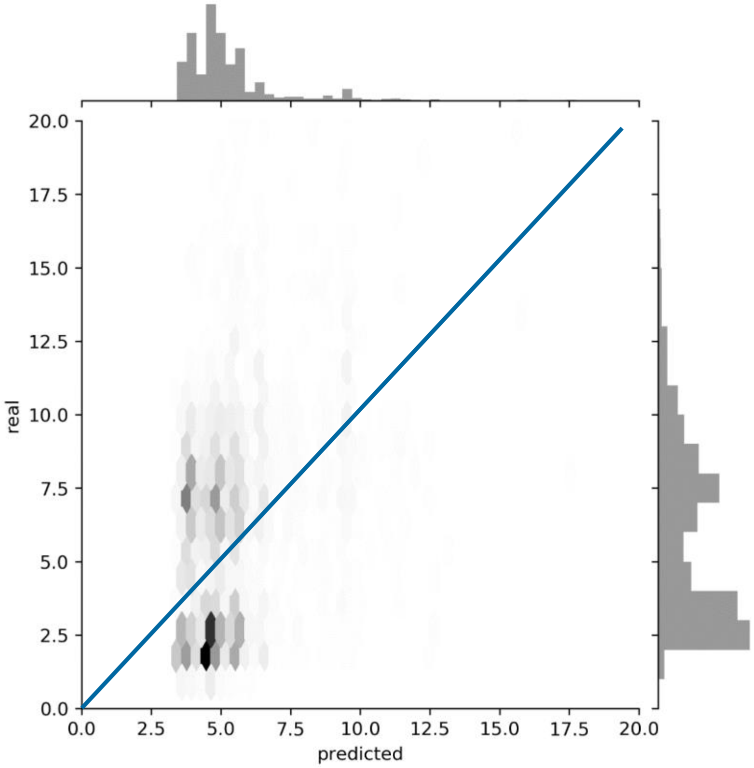
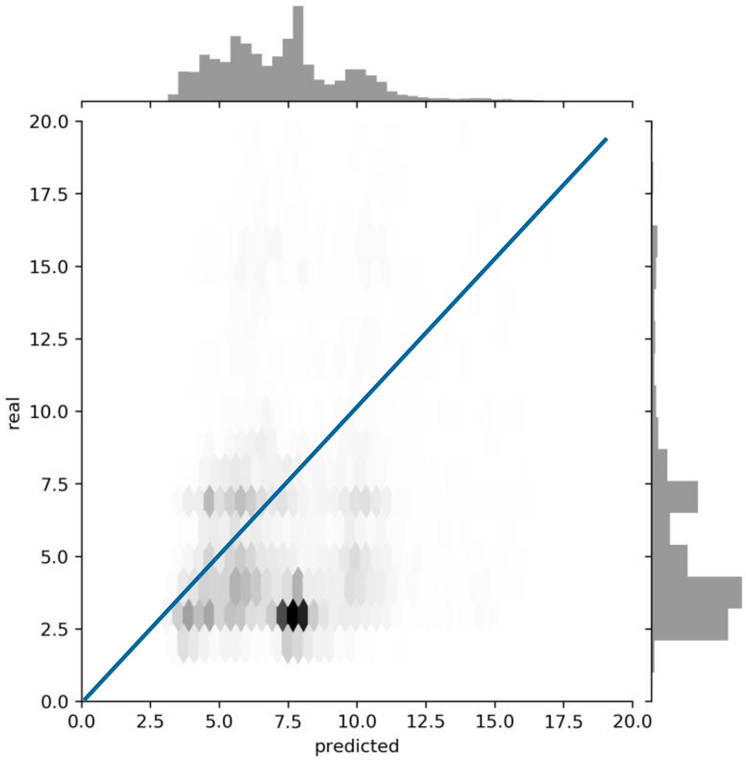


Hradec Kralove (model Udine)

$MAE = 2.89$, $RMSE = 4.0$



Udine (model Hradec Kralove)

$MAE = 3.64$, $RMSE = 4.99$

What matters for the prediction?

- Generalization in spatial models Meyer et al. (2019)
- Sampling: urban *vs.* rural, region-specific *vs.* whole Europe
- Algorithm, model and feature selection

Implications for the OSM community

- Every building mapped counts.

- Buildings in low-data settings are most important, especially in the Global South.

- ‘Number of floors’ are easier to map and obvious predictors (currently also ~12M worldwide).

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