Solar PV technology at scale: how can *AI* help?

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Solar and *the building*

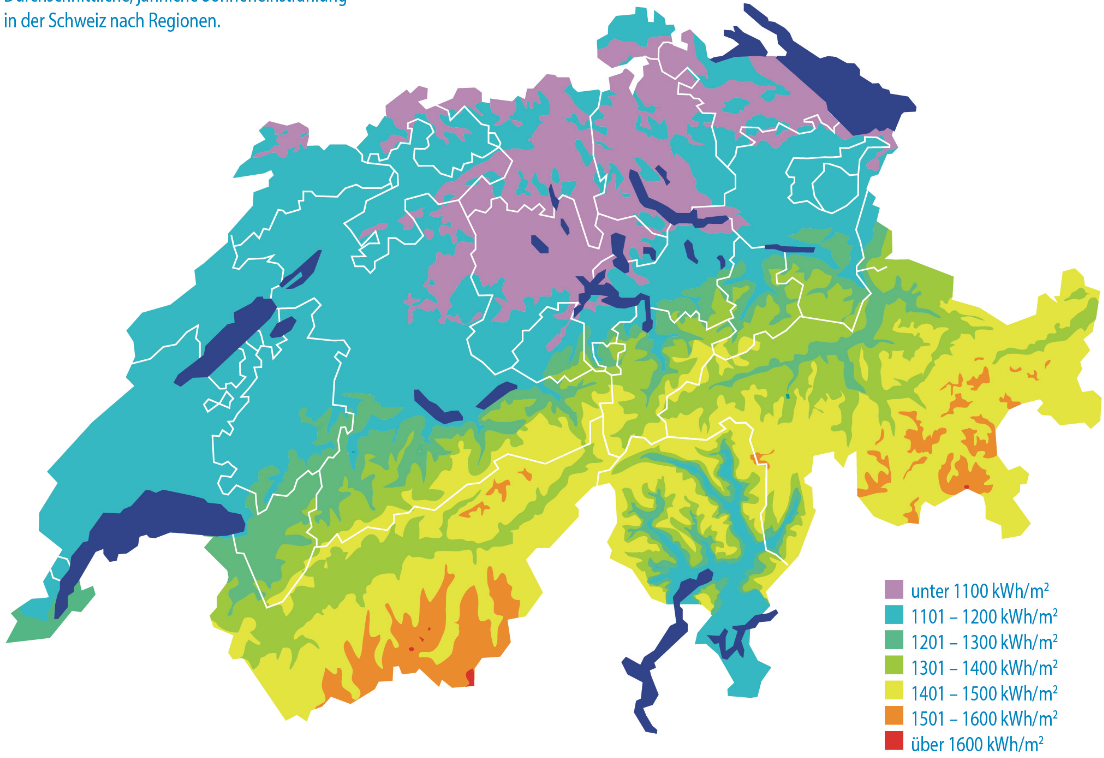
Easy.

Solar and *the city*

Challenging.

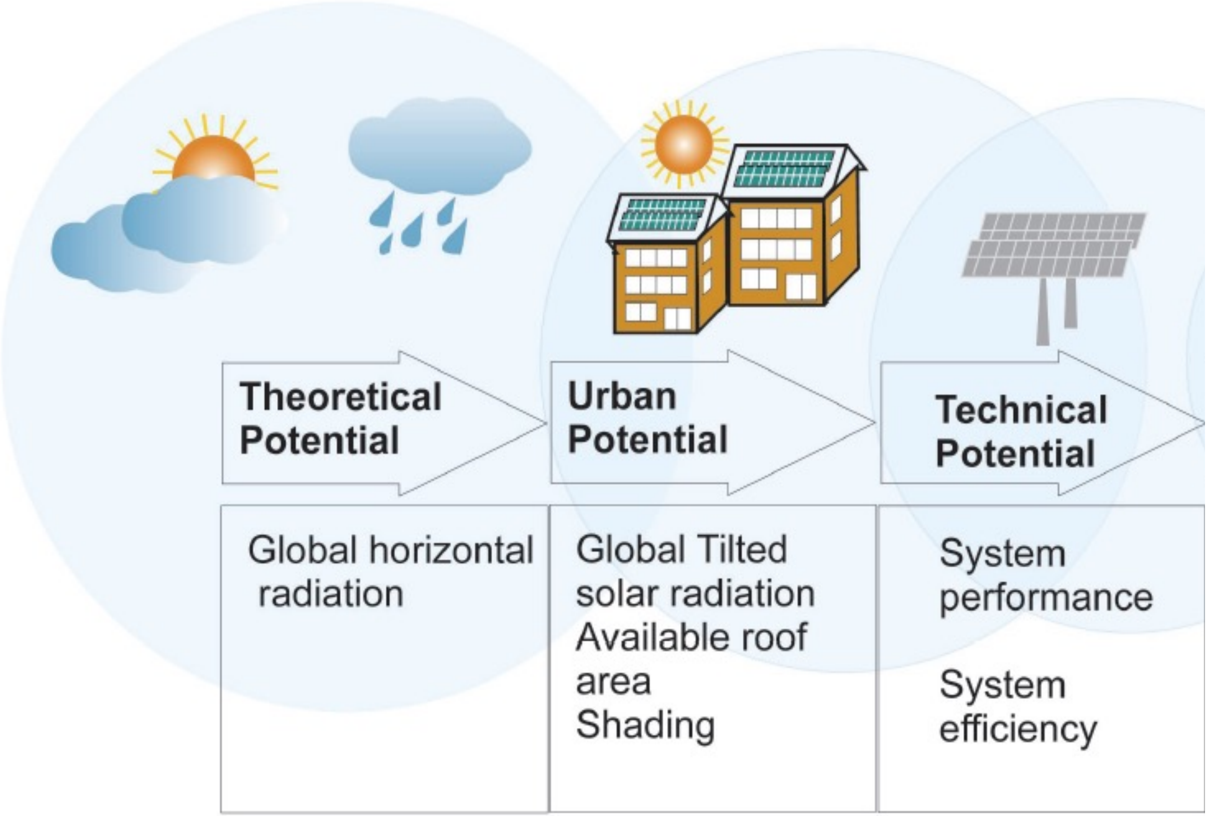
Solar and *the country*

Only for braves.



Durchschnittliche, jährliche Sonneneinstrahlung in der Schweiz nach Regionen.

Rooftop solar PV potential for CH



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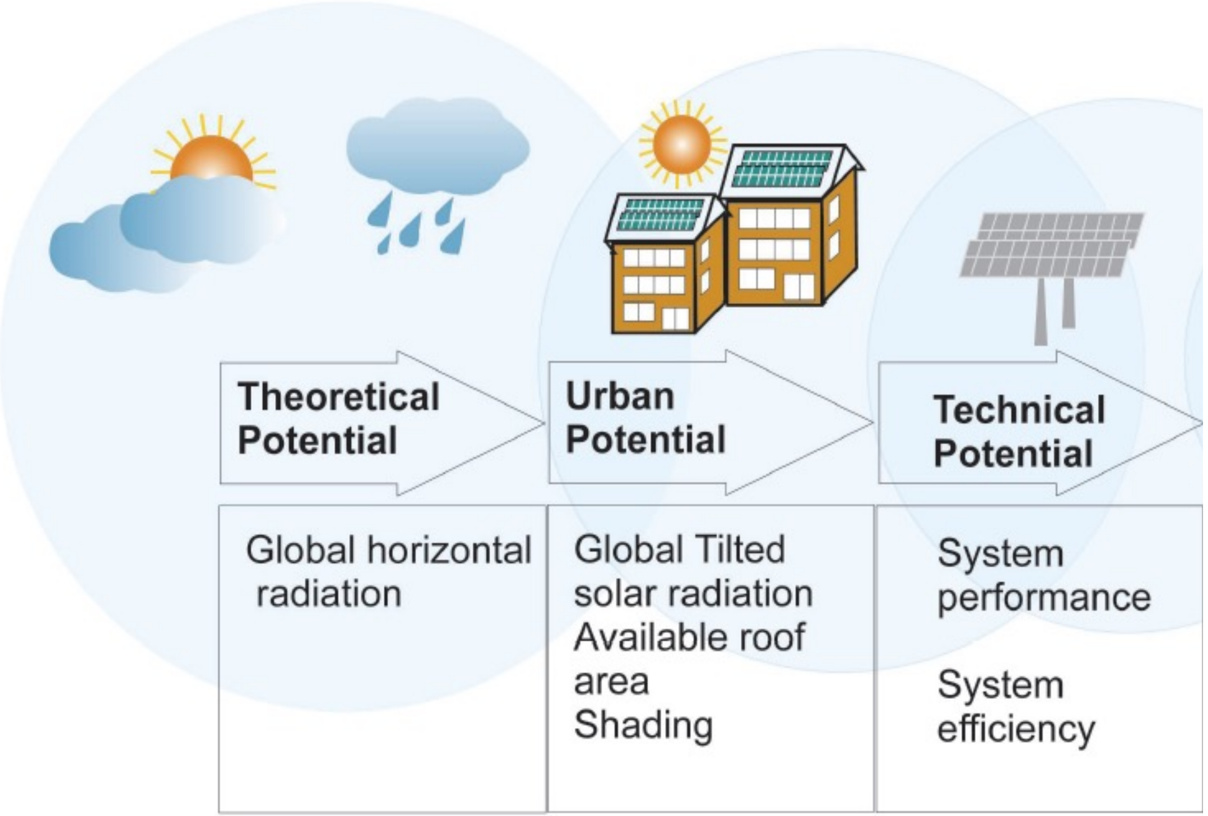
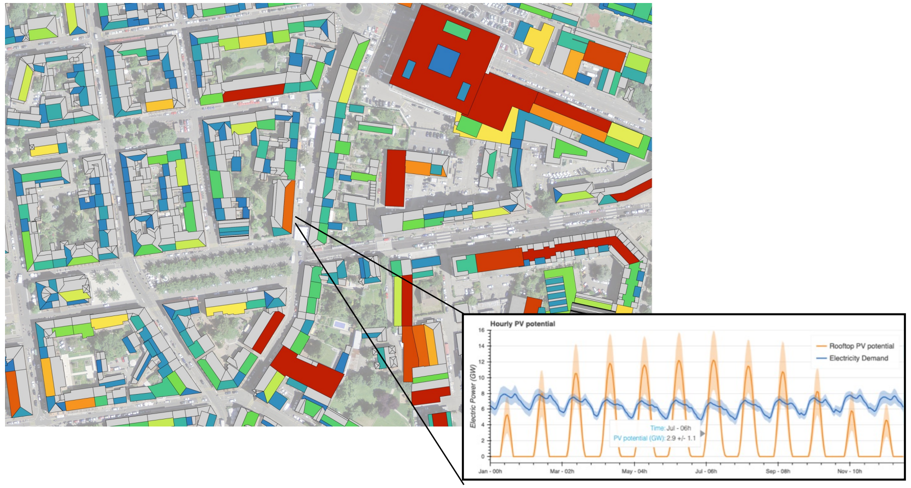


[Walch et al, Big data mining for the estimation of hourly rooftop photovoltaic potential and its uncertainty, 2020]

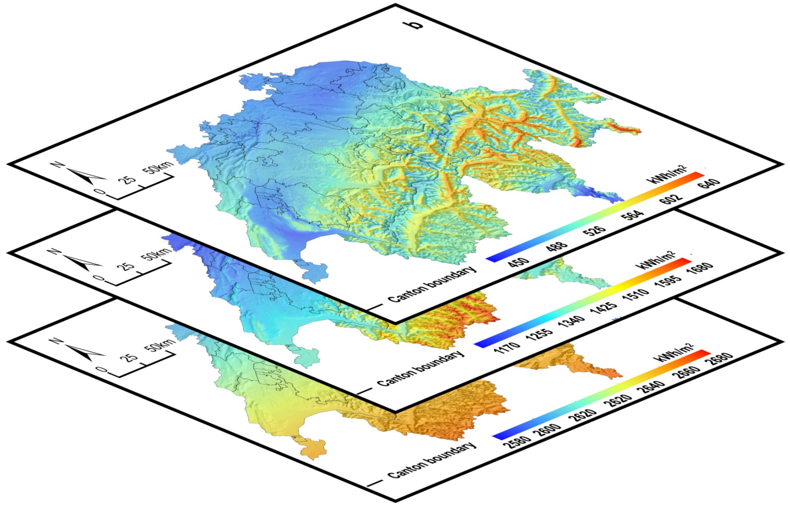


First attempt to go at hourly scale for each building of Switzerland

Data, resolution and coverage

Meteorological data

8760 hours - 12 yrs - (1.6 x 2.3) km^2



- Solar radiation
- Temperature

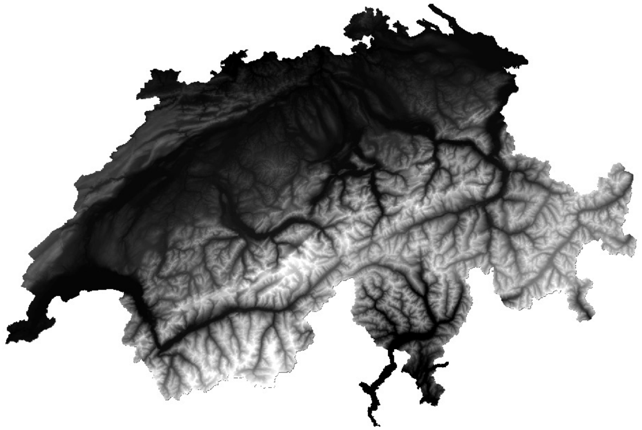
Building data

9.6M roofs

- Slope/orientation
- Footprint
- Superstructures (only for GVA)

Digital elevation models

2 x 2 m^2 / 0.5 x 0.5 m^2 only for GVA



- Shadow

Machine Learning: high resolution at large scale

Supervised regression : Extreme Learning Machine (ELM) Ensemble / Random Forest (RF)

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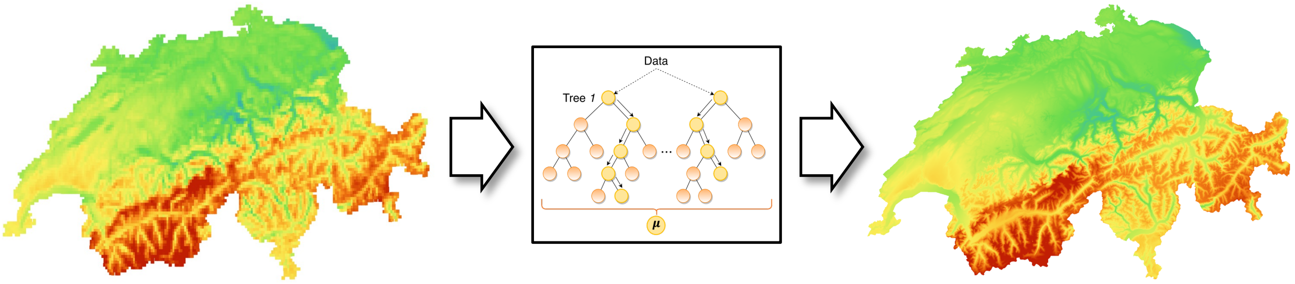
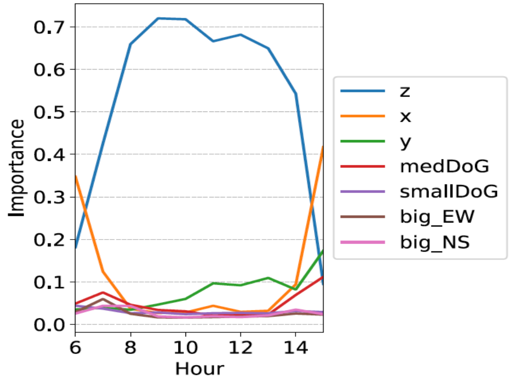
Irradiance





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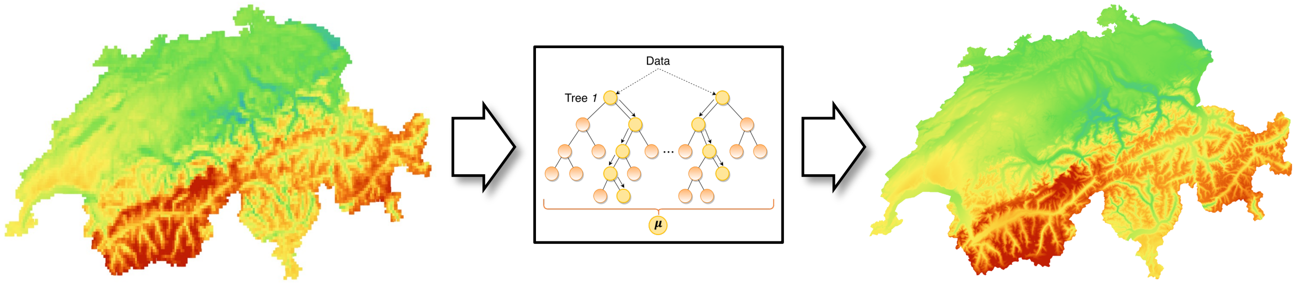
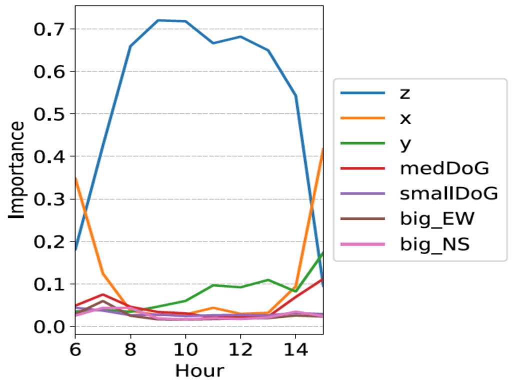
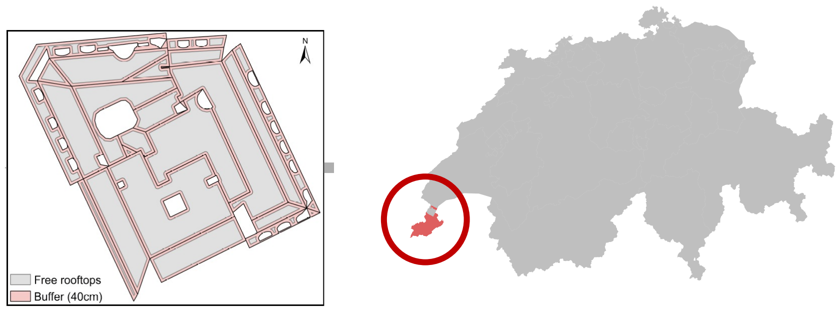




Suitable rooftop area and shading



Only for GVA canton

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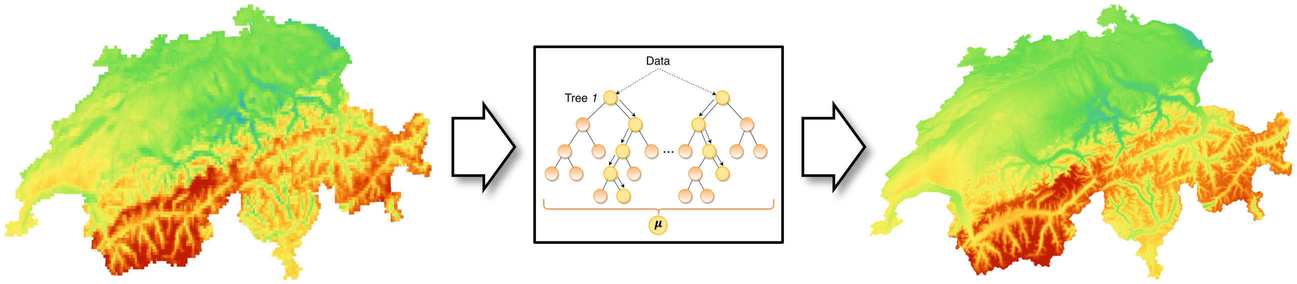

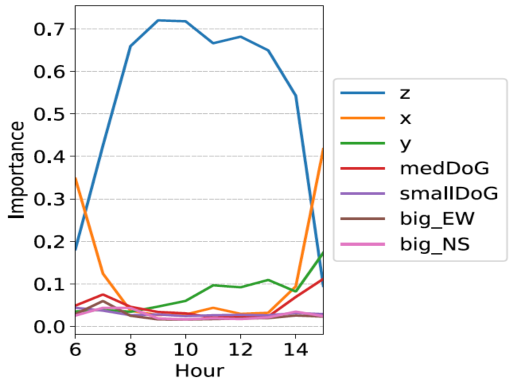

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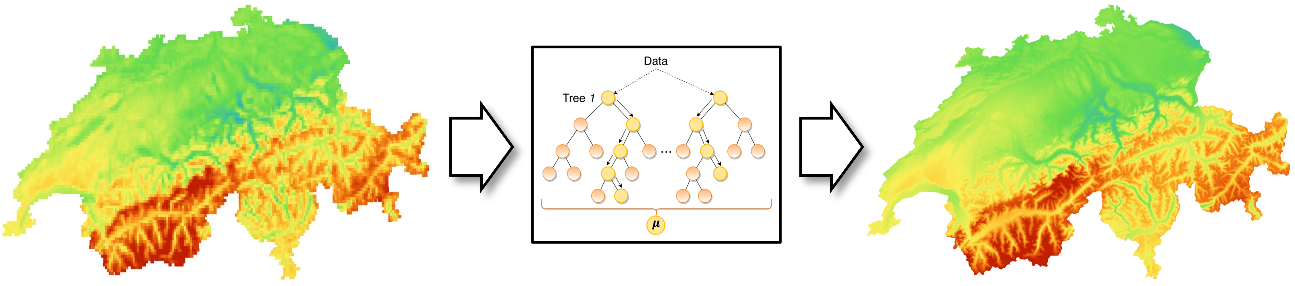

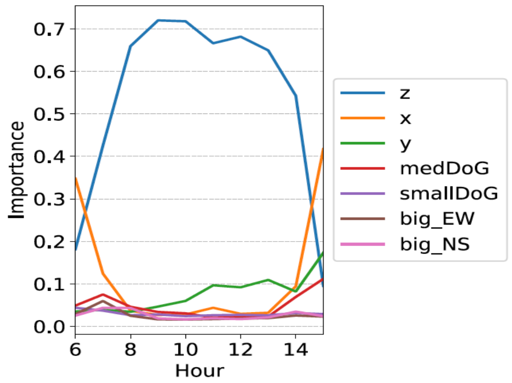

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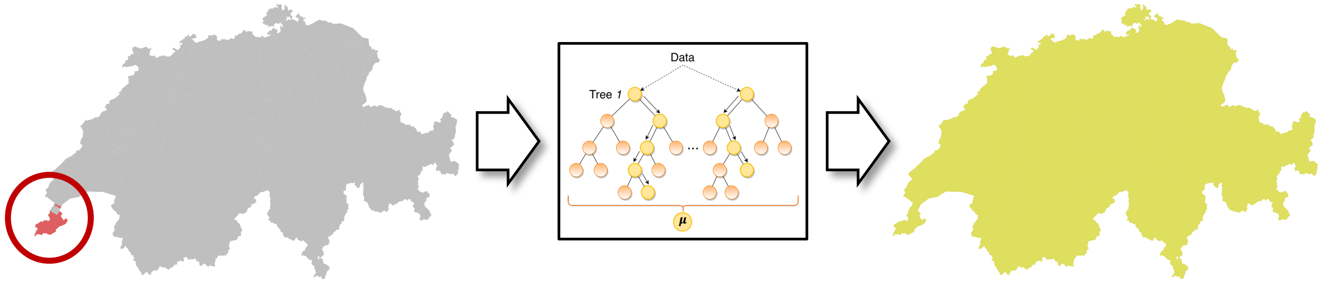

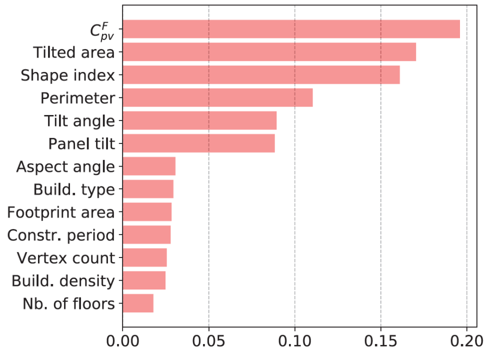

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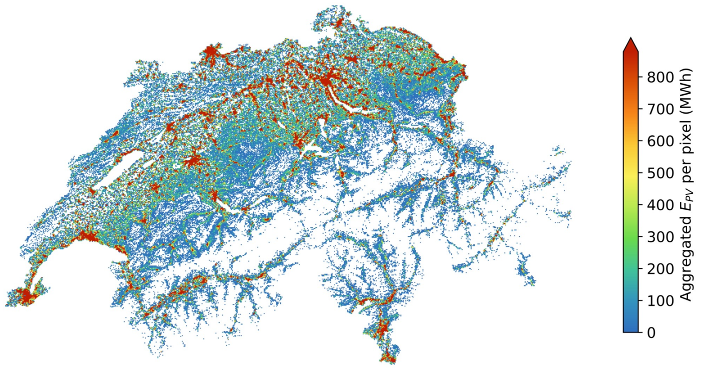
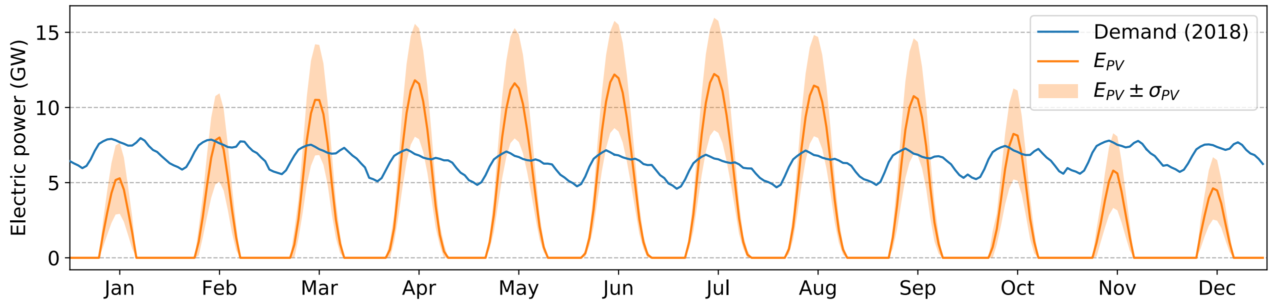
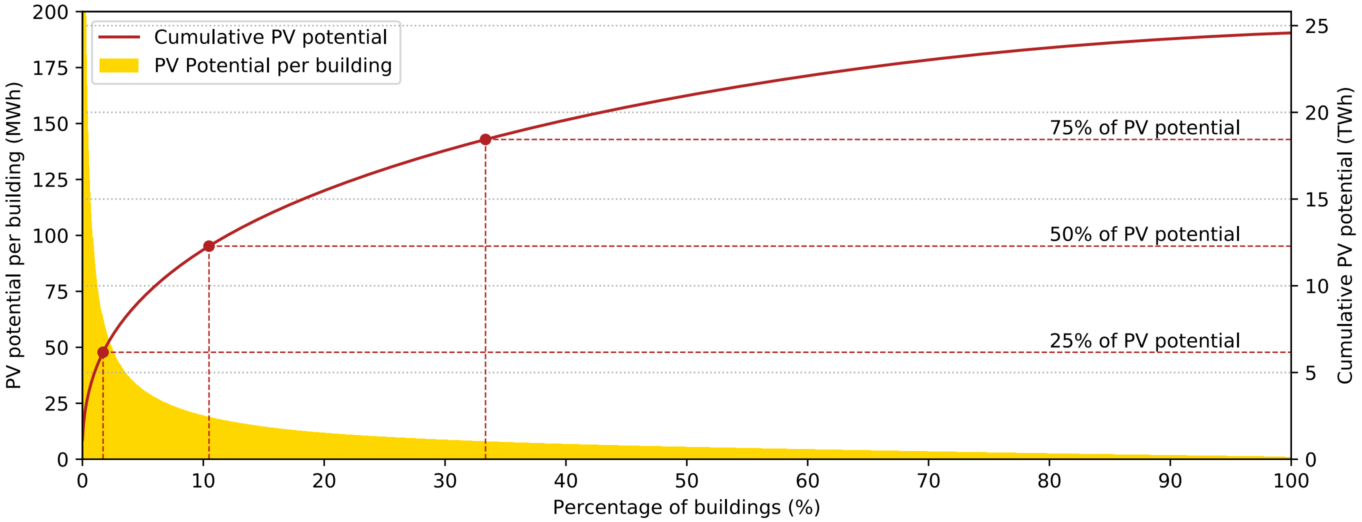


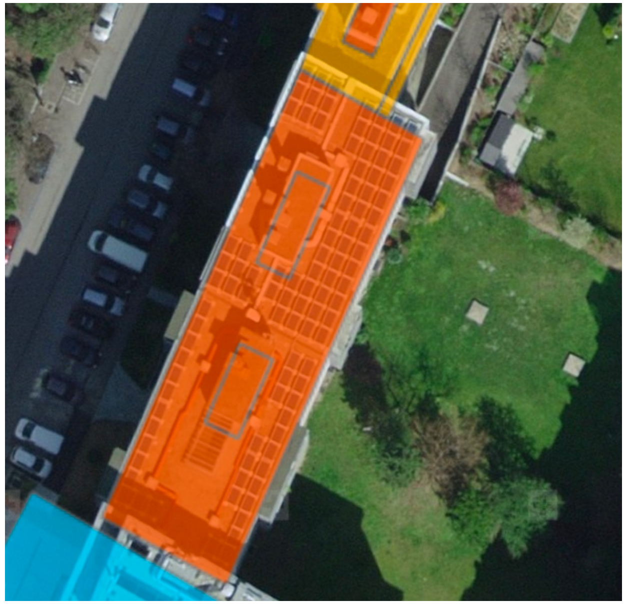


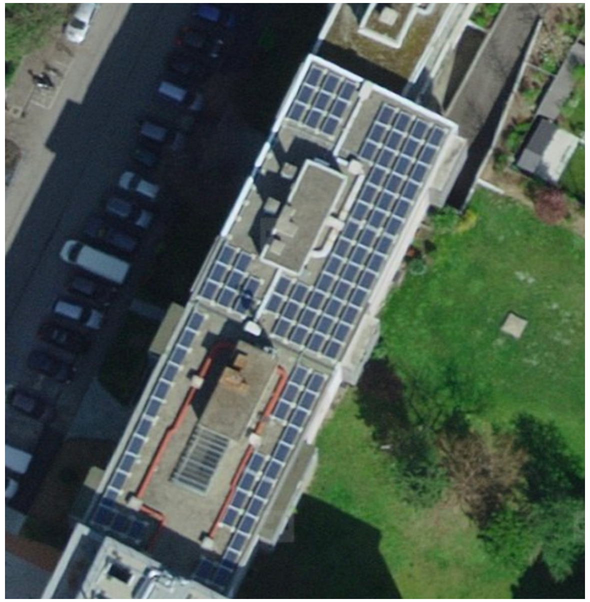


If all the suitable roofs were exploited, 40% of Swiss electricity demand (2018) can be hit

Available area for PV: dealing w/ superstructures

Dormers, chimneys, HVAC, windows typically ignored, but they are not “available”





[Sonnendach, Swisstopo BFE]

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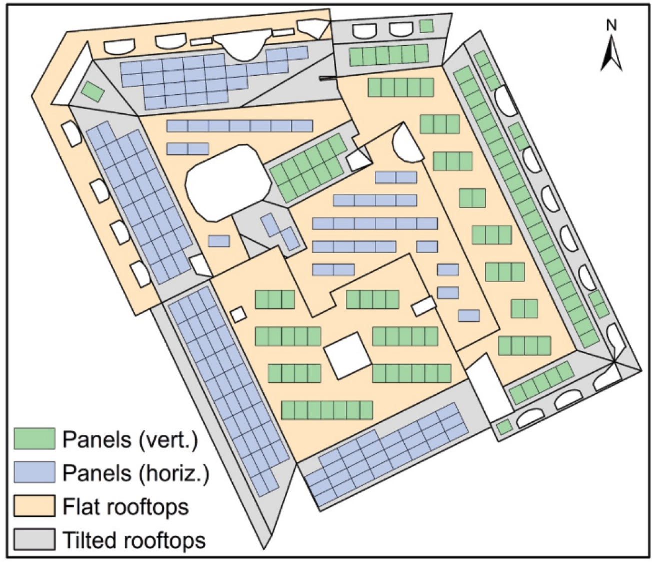


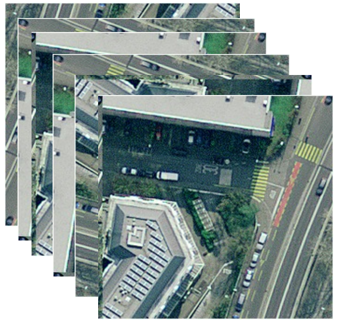
[Sonnendach, Swisstopo BFE]

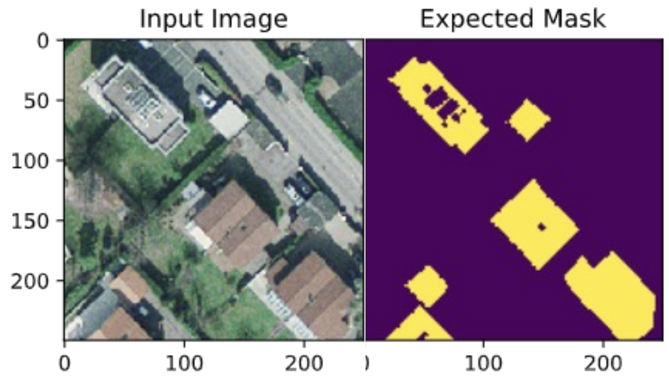
Custom-fitting not scalable to 9.6 million rooftops in CH

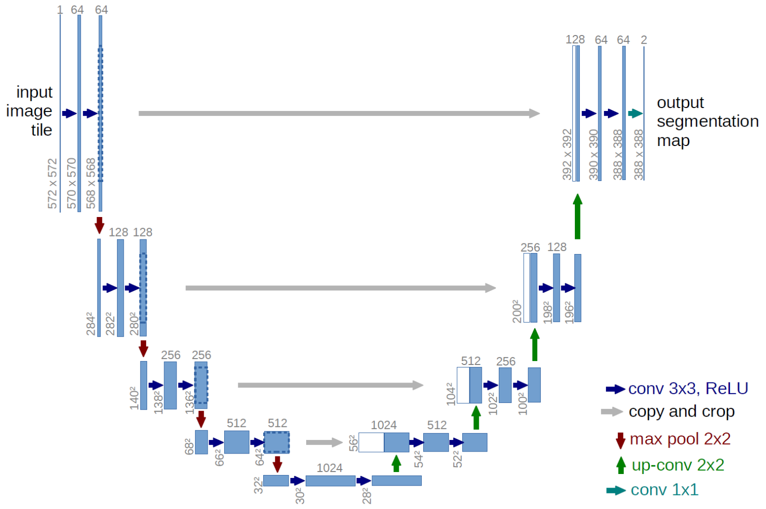
RF regression is one way, but can be improved

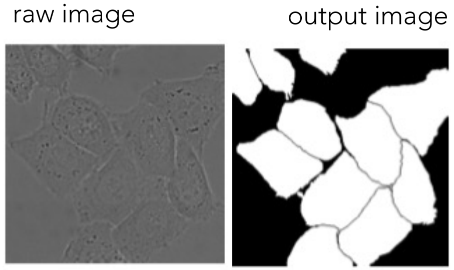
Leveraging high-res aerial images and CV

- Aerial images at high resolution (Swiss Federal Office of Topography)
- Convolutional Neural Networks for pixel-wise semantic segmentation (U-Net)
- 3D rooftop dataset (Sonnendach, Swiss Federal Office of Energy) for post-processing









[O. Ronneberger et al.]

A more realistic quantification

- Virtually placing 1.6 m^2 panels onto the detected available areas from CNN
- Comparing to the RF large-scale estimate (same algorithm to virtually install PVs)

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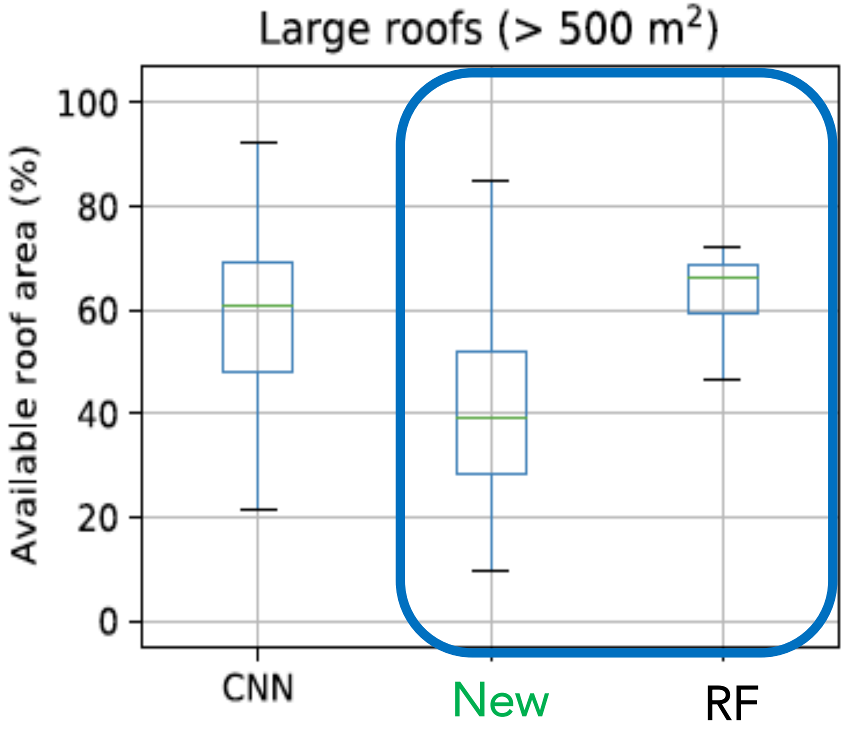


[Castello et al., Quantification of the suitable rooftop area for solar panel installation from overhead imagery using Convolutional Neural Networks, 2021]

Smaller median fraction of available area than RF approach for large roofs

SDSC

ETH zürich

PAUL SCHERRER INSTITUT

PSI

Empa

Materials Science and Technology

EPFL

WSL

Eidg. Forschungsanstalt für Wald
Schnee und Landschaft WSL

eawag

aquatic research

The solar energy potential

Theoretical

- Global solar horizontal radiation (from direct and diffuse)

$$G_h(t) = G_B(t) + G_D(t)$$

Geographical/Urban

- Radiation over tilted rooftops (G_t) and suitable areas for PV (A_{PV}) considering rooftops' slope and direction, along with shading

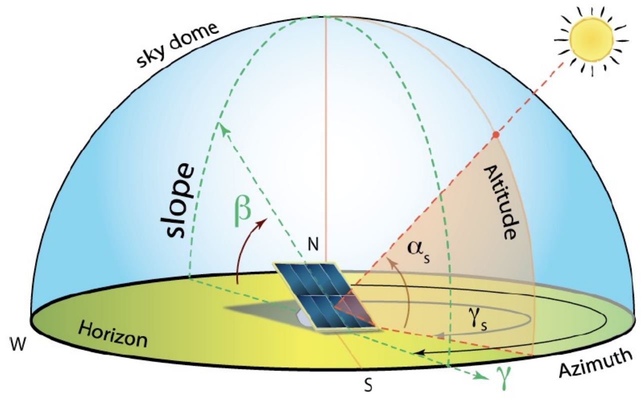
$$G_t(t) = (1 - S_{sh}(t)) * G_{Bt}(t) + SVF * G_{Dt}(t) + G_{Rt}(t)$$

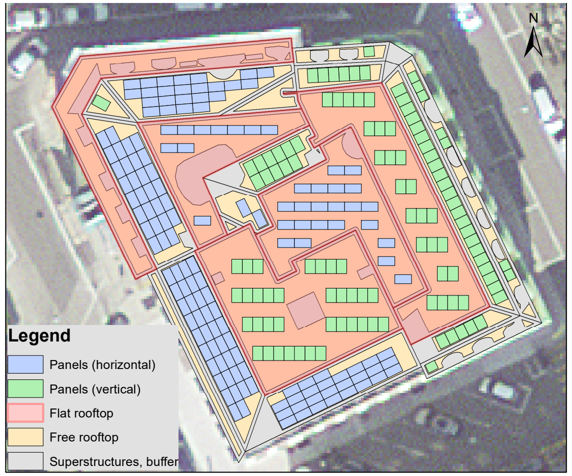
$$A_{PV} = A_t * C_{pv} * (1 - C_{sh})$$

Technical

- Losses from panel efficiency (η_{PV}, around 0.17) and performance ratio (PF, around 0.8)

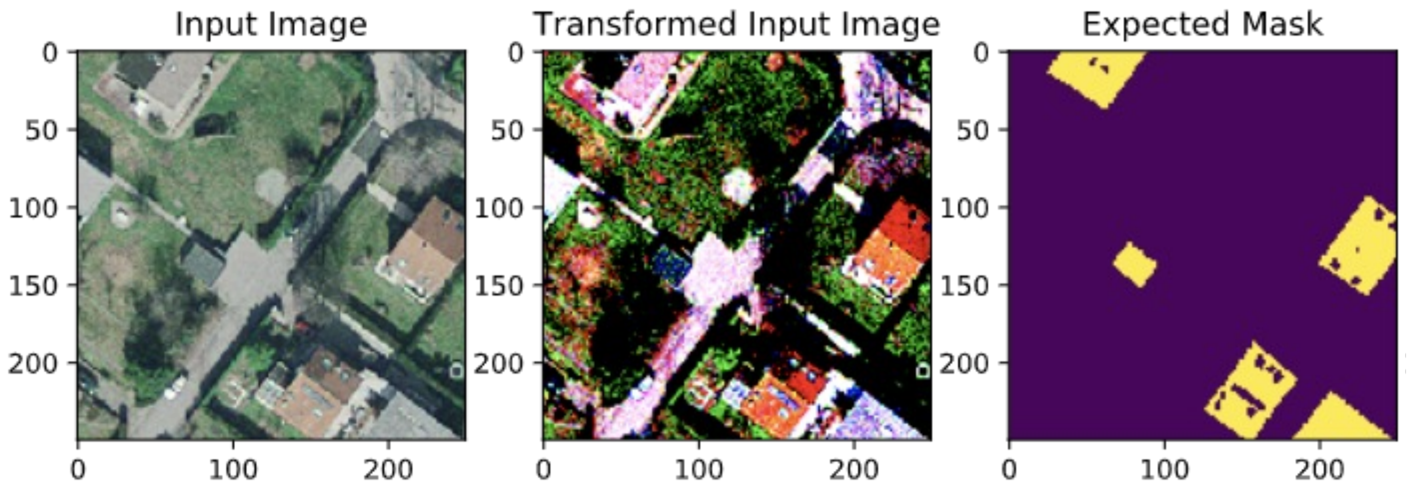
$$E_{PV} = G_t(t) * A_{PV} * \eta_{PV}(t) * PF(t)$$





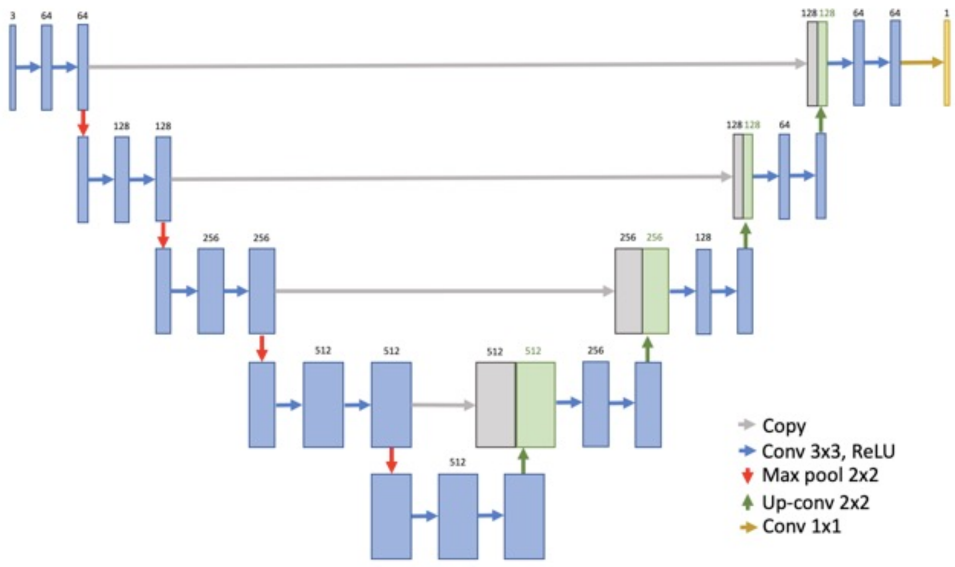
Example of data preparation

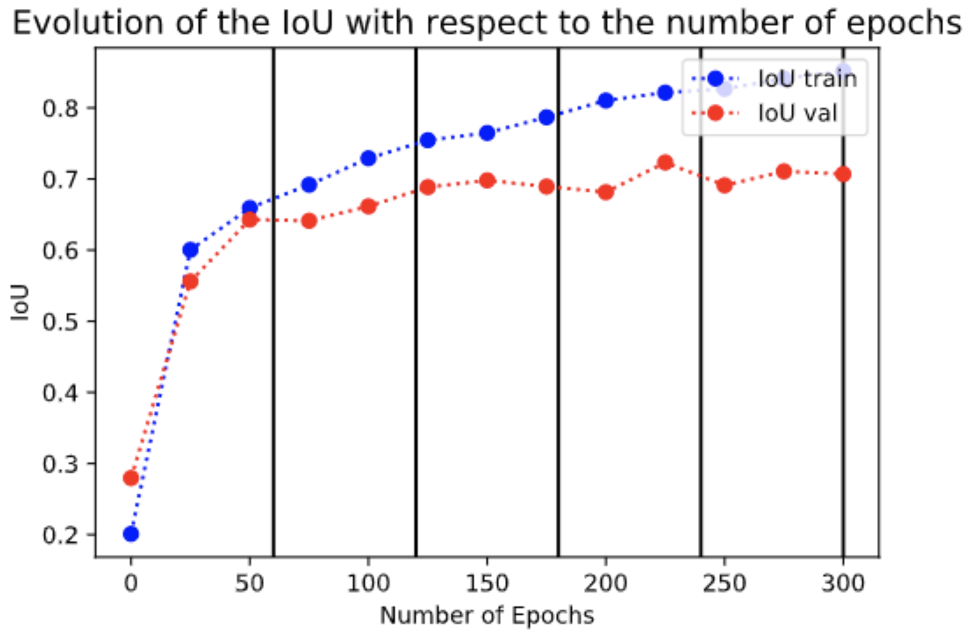
- Increased saturation + random crop/flip + gaussian noise



- Labelling: 524 imgs, ~12 hrs
- Binary classification:
  - 1 = area for PV (TP)
  - 0 = background (TN)

The CNN training





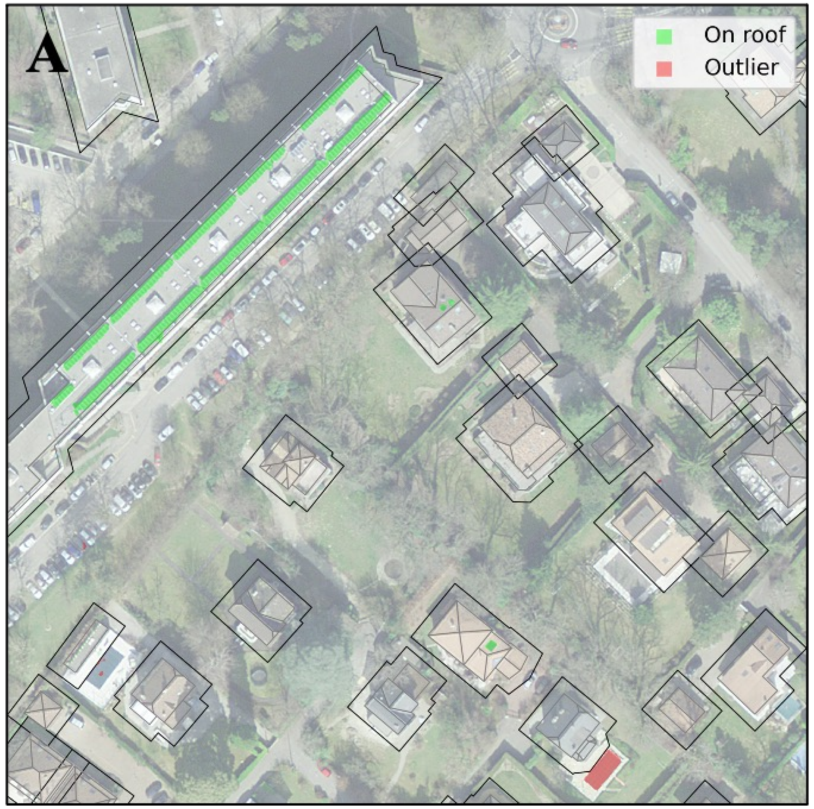
	IoU	Accuracy	Recall	Precision
Training	0.8823	0.9794	0.9299	0.9437
Validation	0.7211	0.9464	0.8360	0.8508
Test	0.6420	0.9307	0.7522	0.7874

Geospatial post-processing

- 3D rooftop dataset from Sonnendach (SFOE)
- Adding contextual information, such as the size, tilt and orientation and location of the roof
- Shapes are buffered to account for misalignments

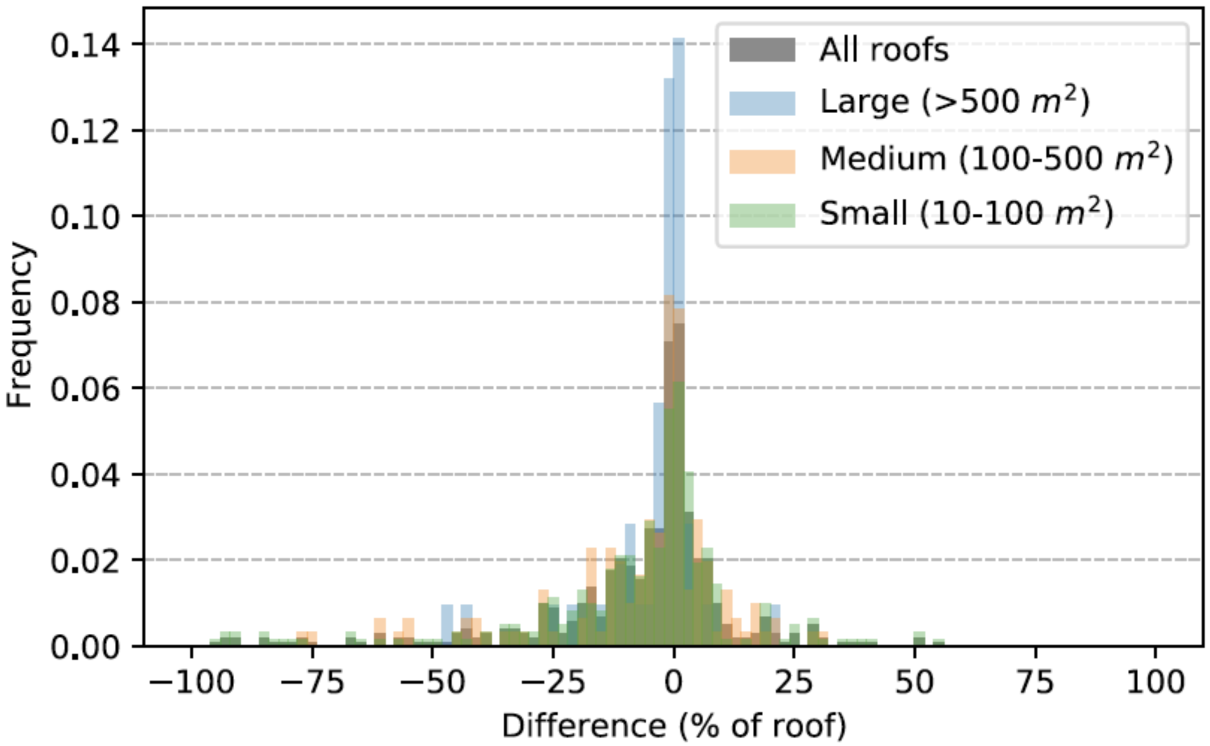
As a result:

- Remove false positive pixels outside buildings
- Correct the area for the roof tilt (cosine)



Results

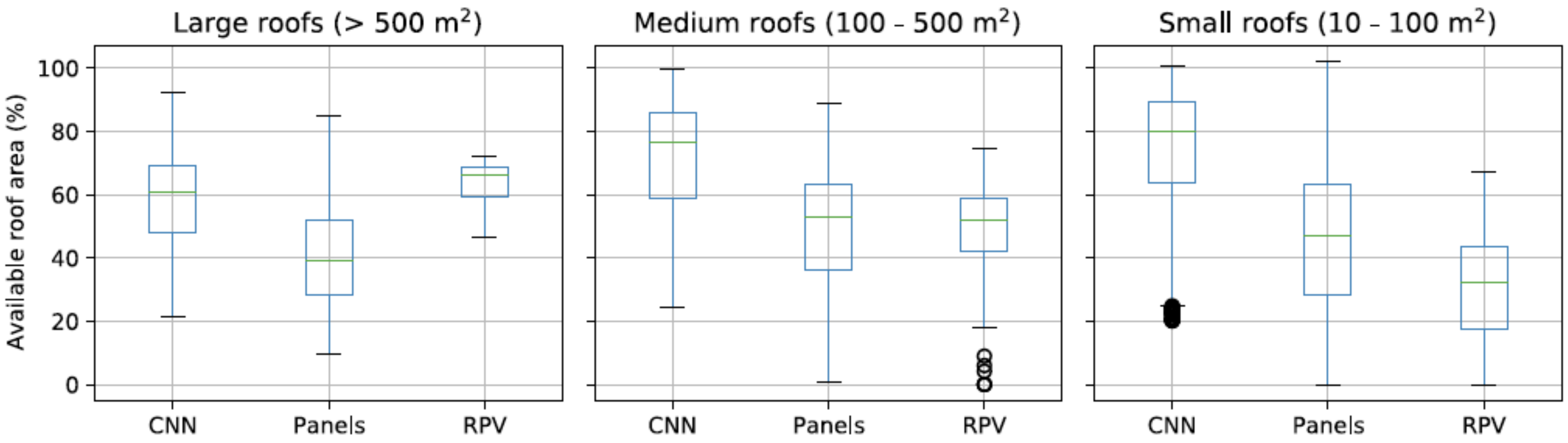
CNN-based model applied to two areas of Geneva (2391 buildings, mostly residential)



Underestimate the available area per roof by 8%

(test set of 52 images)

How good compared to others?



- Panels and RPV directly comparable
- Available area on large roofs seems overestimated by RPV (HVAC?)
- Overall, the overestimation is offset by smaller detected area for small roofs

	All roofs		
	CNN	*Panels*	*RPV*
Total area (10^3 m^2)	98.5	65.8	65.4
Mean % of roof	74	45.4	33.1
Std. % of roof	19.6	22.5	17.9
Median % of roof	79	47.7	35