Towards better estimates of wind power potentials in the Alps

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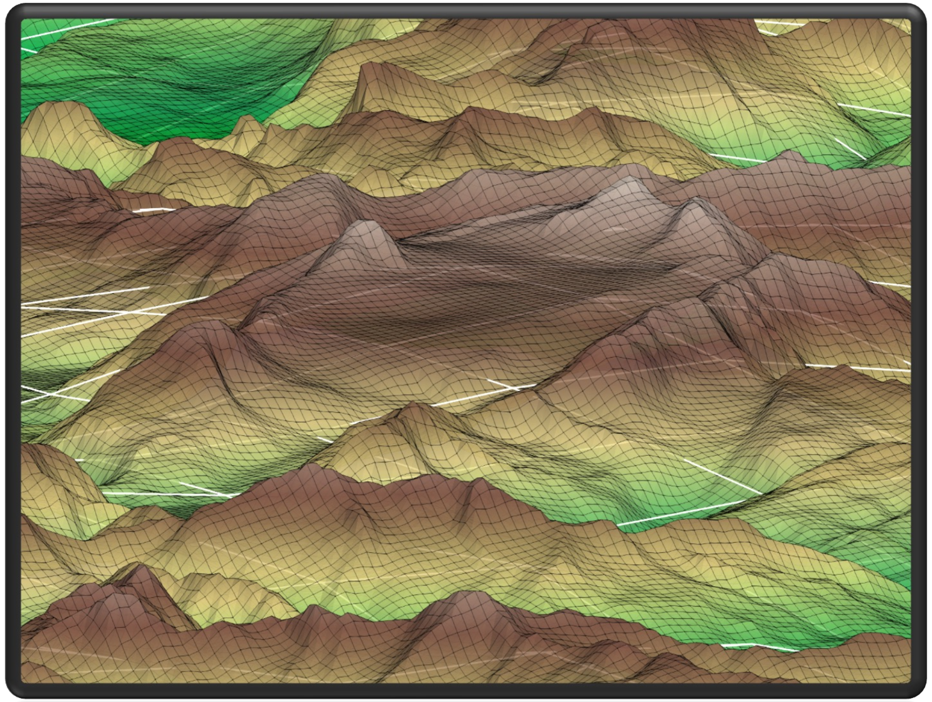


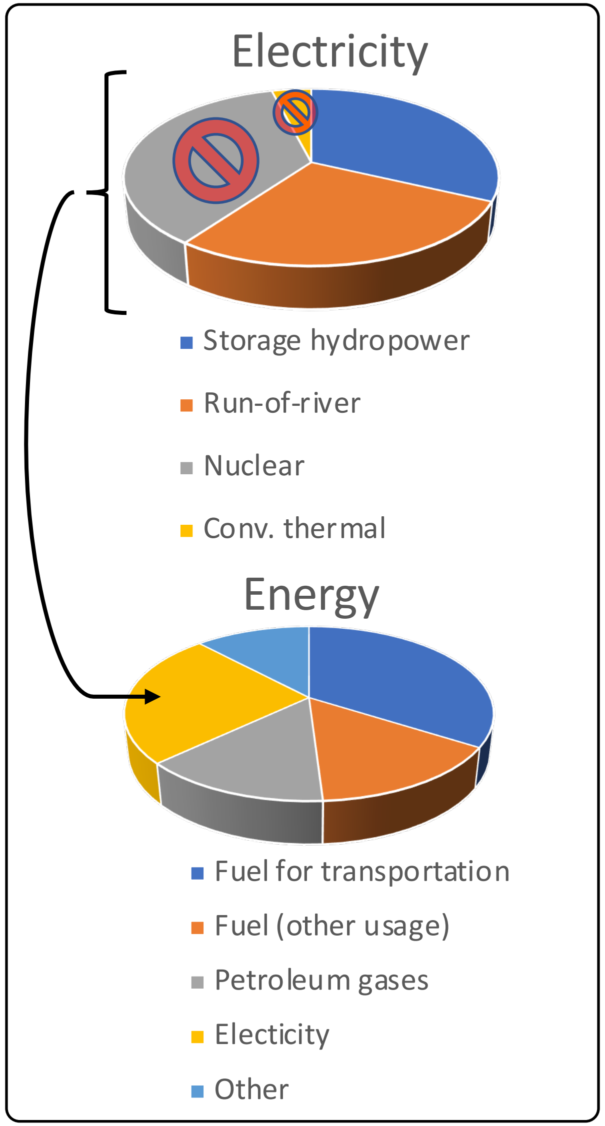
I. Some context: facing winter energy deficits

II. Wind power: an ideal complement to hydropower

III. Wind-Topo: a deep learning approach to wind downscaling
   a. Datasets
   b. Architecture
   c. Results

IV. Conclusion and outlook

I. Some context: facing winter energy deficits



Source: Swiss Federal Office of Energy

The challenge of the Swiss energy transition:

- **40 %** of current electricity should come from photovoltaic (PV) and wind energy

- This requires the installation of either:

  \- **115 km²** of PV panels (18% efficiency)
  currently installed: 13 km²

  All south oriented Swiss roofs
  or 27000 soccer fields
  or 7500x EPFL solar park

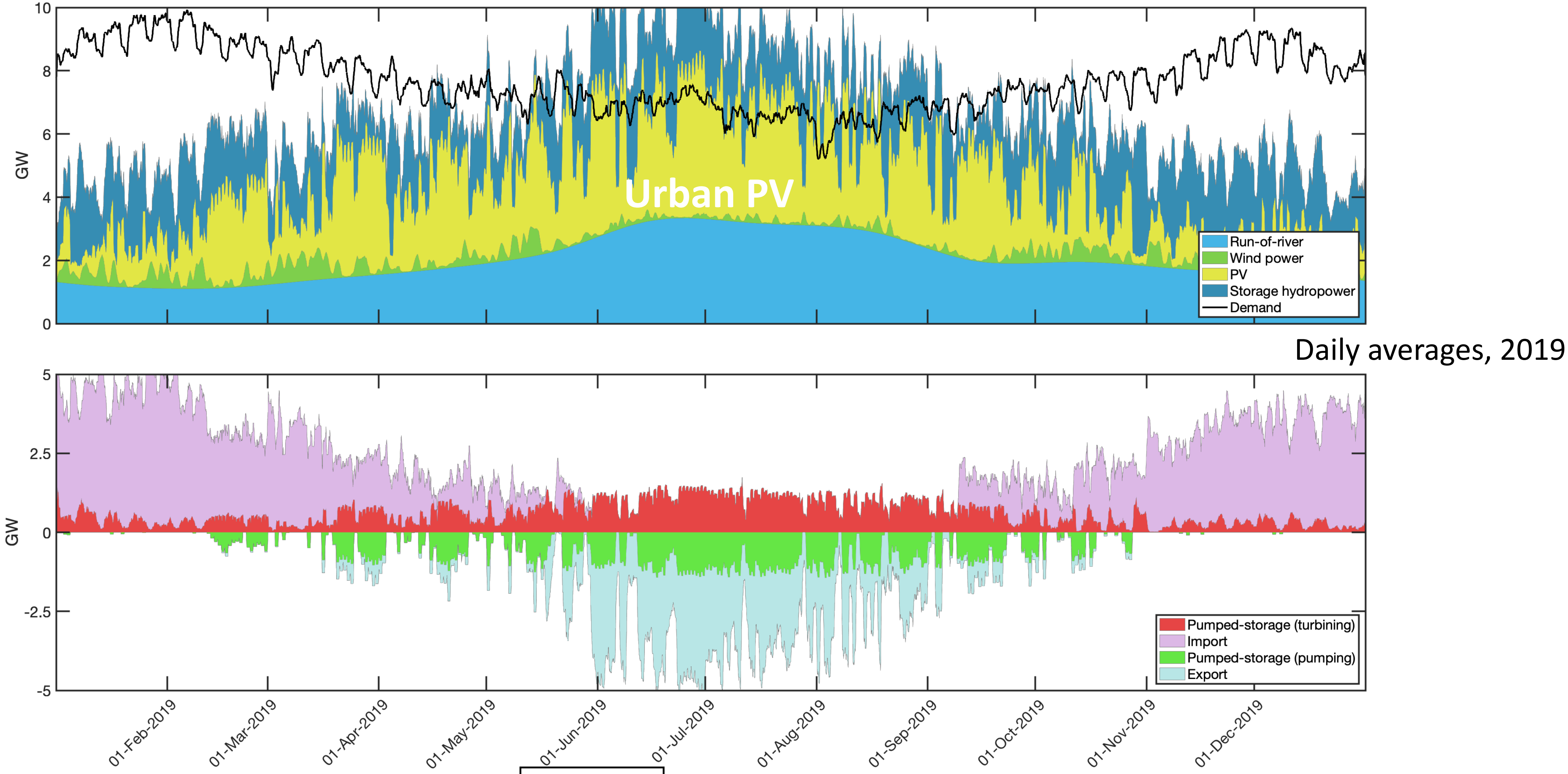
  \- **6000** wind turbines (3 MW each)
  currently installed : 42

  12x the largest US wind farm

- Effort **x10** under current energy consumption and 100% electrification scenario

Best portfolio to complement hydro?

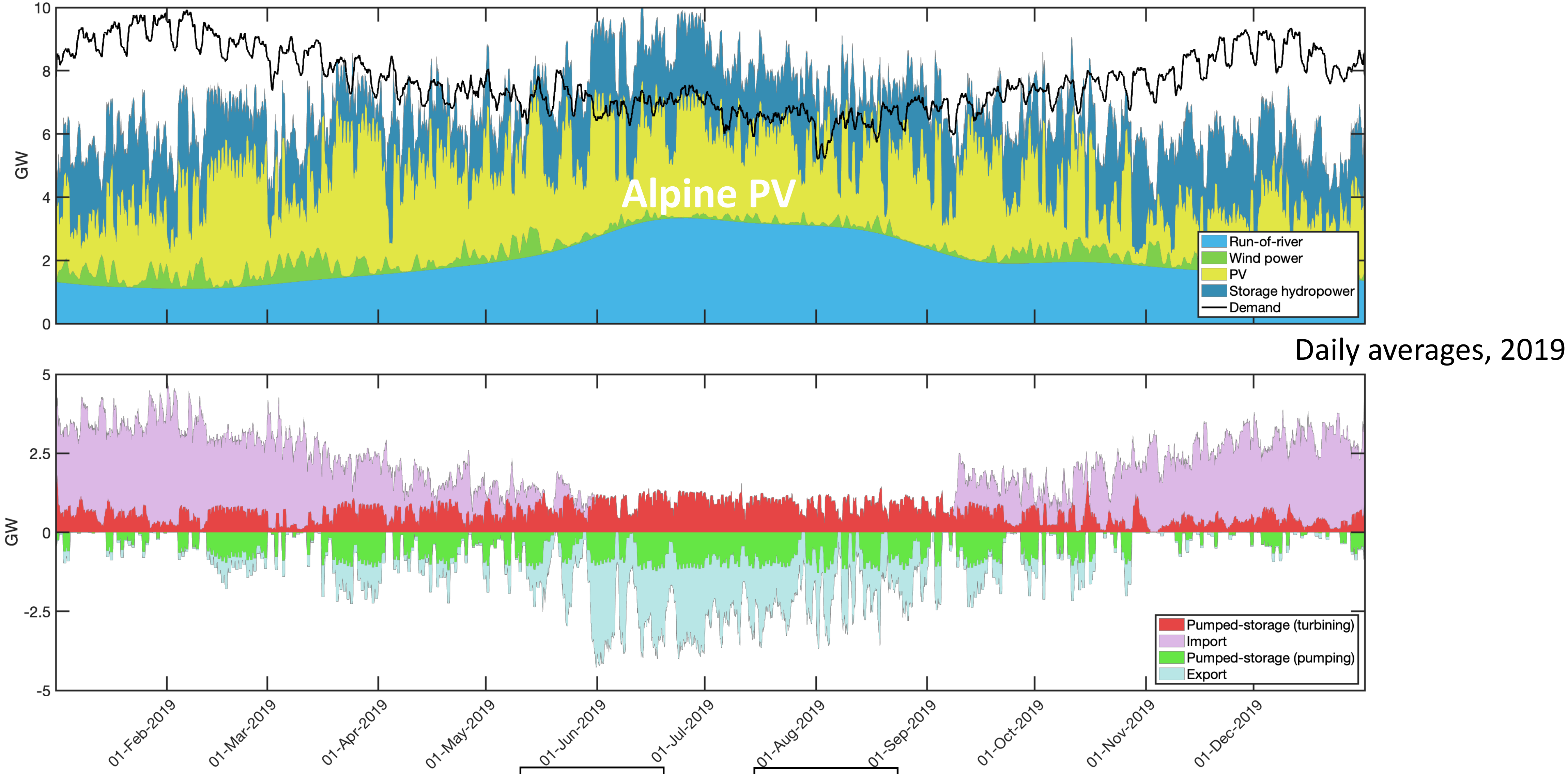
I. Some context: facing winter energy deficits



(PV + Wind: 15 GW)

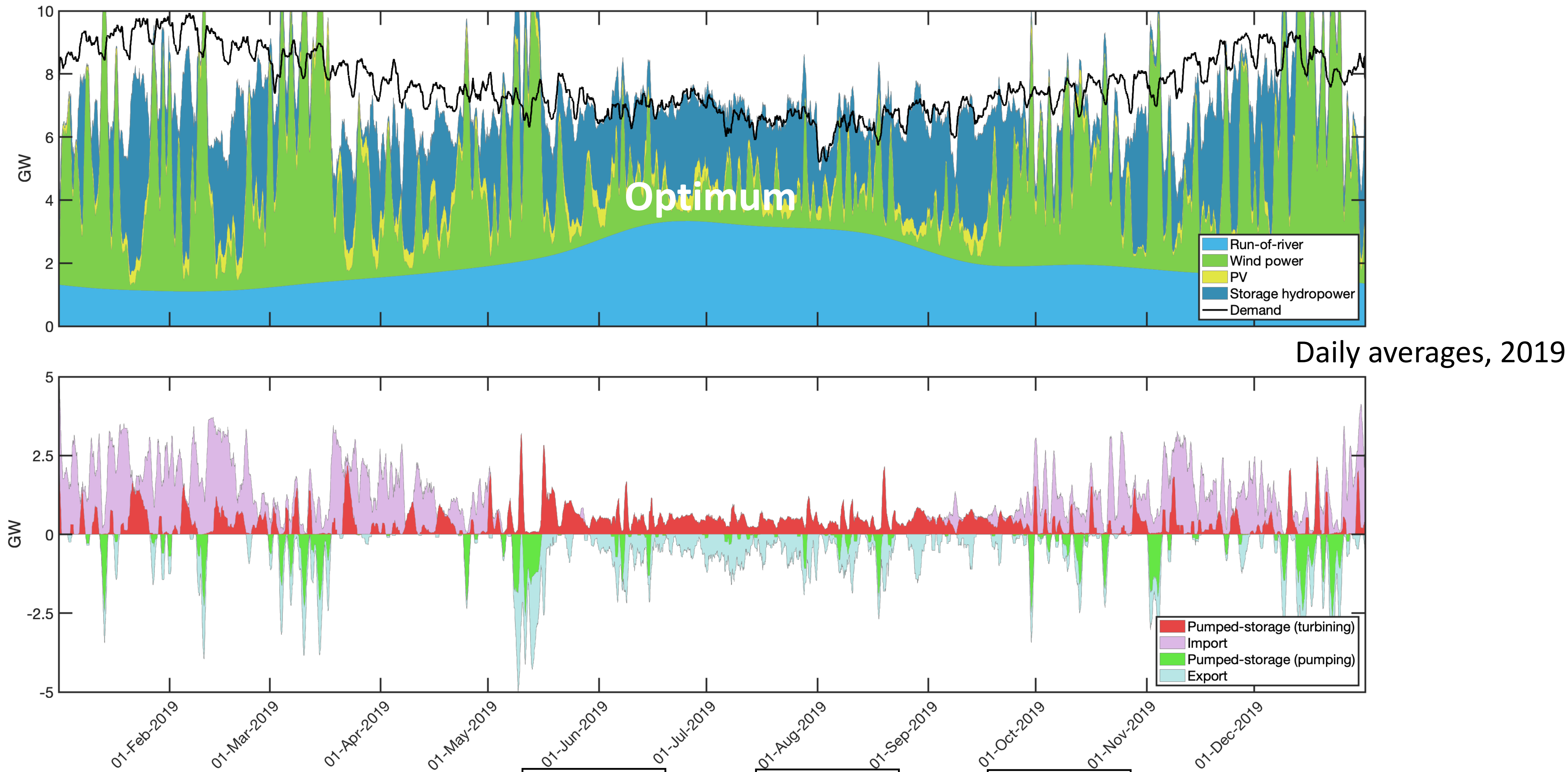
Winter deficit: 14.5 TWh

I. Some context: facing winter energy deficits



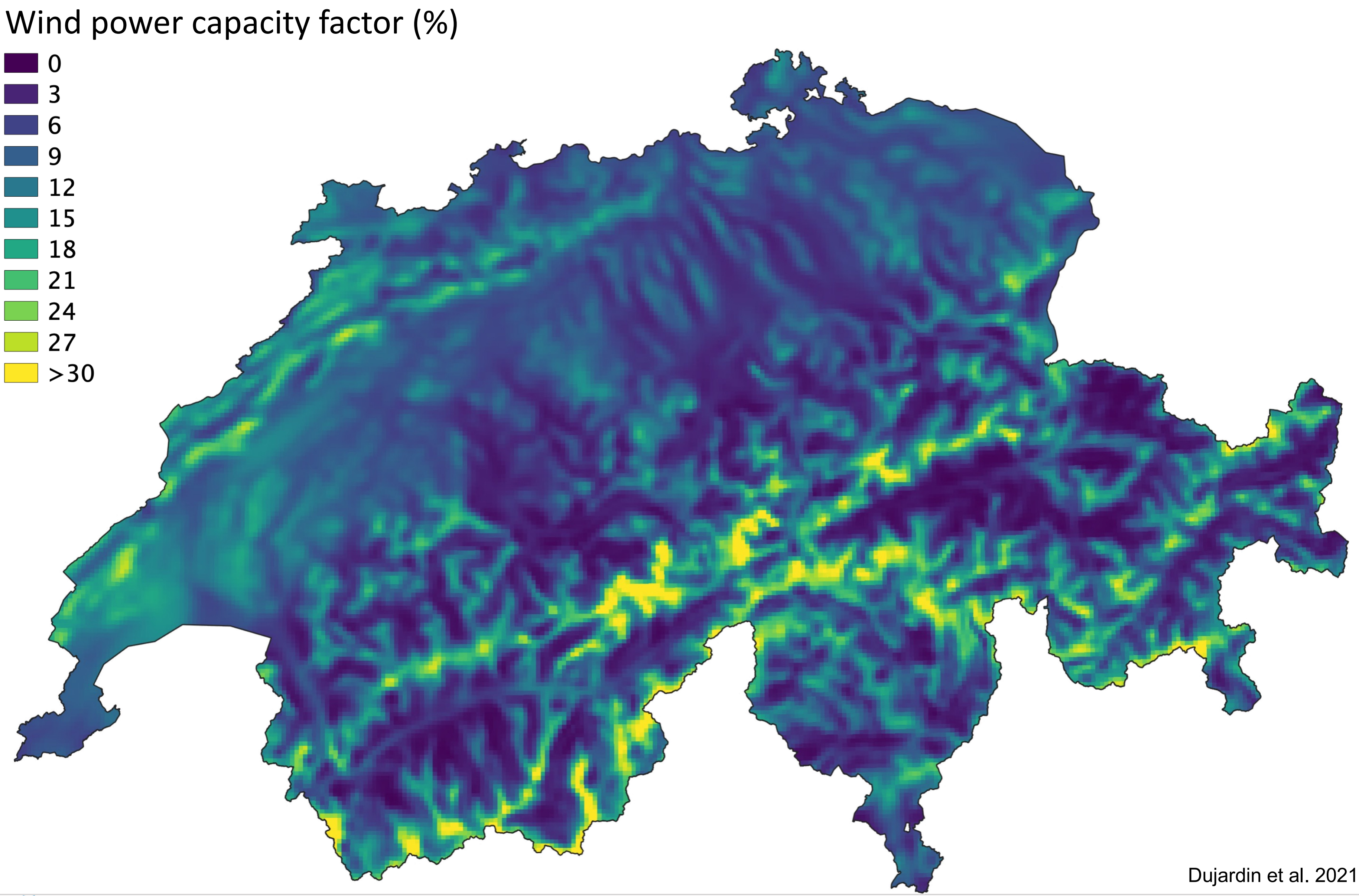
(PV + Wind: 15 GW) **Winter deficit**: $\boxed{14.5 \text{ TWh}} \longrightarrow \boxed{11.7 \text{ TWh}}$

I. Some context: facing winter energy deficits



(PV + Wind: 15 GW) **Winter deficit:** 14.5 TWh (8% Wind) → 11.7 TWh (8% Wind) → 6.5 TWh (88% Wind) (3 TWh inevitable)

II. Wind power: an ideal complement to hydropower



Dujardin et al. 2021

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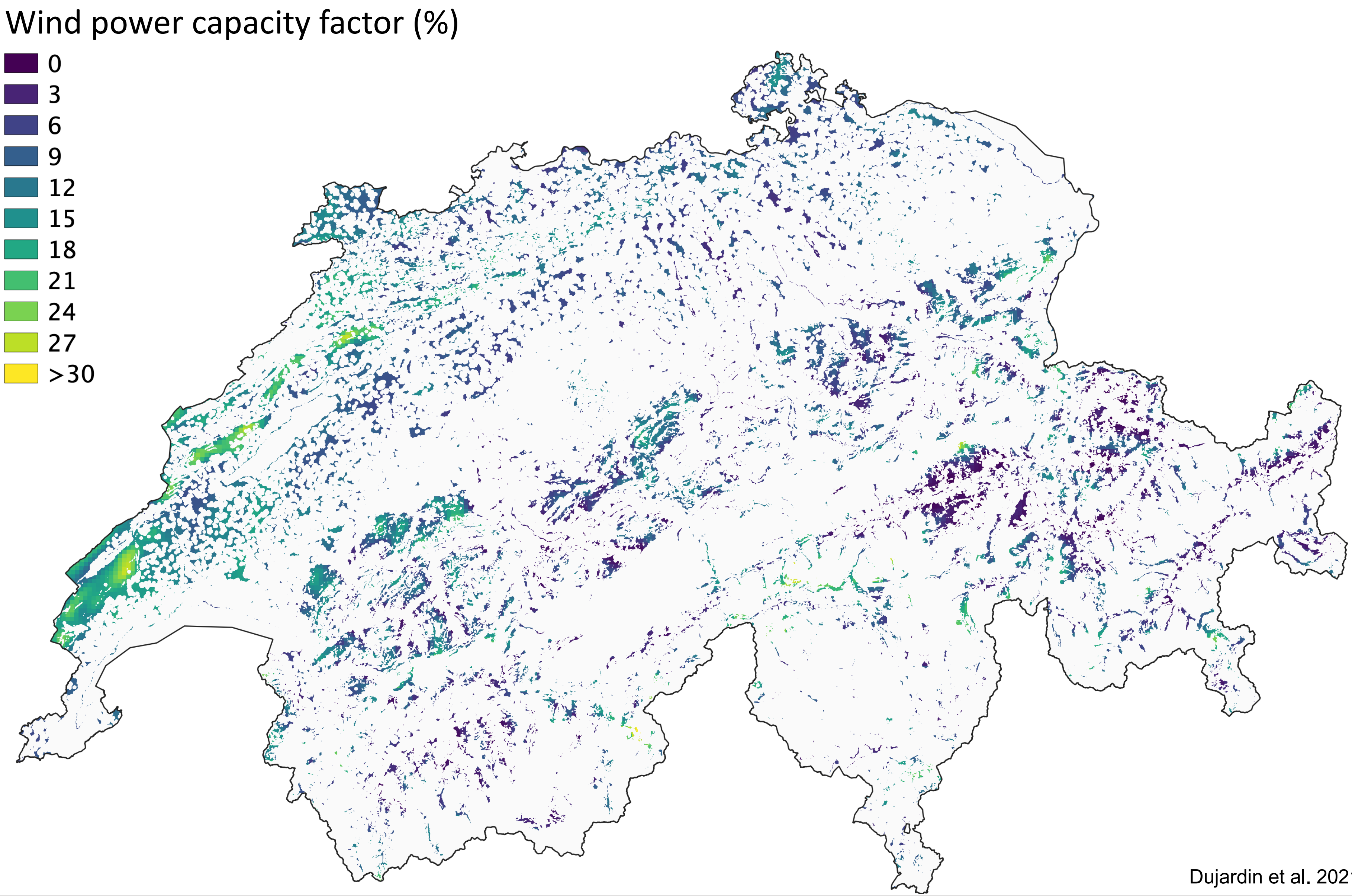

Dujardin et al. 2021

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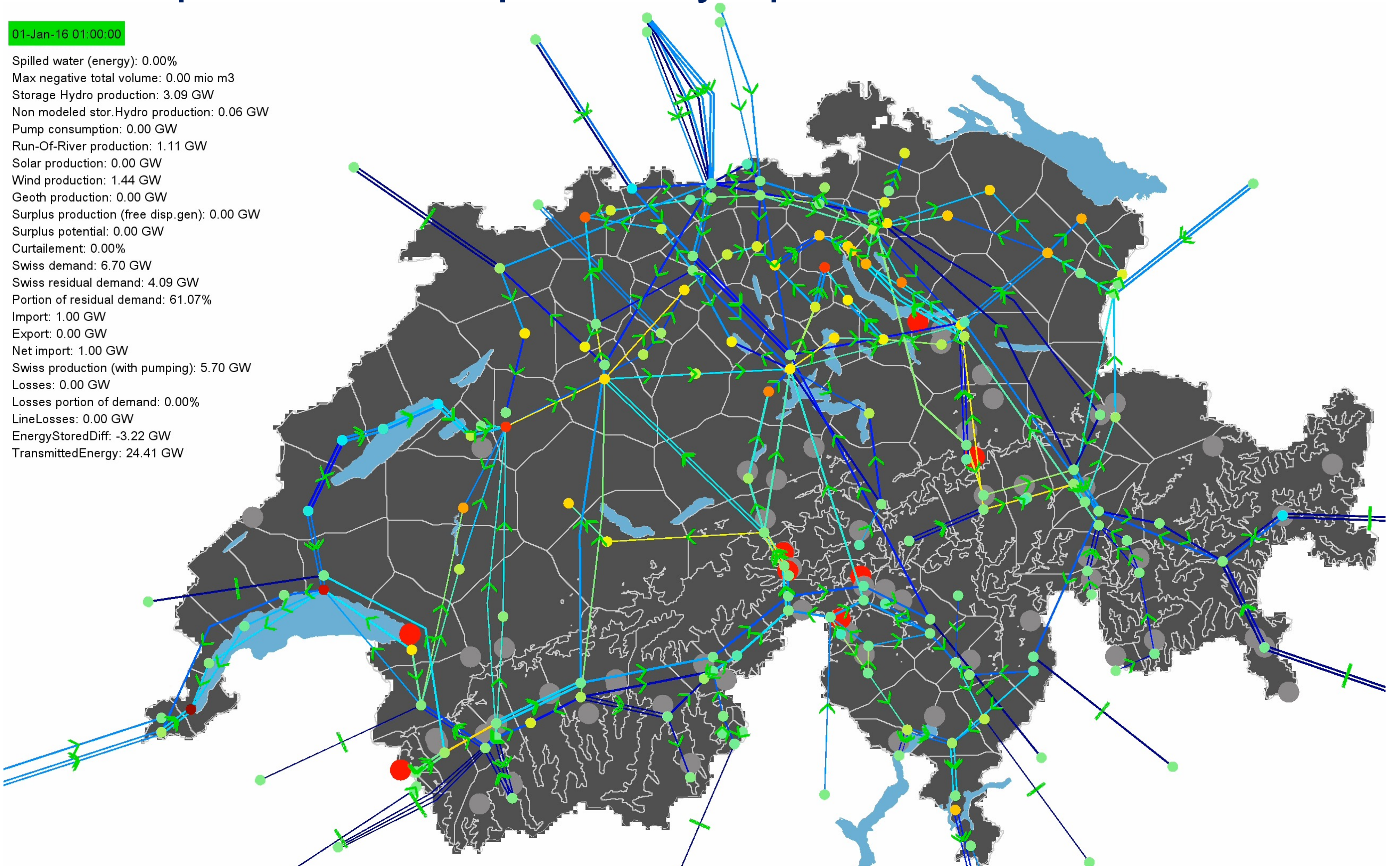
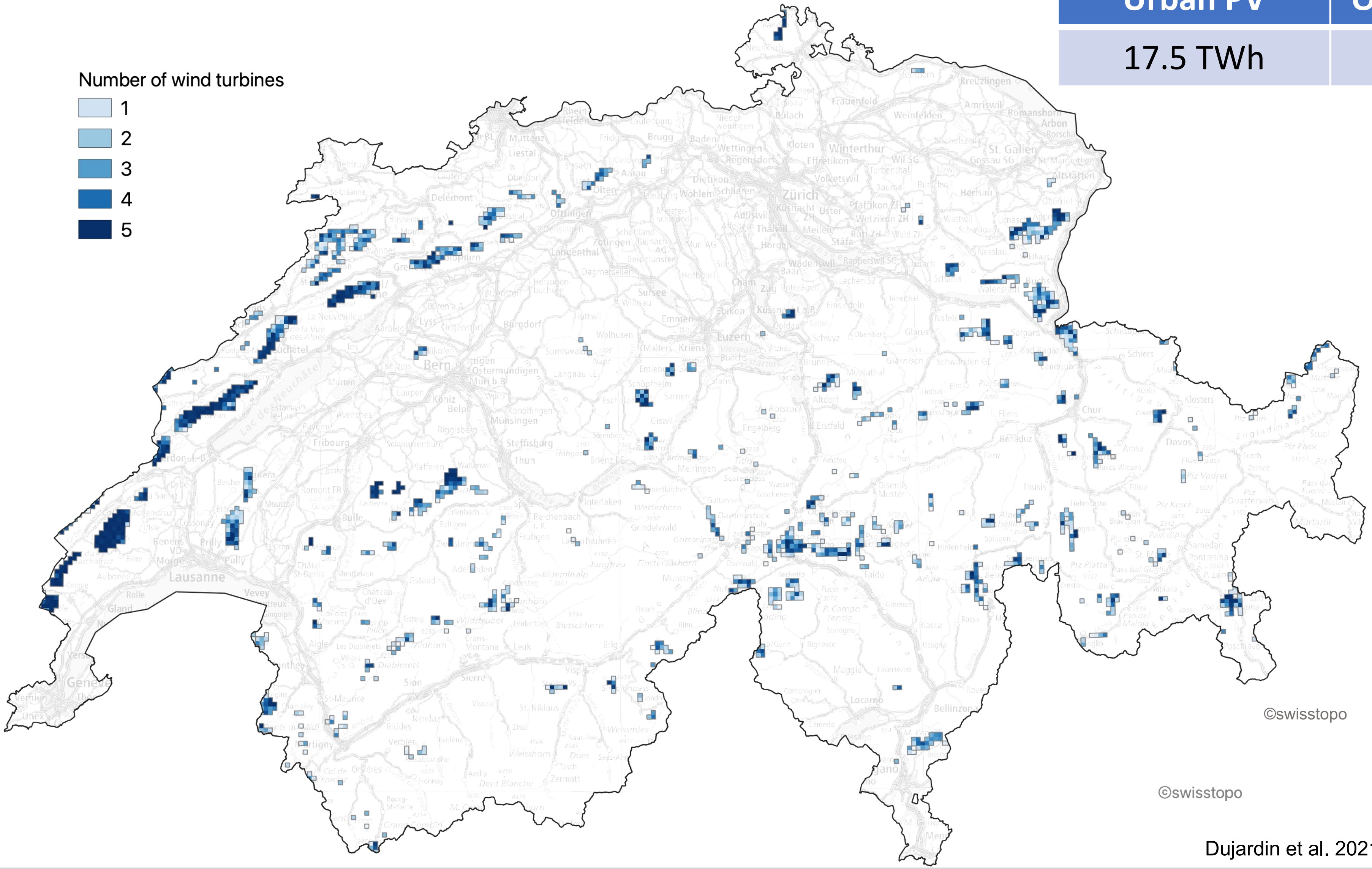


II. Wind power: an ideal complement to hydropower

Winter deficit

Urban PV	Opti PV + Wind
17.5 TWh	3.5 TWh

(year 2016)



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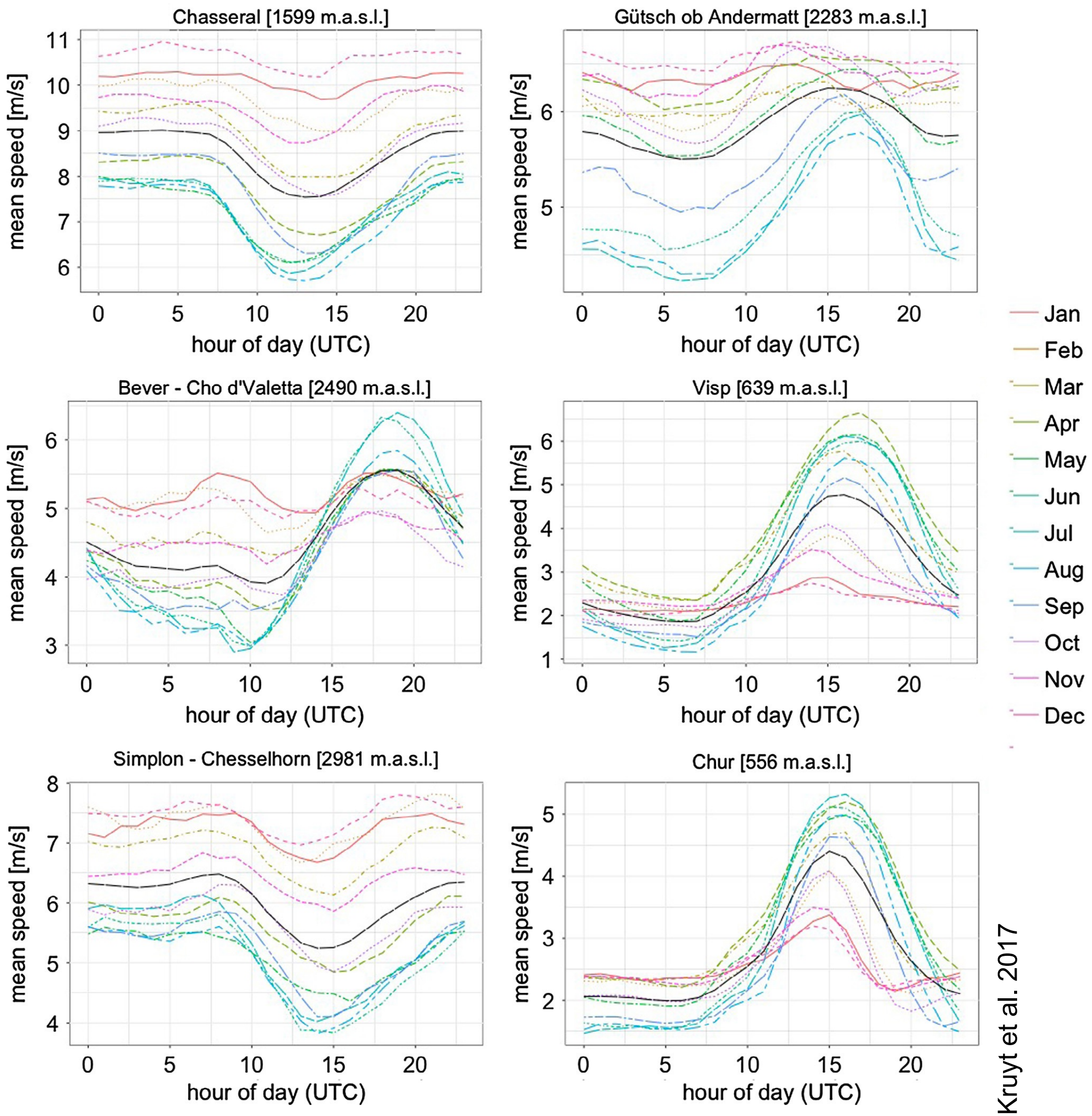
II. Wind power: an ideal complement to hydropower



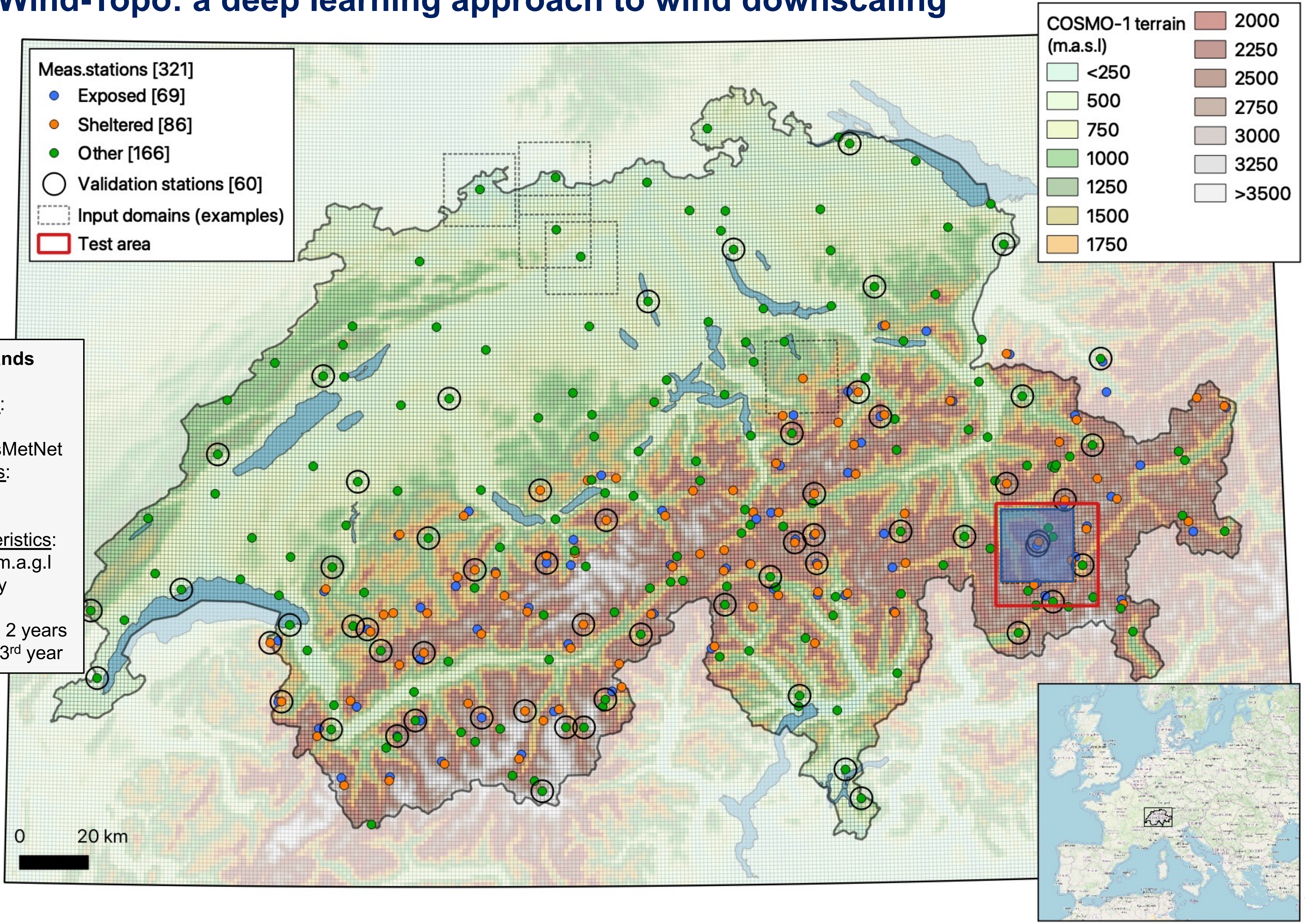
Kruyt et al. 2017

Complex topography → High heterogeneity

Small (sub-grid) scale effects like:

- Sheltering
- Ridge acceleration
- Thermally driven flows

III. Wind-Topo: a deep learning approach to wind downscaling



Predictands

Stations :
- IMIS
- SwissMetNet

Variables:
- u
- v

Characteristics:
- 7-10 m.a.g.l
- Hourly

Period:
- Train: 2 years
- Test: 3rd year

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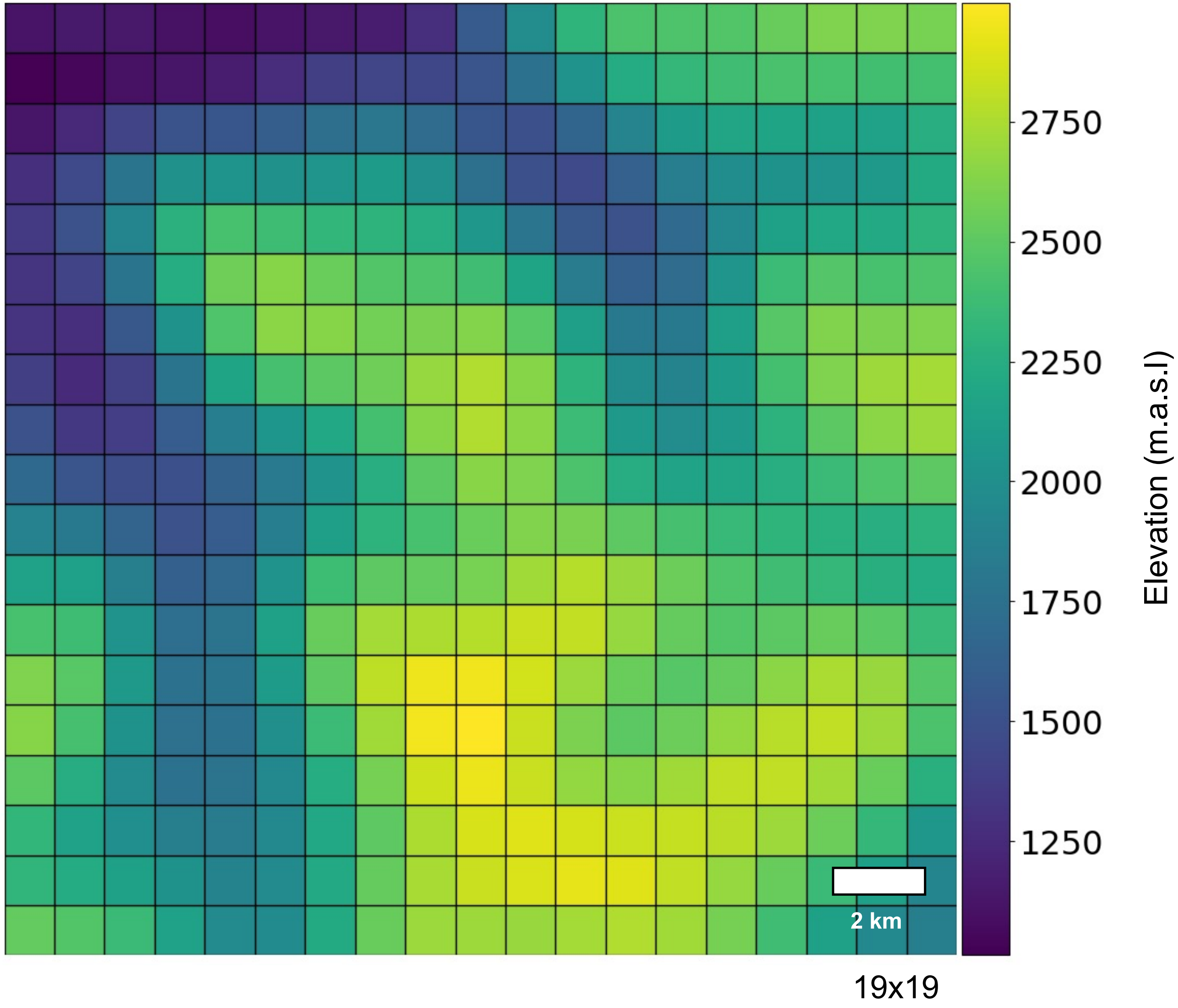
III. Wind-Topo: a deep learning approach to wind downscaling

COSMO-1 data (low-res predictor)

Resolution:
- 19 × 19 pixels
- 1.113 km / pixel
- 21 × 21 km

Variables (# layers):
- z_{cosmo} (1)
- u_{cosmo} (5)
- v_{cosmo} (5)
- w' (5) *
- $\Delta\theta$ / Δh (4) **
- q_s (1)

Period:
- Same times as measurements



* $w' = w_{cosmo} - w_{(from\ u,\ v,\ terrain)}$

** $\Delta\theta$ / Δh: gradient of potential T° between 2 layers

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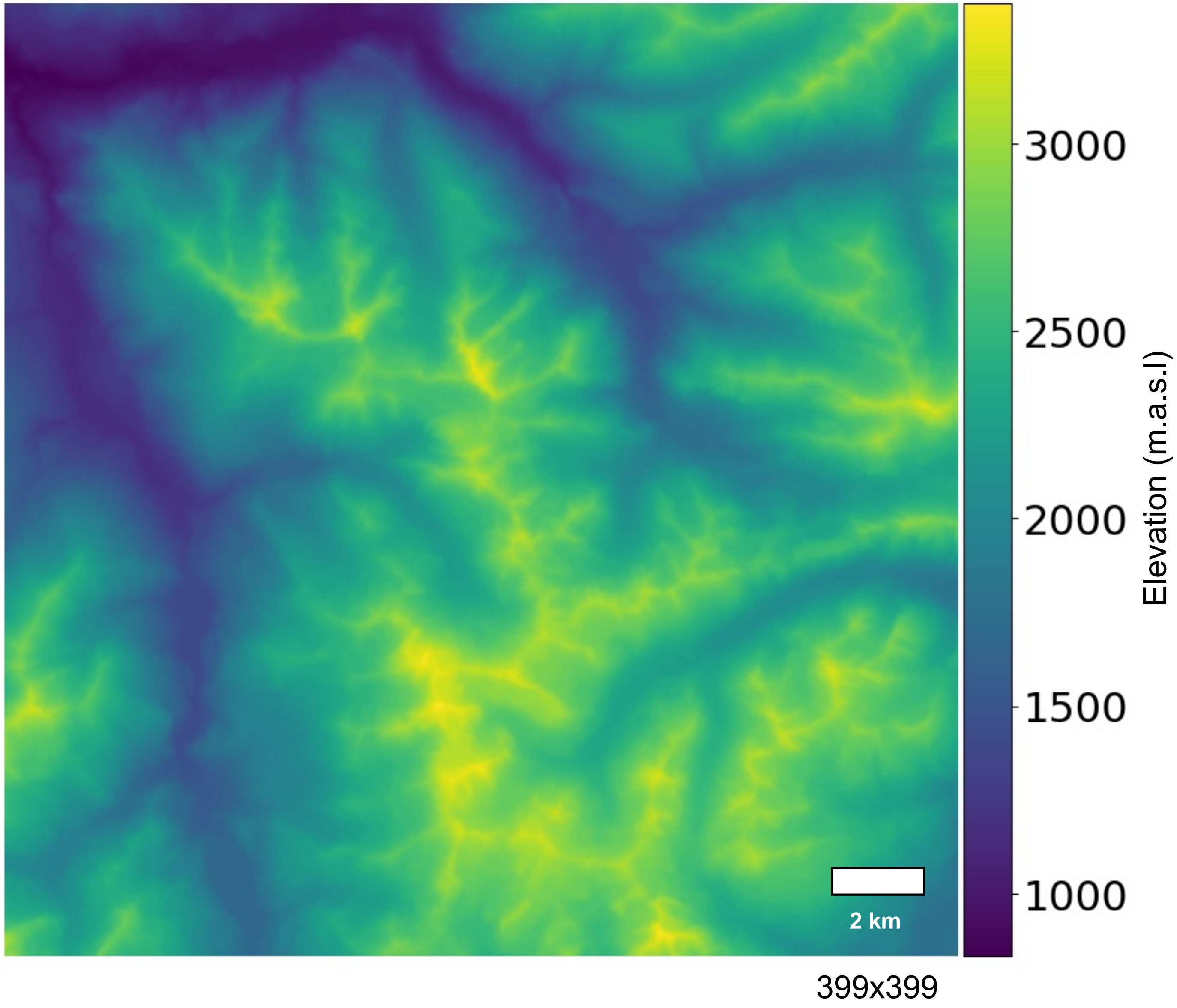
III. Wind-Topo: a deep learning approach to wind downscaling

Topographic data (high-res predictor)

Resolution:
- 399 × 399 pixels
- 53 m / pixel
- 21 × 21 km

Variables (# layers):
- z_{topo} (1)
- slope (1)
- aspect (1)



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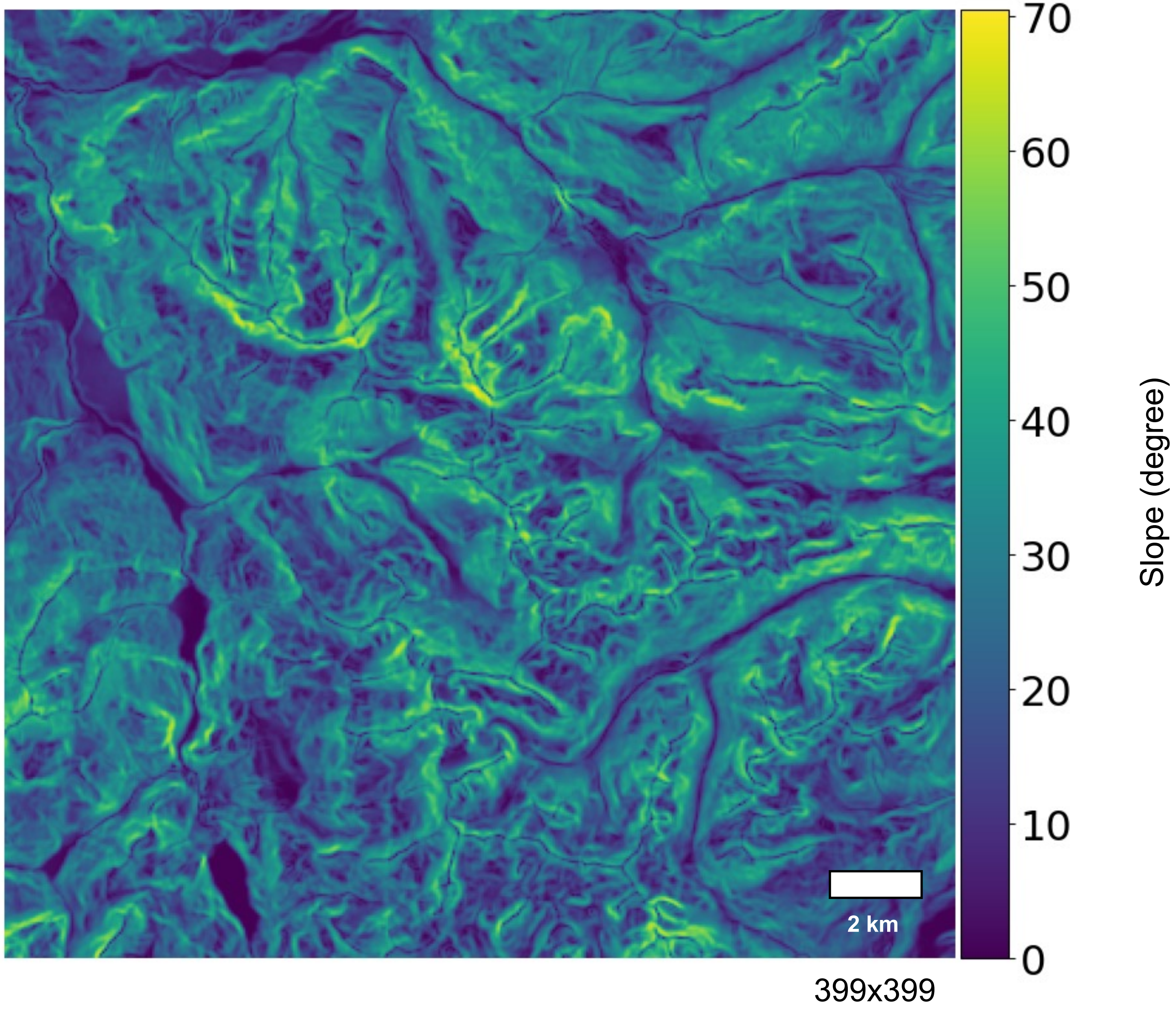

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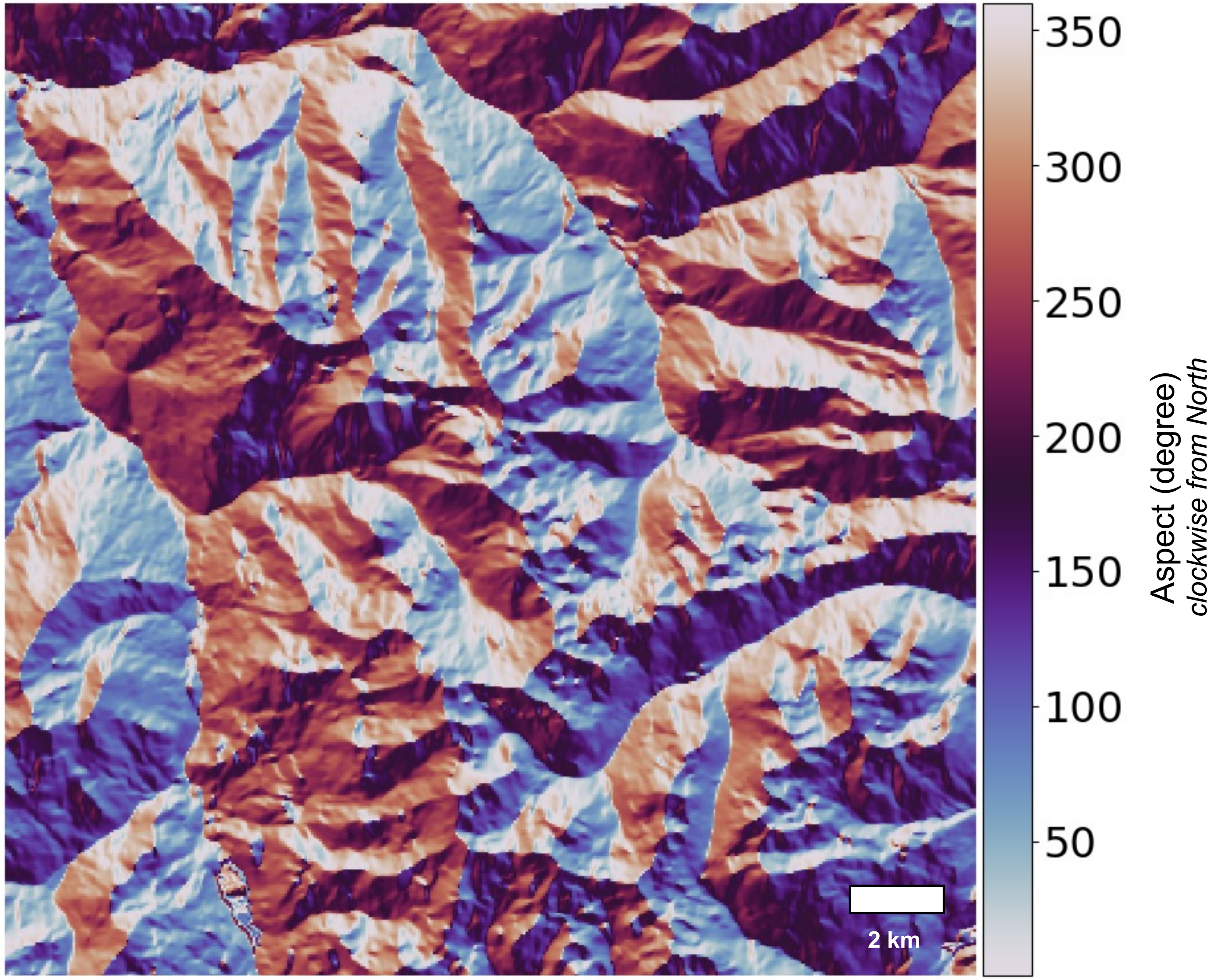

399x399

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III. Wind-Topo: a deep learning approach to wind downscaling

Computation of time-dependent topographic descriptors

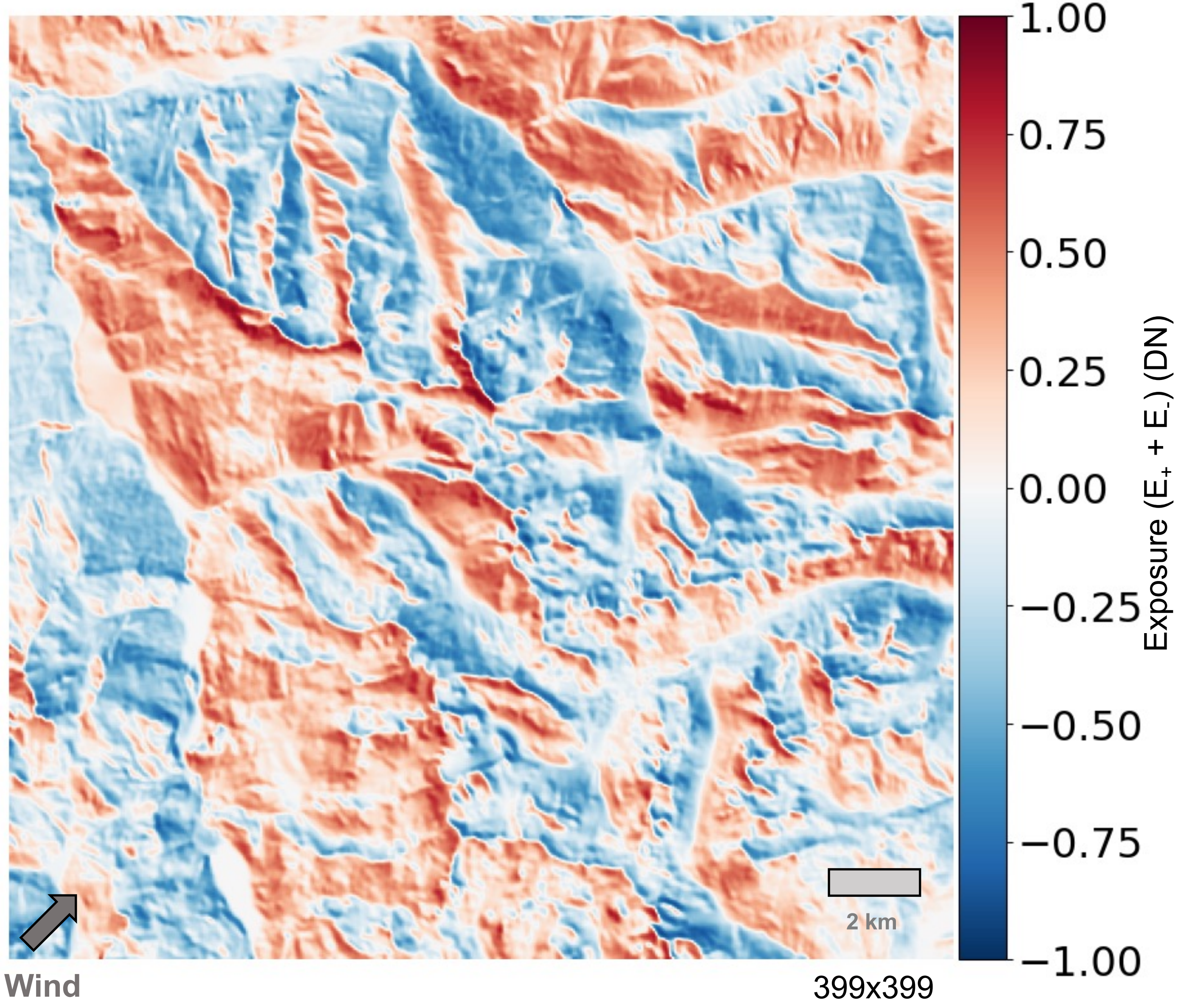
Needs:
- u_{cosmo}, v_{cosmo}
- slope
- aspect

Outputs:
- E+ (1)
- E- (1)
- Δu_{tan} (1)
- Δv_{tan} (1)

$$\begin{cases} E_{+} = max(sin(\alpha),0) \\ E_{-} = min(sin(\alpha),0) \end{cases}$$

where,

$$\begin{cases} \alpha = arctan(tan(slope)cos(\delta)) \\ \delta = arctan2(-v_c,-u_c) - aspect \end{cases}$$



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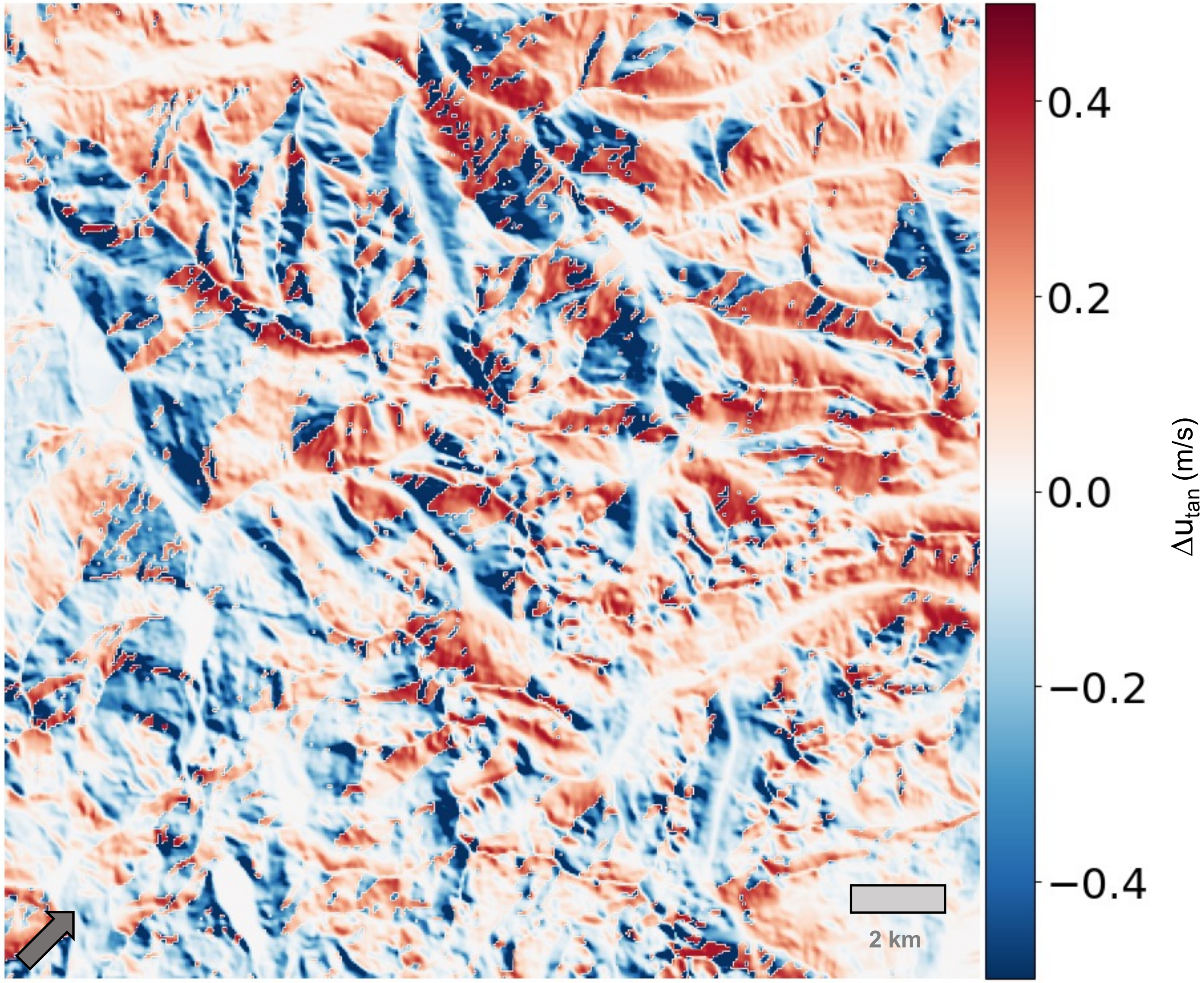
$$\begin{cases} \Delta u_{tan} = (cos(\beta)-1)u_c - sin(\beta)v_c \\ \Delta v_{tan} = sin(\beta)u_c + (cos(\beta)-1)v_c \end{cases}$$

where,

$$\begin{cases} \beta = (\frac{\pi}{2} - |\delta|)sign(\delta)sin(slope) \\ with, \delta \in]-\pi,\pi] \end{cases}$$



Wind (1.41 m/s: u = 1, v = 1)

399x399

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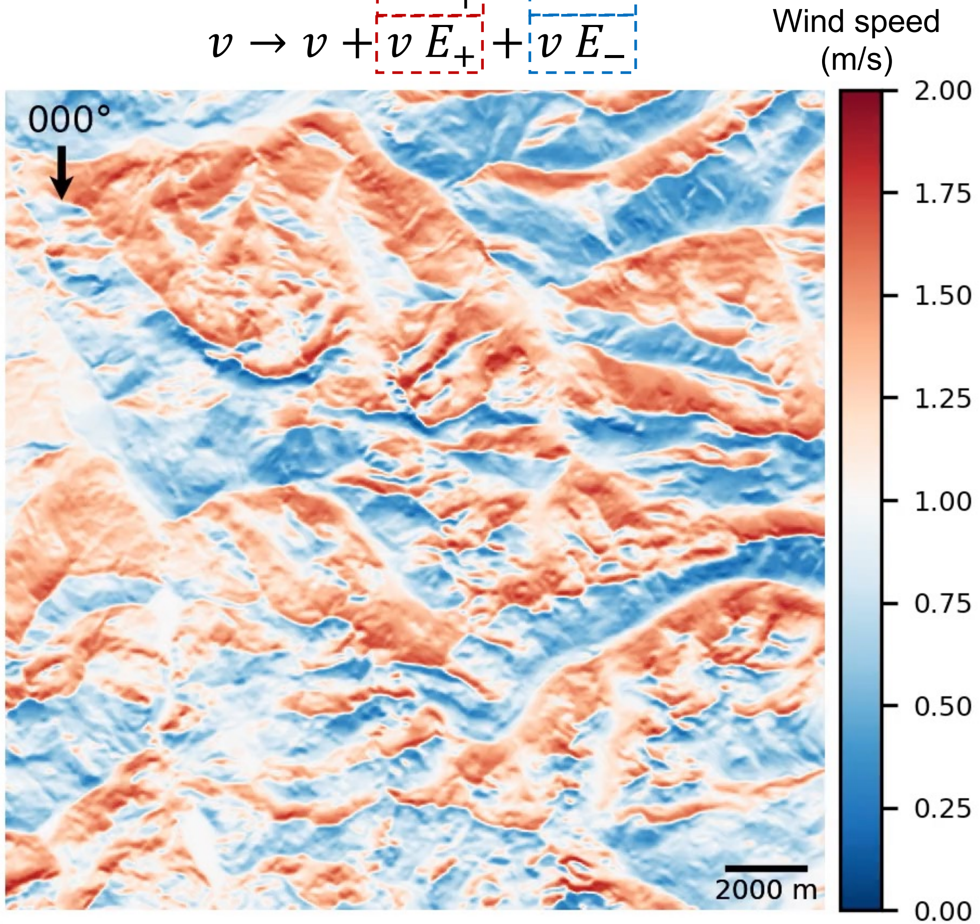
III. Wind-Topo: a deep learning approach to wind downscaling

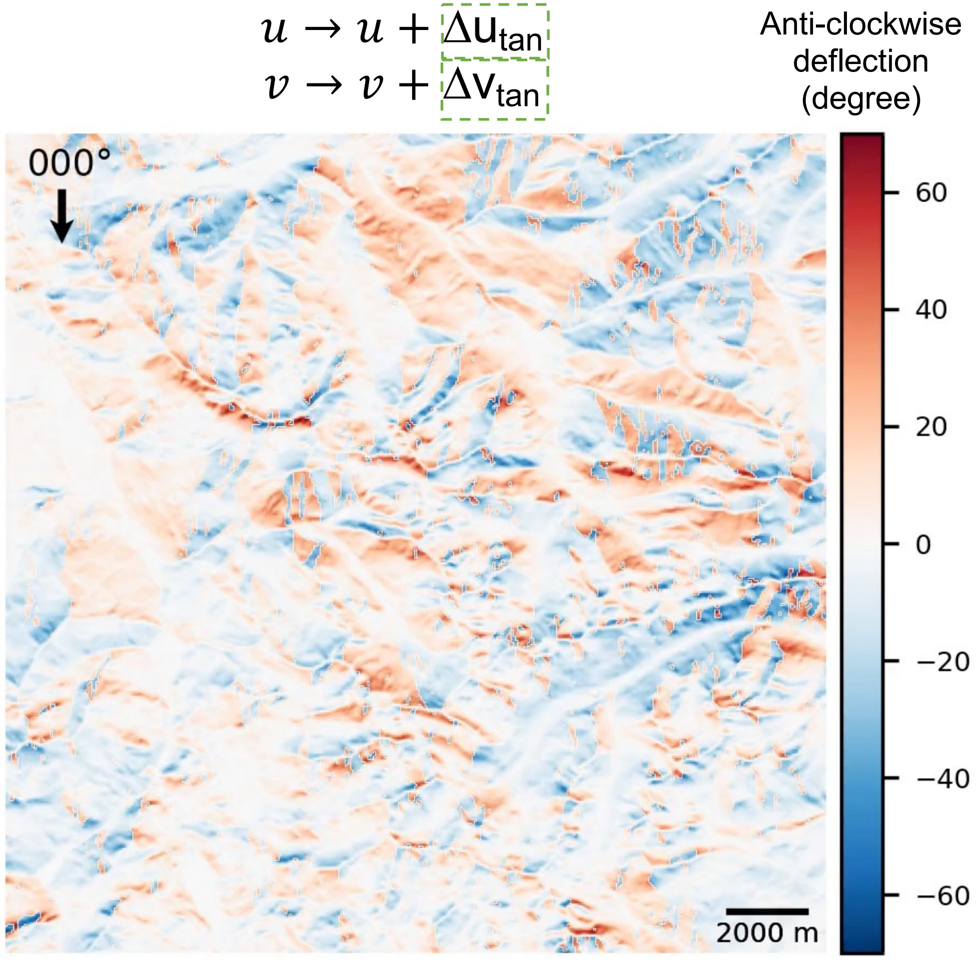
Example of exposure

$$u \rightarrow u + \boxed{u\,E_+} + \boxed{u\,E_-}$$
$$v \rightarrow v + \boxed{v\,E_+} + \boxed{v\,E_-}$$

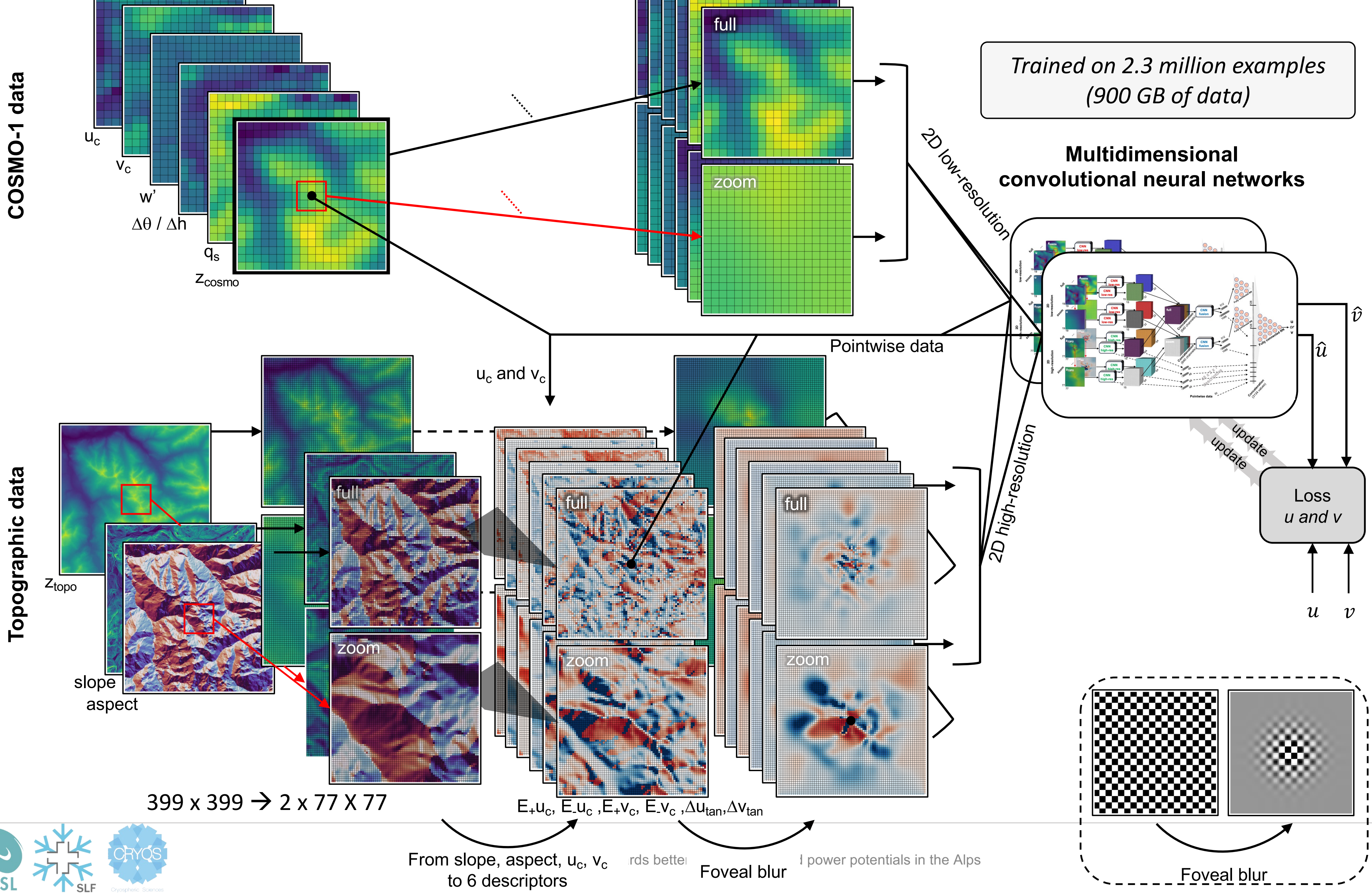


Example of deflection

$$u \rightarrow u + \boxed{\Delta u_{tan}}$$
$$v \rightarrow v + \boxed{\Delta v_{tan}}$$



III. W : a deep learning approach wnscaling



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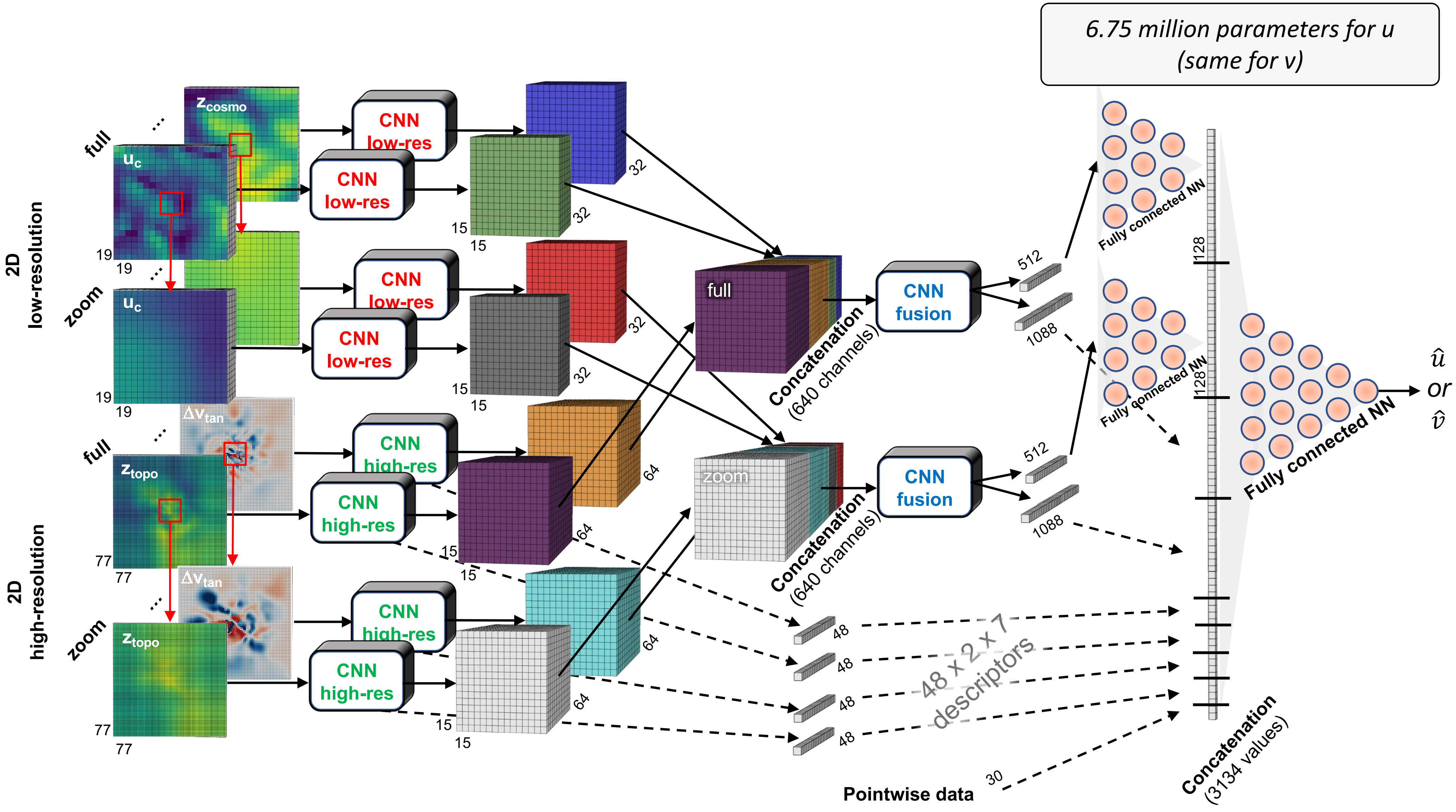
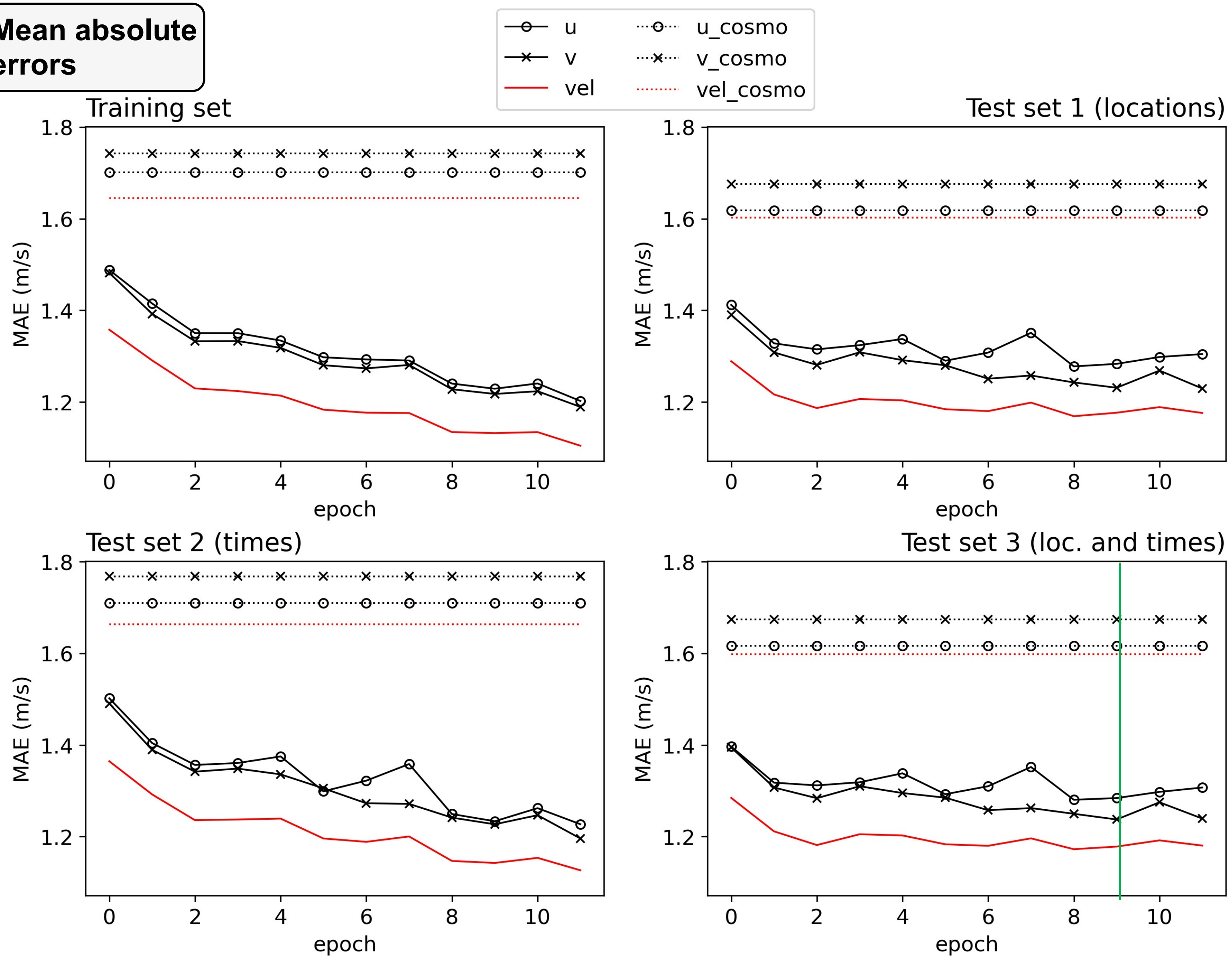


III. Wind-Topo: a deep learning approach to wind downscaling

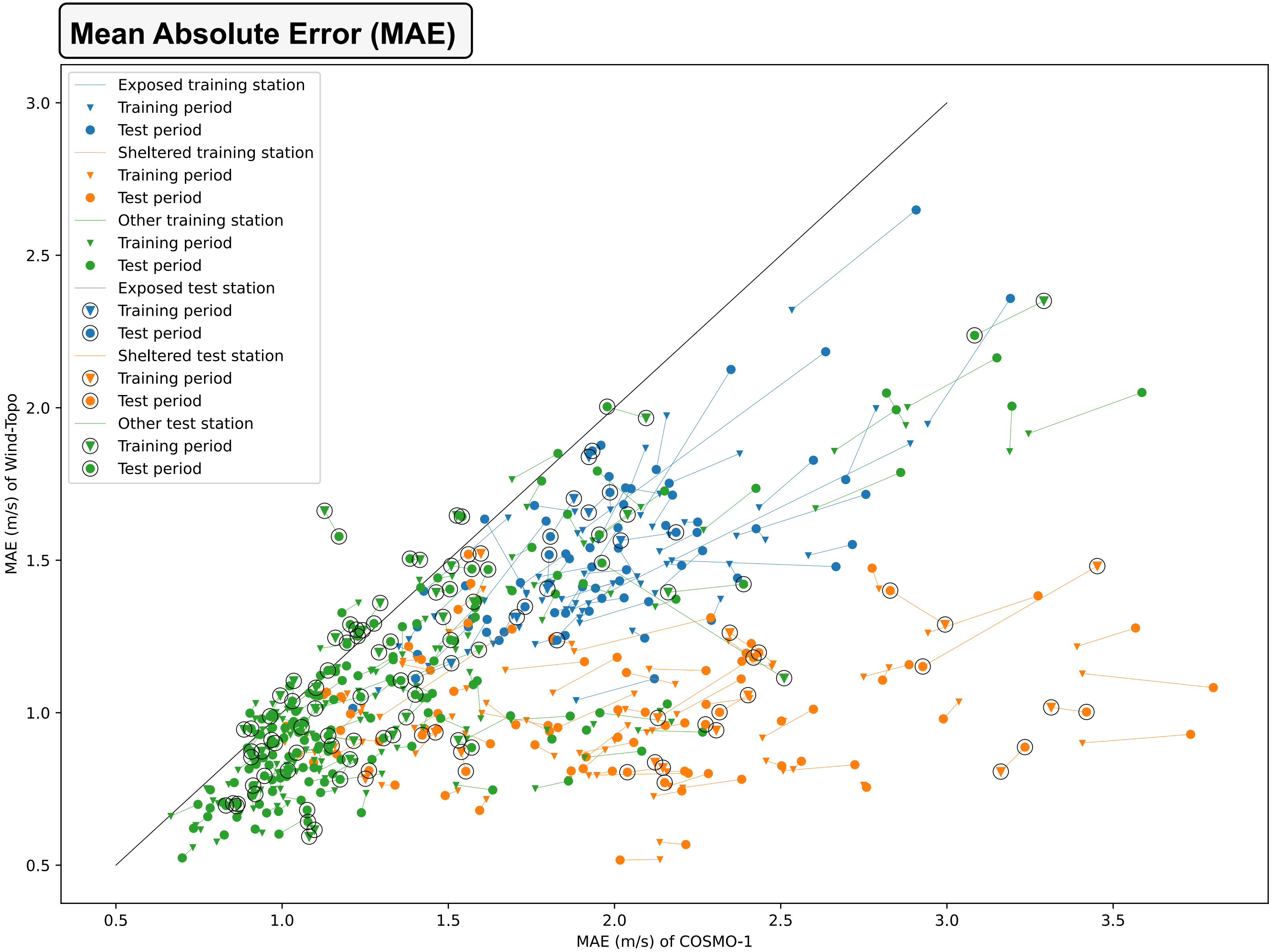
Mean absolute errors



Training set:
261 stations
01 Oct. 2015 – 01 Oct. 2016
and
01 Oct. 2017 – 01 Oct. 2018
Test set 3:
60 stations
01 Oct. 2016 – 01 Oct. 2017

1 epoch = 1 pass through the entire training set

III. Wind-Topo: a deep learning approach to wind downscaling



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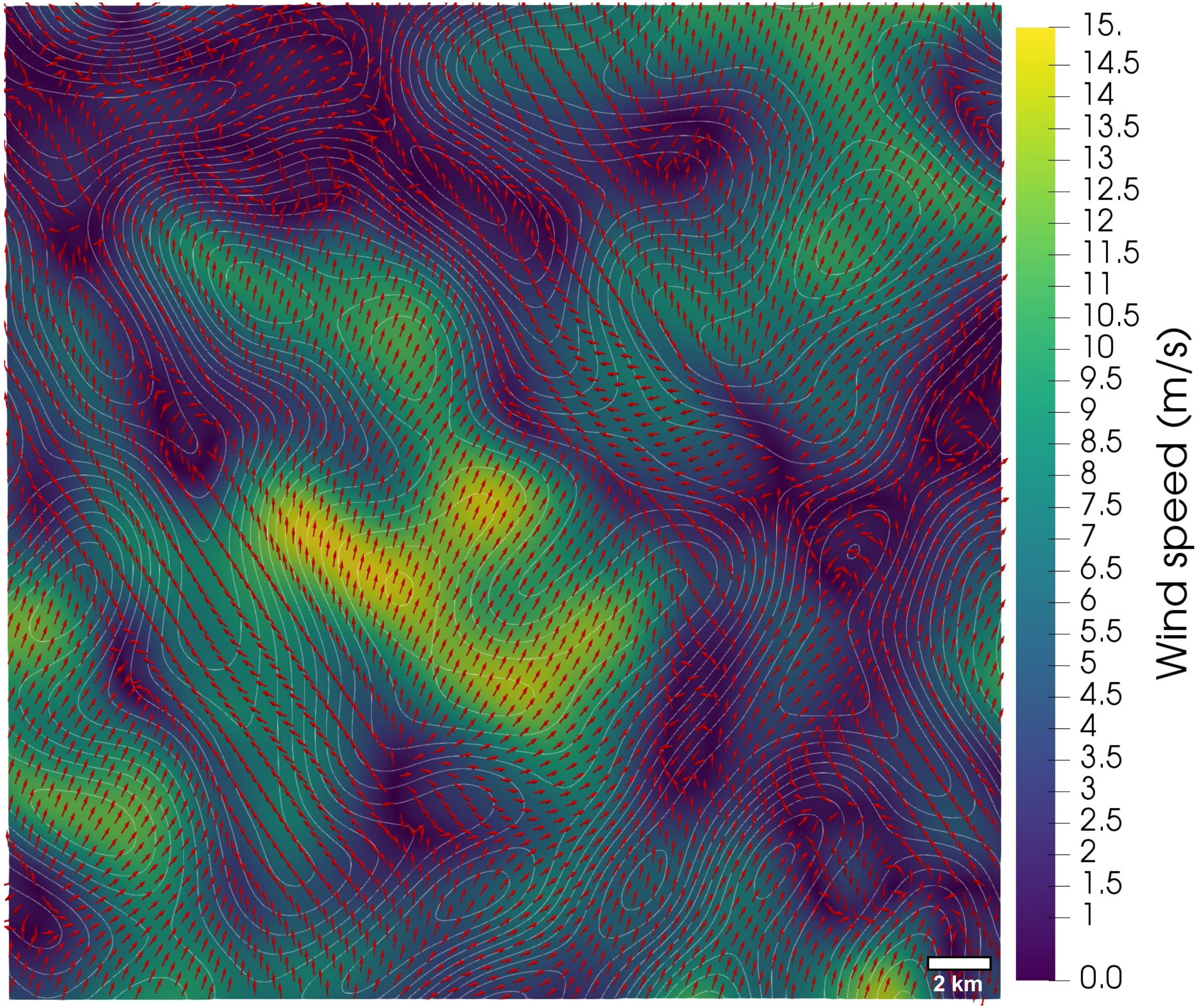
III. Wind-Topo: a deep learning approach to wind downscaling

COSMO-1
at 20:00 23 Oct. 2016



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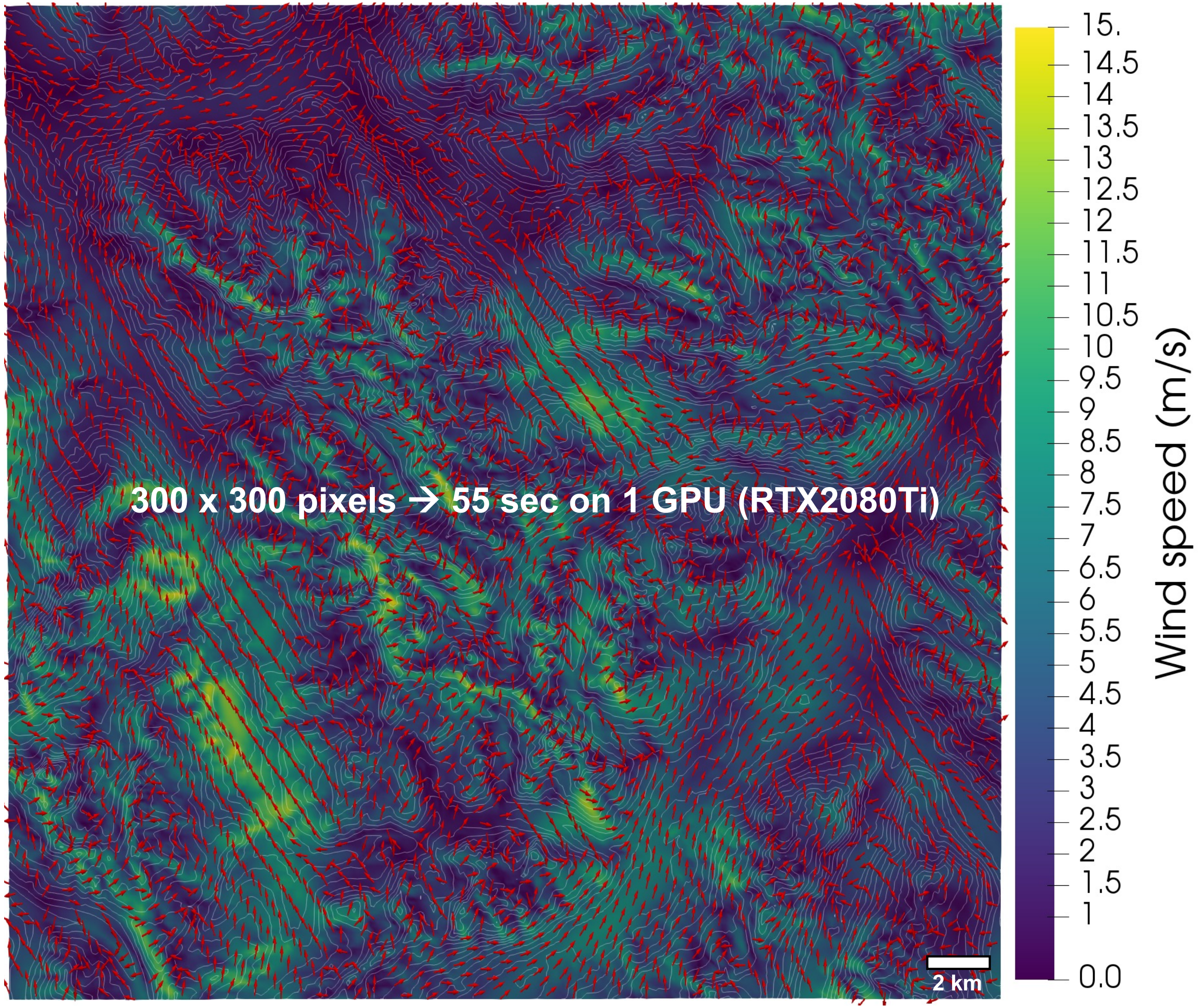
Wind-Topo
at 20:00 23 Oct. 2016



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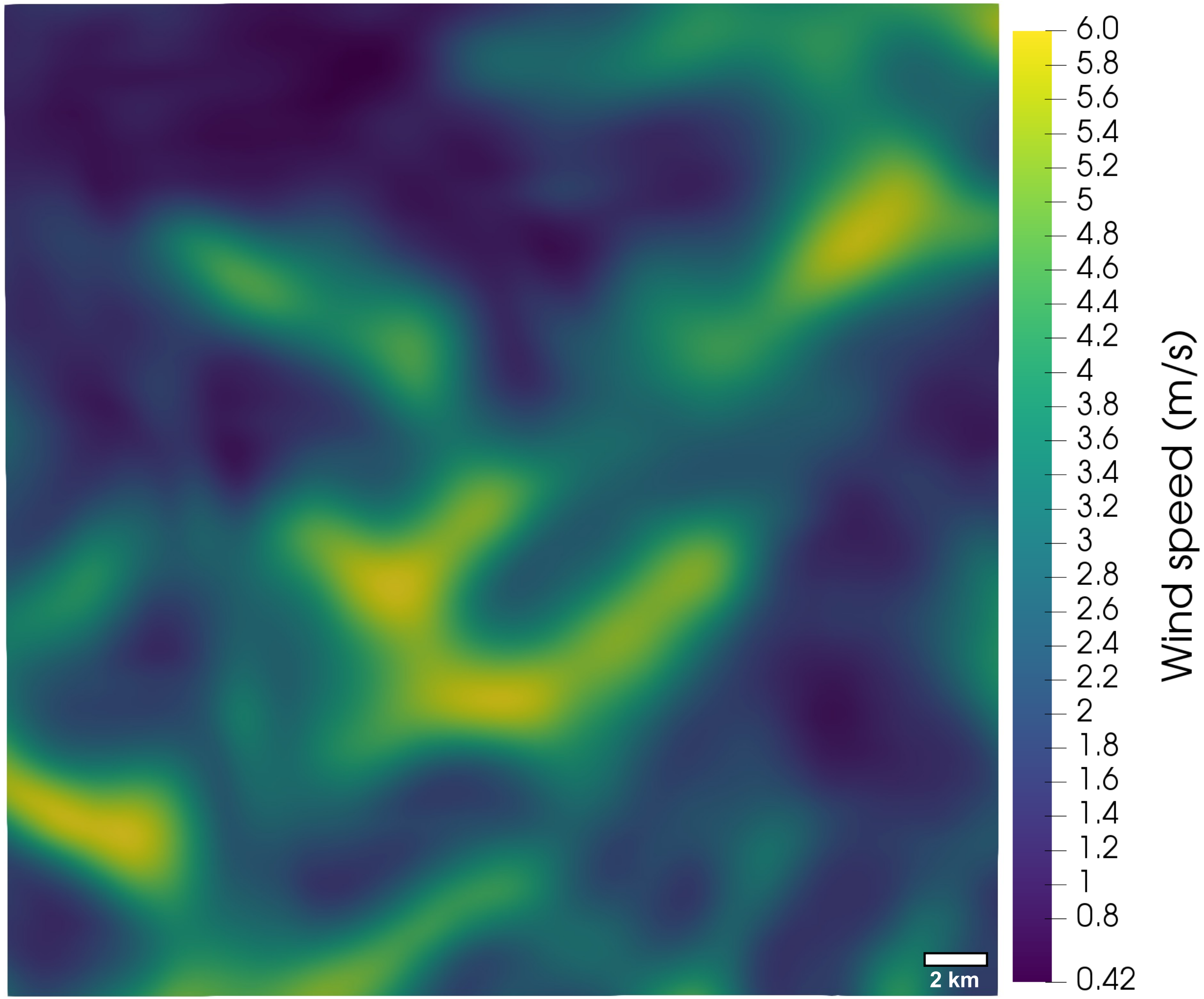
III. Wind-Topo: a deep learning approach to wind downscaling

1 year hourly



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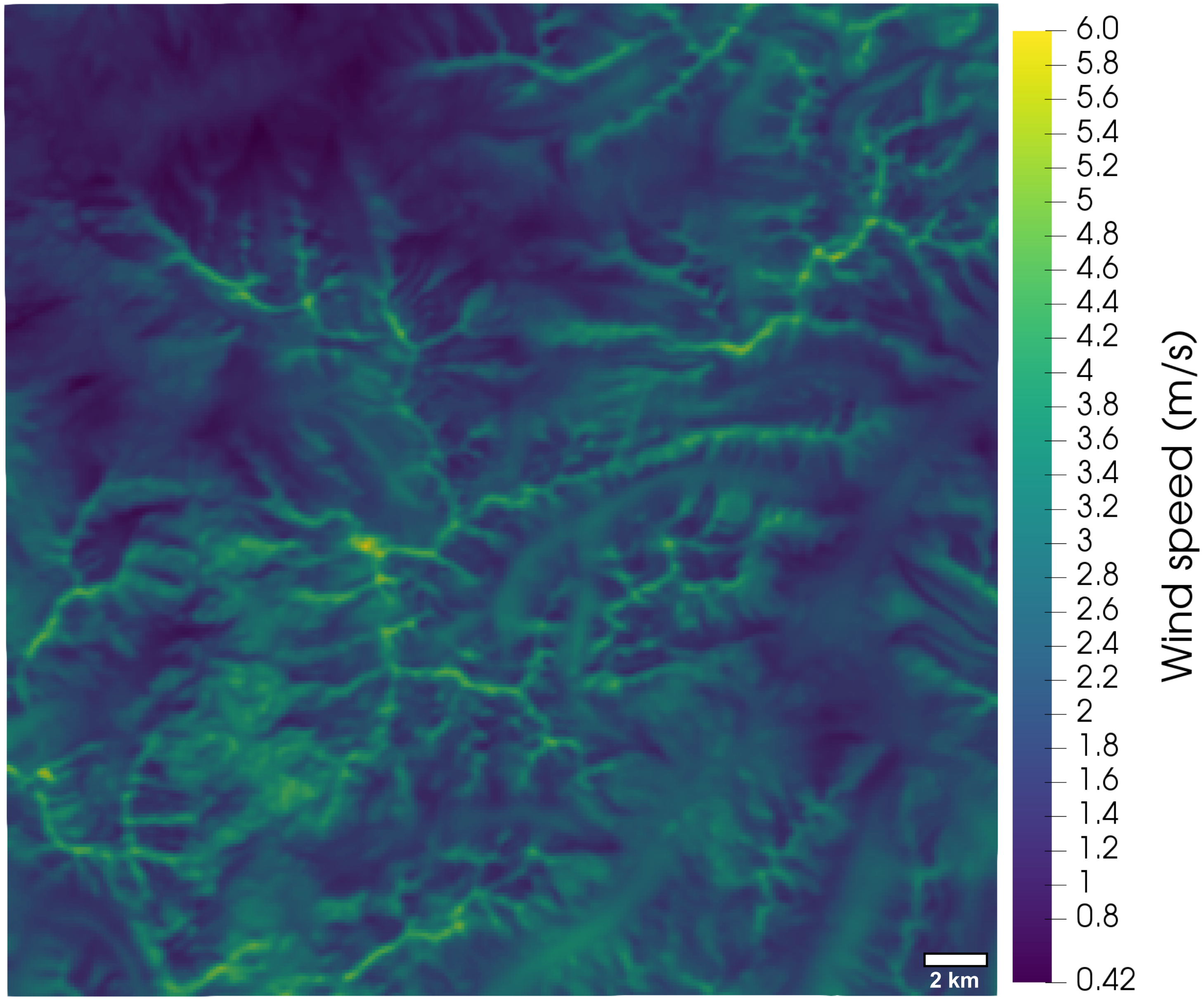

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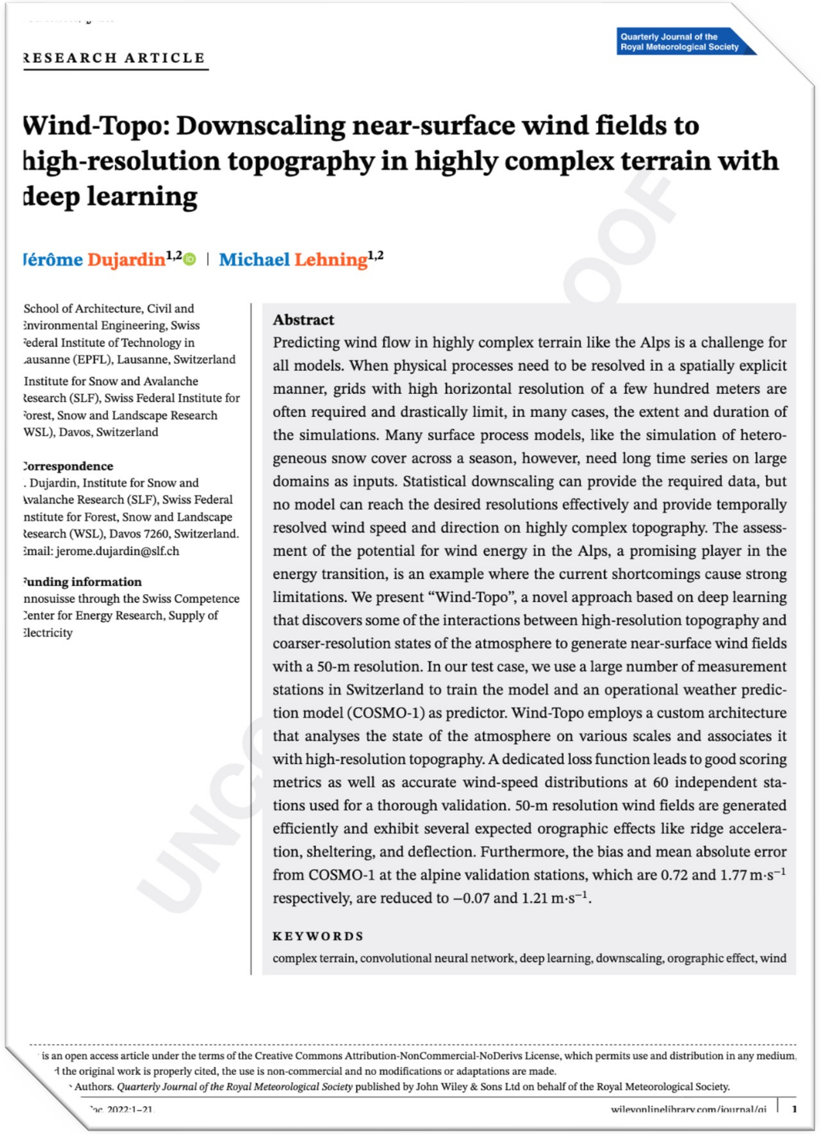
IV. Conclusion and outlook

- Wind energy is the **best complement** to hydropower
- Wind turbines in the Alps are **potentially very profitable** (high capacity factor) and can be integrated near current infrastructure (hydropower, grid)
- But, **large uncertainties** in complex terrain, except for a few monitored locations.
- **Wind-Topo** is a promising step towards **better estimates** ⇒ High resolution
Long time series
Reduced errors
Better distributions

- Need for a **refined map** of potential locations
- From **near-surface** high-resolution wind to **wind power**
- **Economic** case?

https://doi.org/10.1002/qj.4265



RESEARCH ARTICLE

Quarterly Journal of the Royal Meteorological Society

Wind-Topo: Downscaling near-surface wind fields to high-resolution topography in highly complex terrain with deep learning

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Abstract

Predicting wind flow in highly complex terrain like the Alps is a challenge for all models. When physical processes need to be resolved in a spatially explicit manner, grids with high horizontal resolution of a few hundred meters are often required and drastically limit, in many cases, the extent and duration of the simulations. Many surface process models, like the simulation of heterogeneous snow cover across a season, however, need long time series on large domains as inputs. Statistical downscaling can provide the required data, but no model can reach the desired resolutions effectively and provide temporally resolved wind speed and direction on highly complex topography. The assessment of the potential for wind energy in the Alps, a promising player in the energy transition, is an example where the current shortcomings cause strong limitations. We present "Wind-Topo", a novel approach based on deep learning that discovers some of the interactions between high-resolution topography and coarser-resolution states of the atmosphere to generate near-surface wind fields with a 50-m resolution. In our test case, we use a large number of measurement stations in Switzerland to train the model and an operational weather prediction model (COSMO-1) as predictor. Wind-Topo employs a custom architecture that analyses the state of the atmosphere on various scales and associates it with high-resolution topography. A dedicated loss function leads to good scoring metrics as well as accurate wind-speed distributions at 60 independent stations used for a thorough validation. 50-m resolution wind fields are generated efficiently and exhibit several expected orographic effects like ridge acceleration, sheltering, and deflection. Furthermore, the bias and mean absolute error from COSMO-1 at the alpine validation stations, which are 0.72 and 1.77 m·s^{-1} respectively, are reduced to –0.07 and 1.21 m·s^{-1}.

KEYWORDS
complex terrain, convolutional neural network, deep learning, downscaling, orographic effect, wind

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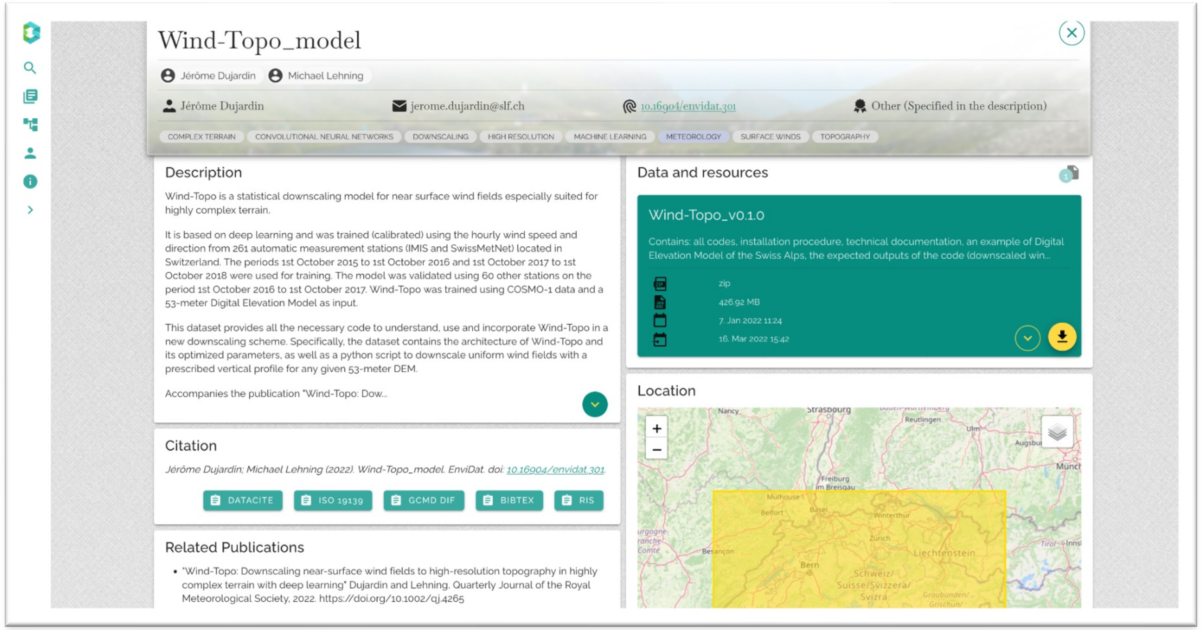
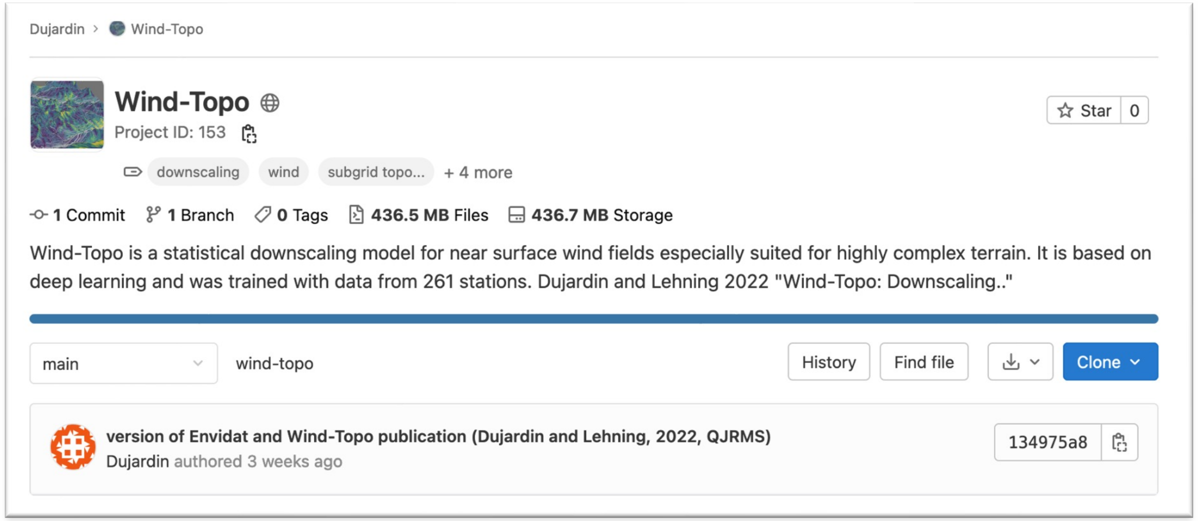
https://doi.org/10.16904/envidat.301



https://gitlabext.wsl.ch/dujardin/wind-topo



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