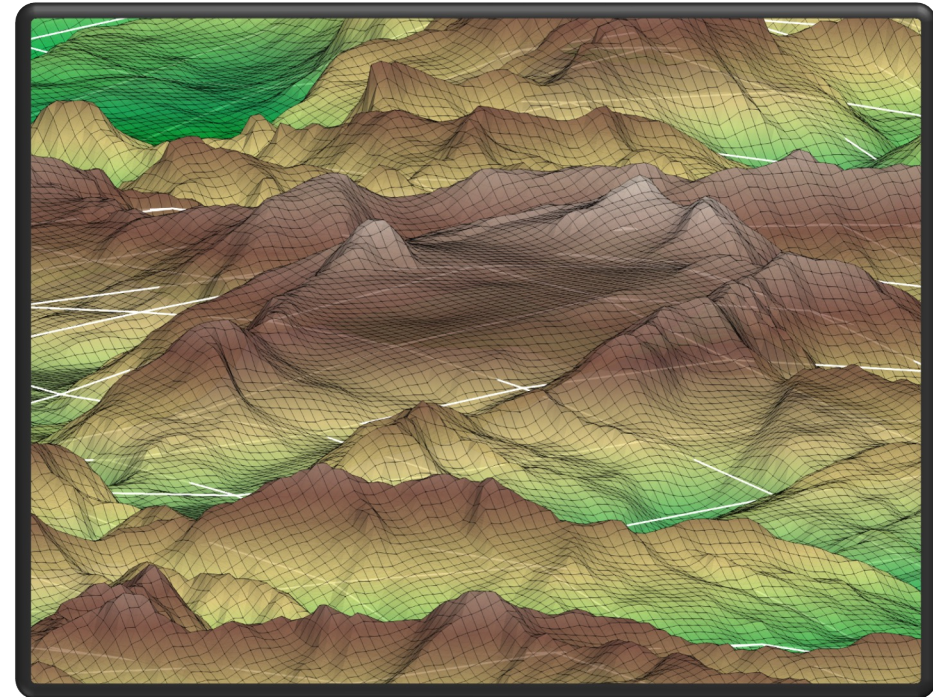


Towards better estimates of wind power potentials in the Alps

Jérôme Dujardin ^{1,2} and Michael Lehning ^{1,2}

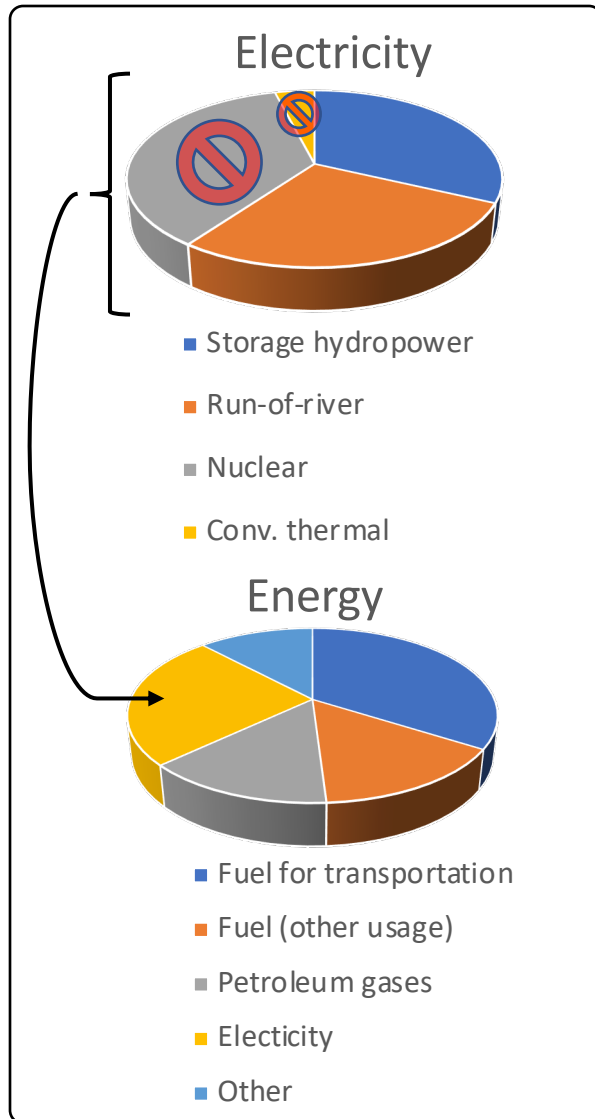
¹ Institute for Snow and Avalanche Research (SLF), Swiss Federal Institute for Forest, Snow and Landscape Research (WSL)
Davos, Switzerland

² Ecole Polytechnique Federale de Lausanne (EPFL)
Lausanne, Switzerland



- 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*

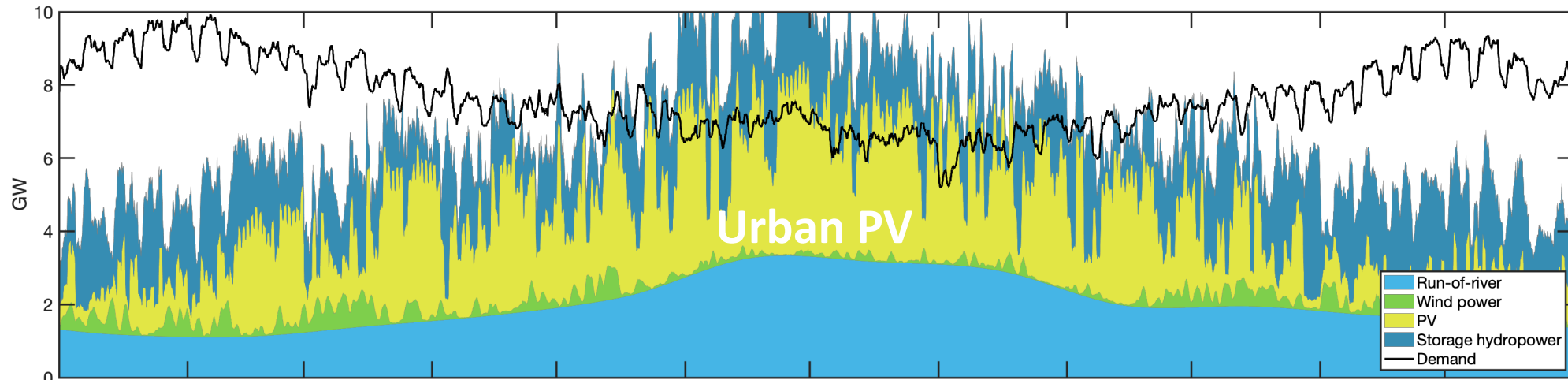
- **6000** wind turbines (3 MW each)
currently installed : 42

12x the largest US wind farm

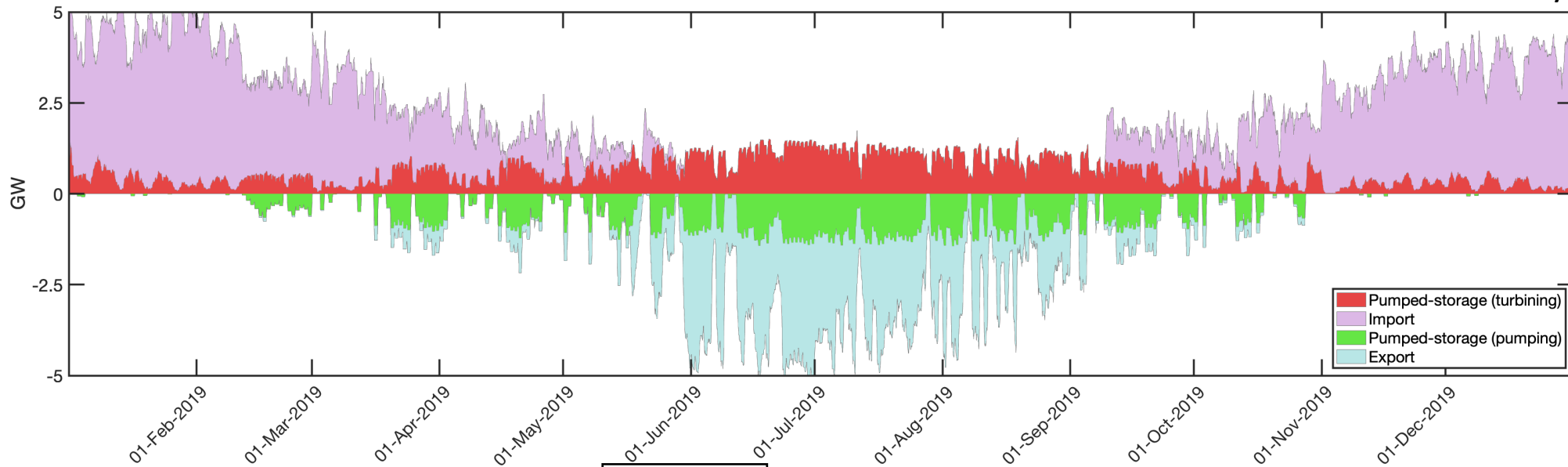
Best portfolio to complement hydro?

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

I. Some context: facing winter energy deficits



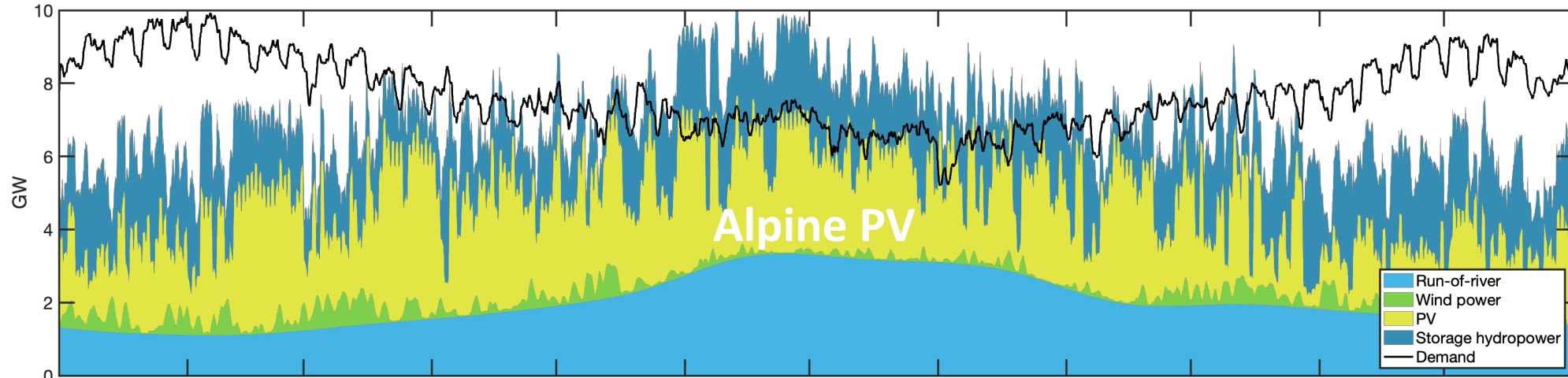
Daily averages, 2019



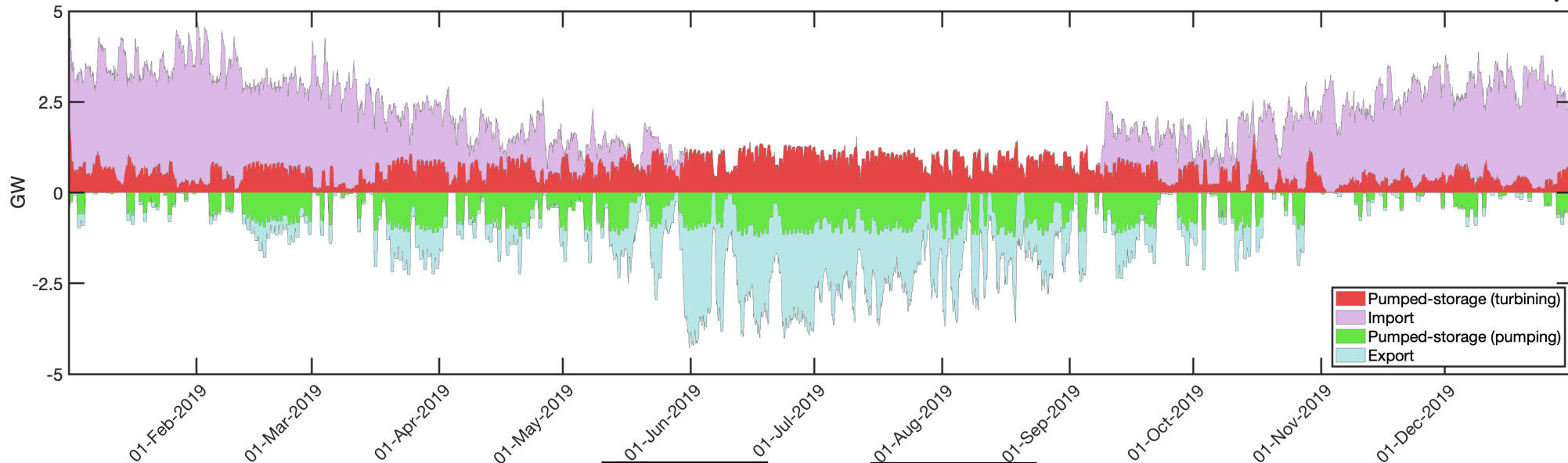
(PV + Wind: 15 GW)

Winter deficit: 14.5 TWh

I. Some context: facing winter energy deficits



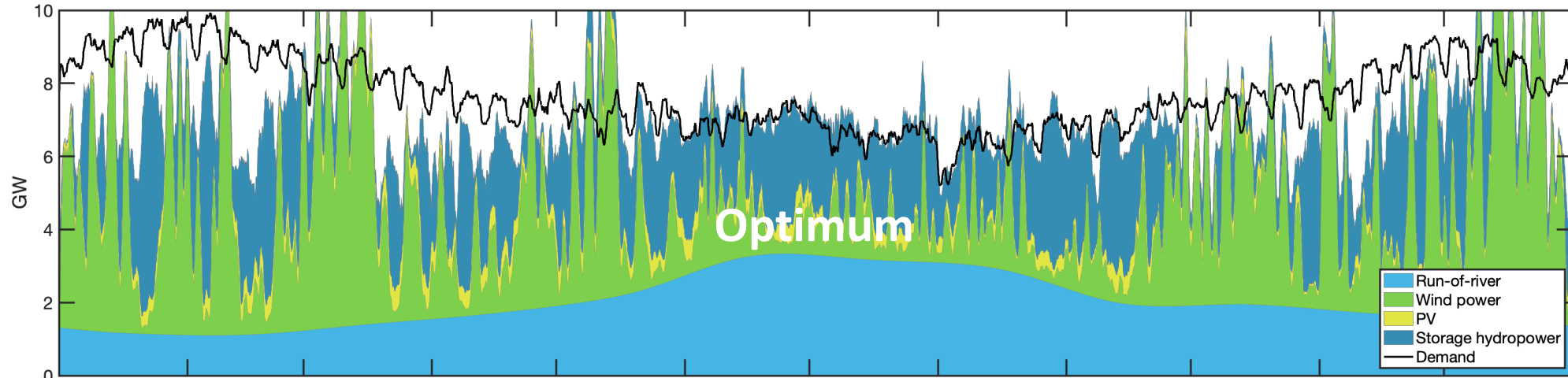
Daily averages, 2019



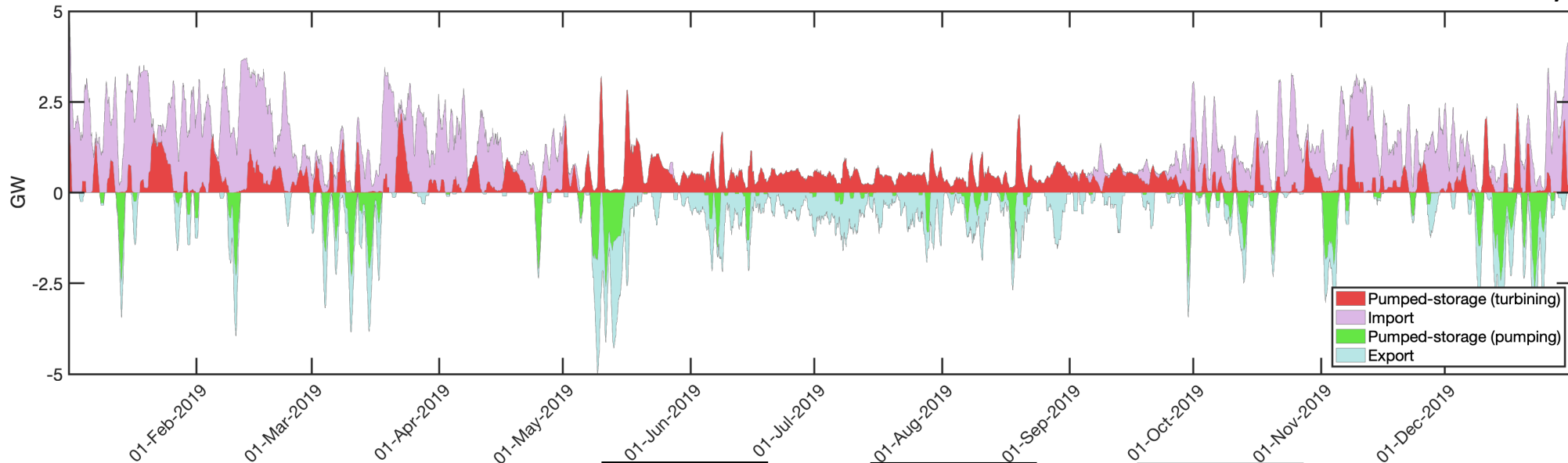
(PV + Wind: 15 GW)

Winter deficit: 14.5 TWh → 11.7 TWh

I. Some context: facing winter energy deficits



Daily averages, 2019

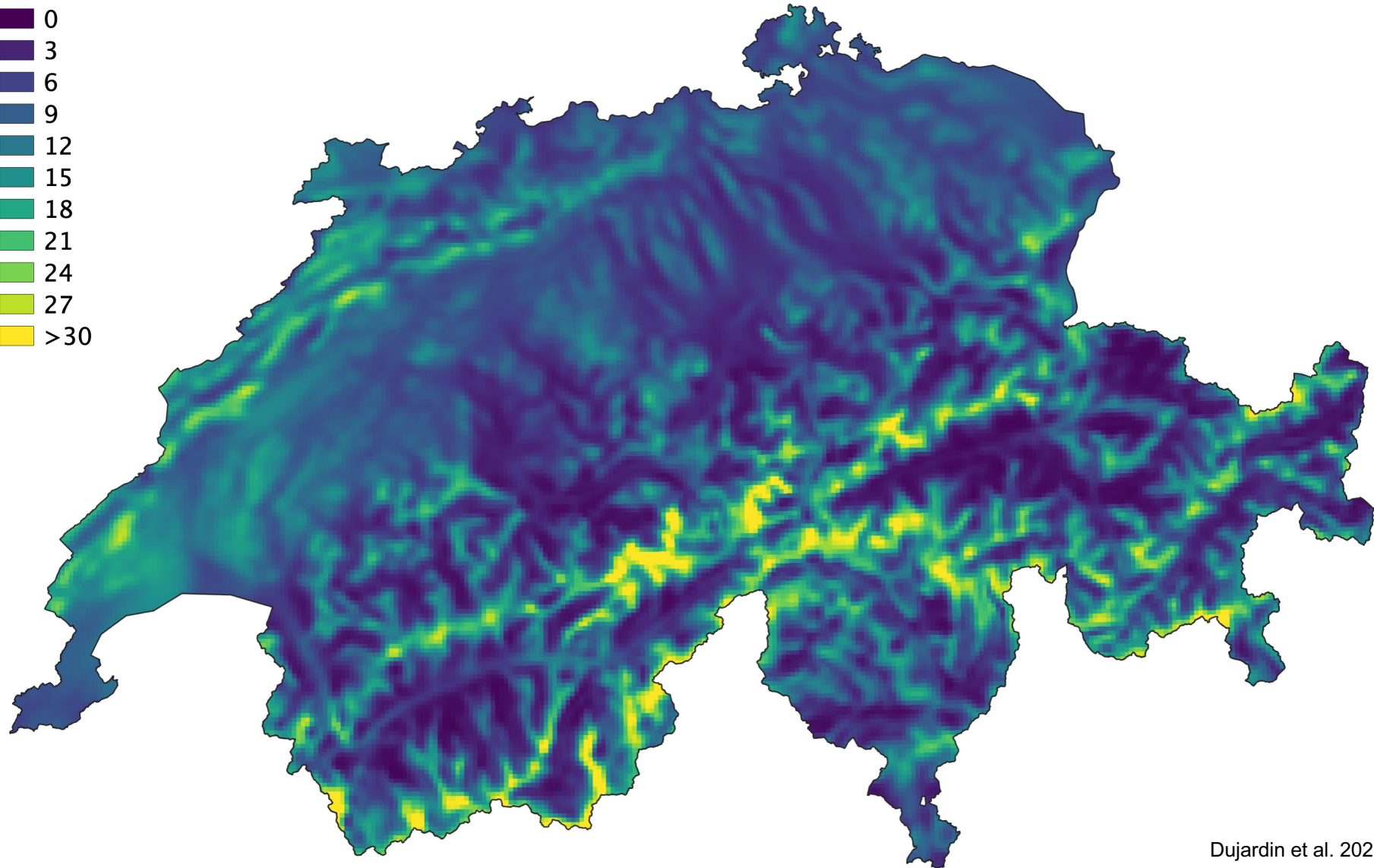
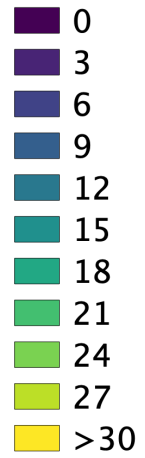


(PV + Wind: 15 GW)

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

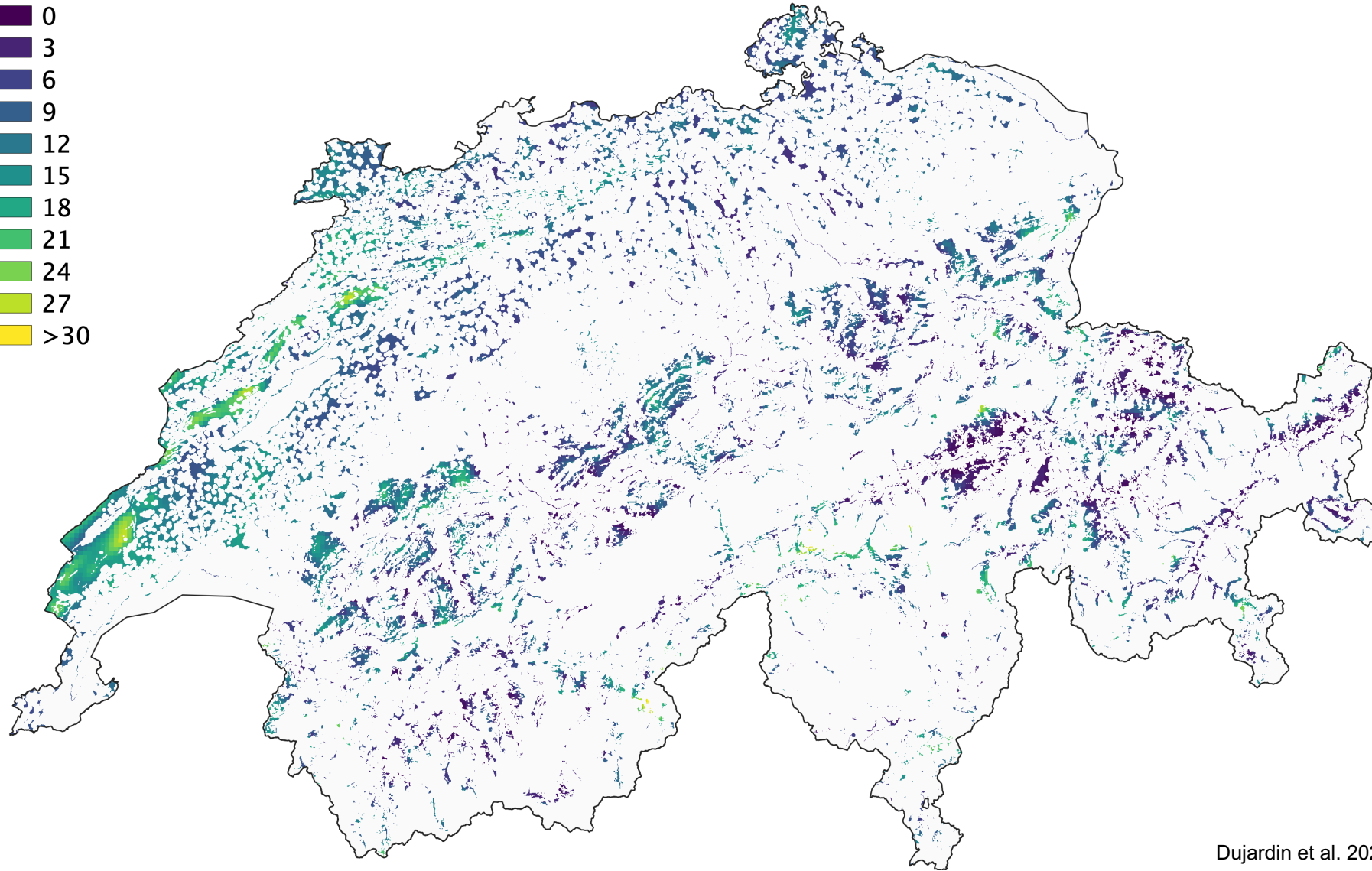
Wind power capacity factor (%)



Dujardin et al. 2021

II. Wind power: an ideal complement to hydropower

Wind power capacity factor (%)



Dujardin et al. 2021

II. Wind power: an ideal complement to hydropower

01-Jan-16 01:00:00

Spilled water (energy): 0.00%

Max negative total volume: 0.00 mio m3

Storage Hydro production: 3.09 GW

Non modeled stor.Hydro production: 0.06 GW

Pump consumption: 0.00 GW

Run-Of-River production: 1.11 GW

Solar production: 0.00 GW

Wind production: 1.44 GW

Geoth production: 0.00 GW

Surplus production (free disp.gen): 0.00 GW

Surplus potential: 0.00 GW

Curtailement: 0.00%

Swiss demand: 6.70 GW

Swiss residual demand: 4.09 GW

Portion of residual demand: 61.07%

Import: 1.00 GW

Export: 0.00 GW

Net import: 1.00 GW

Swiss production (with pumping): 5.70 GW

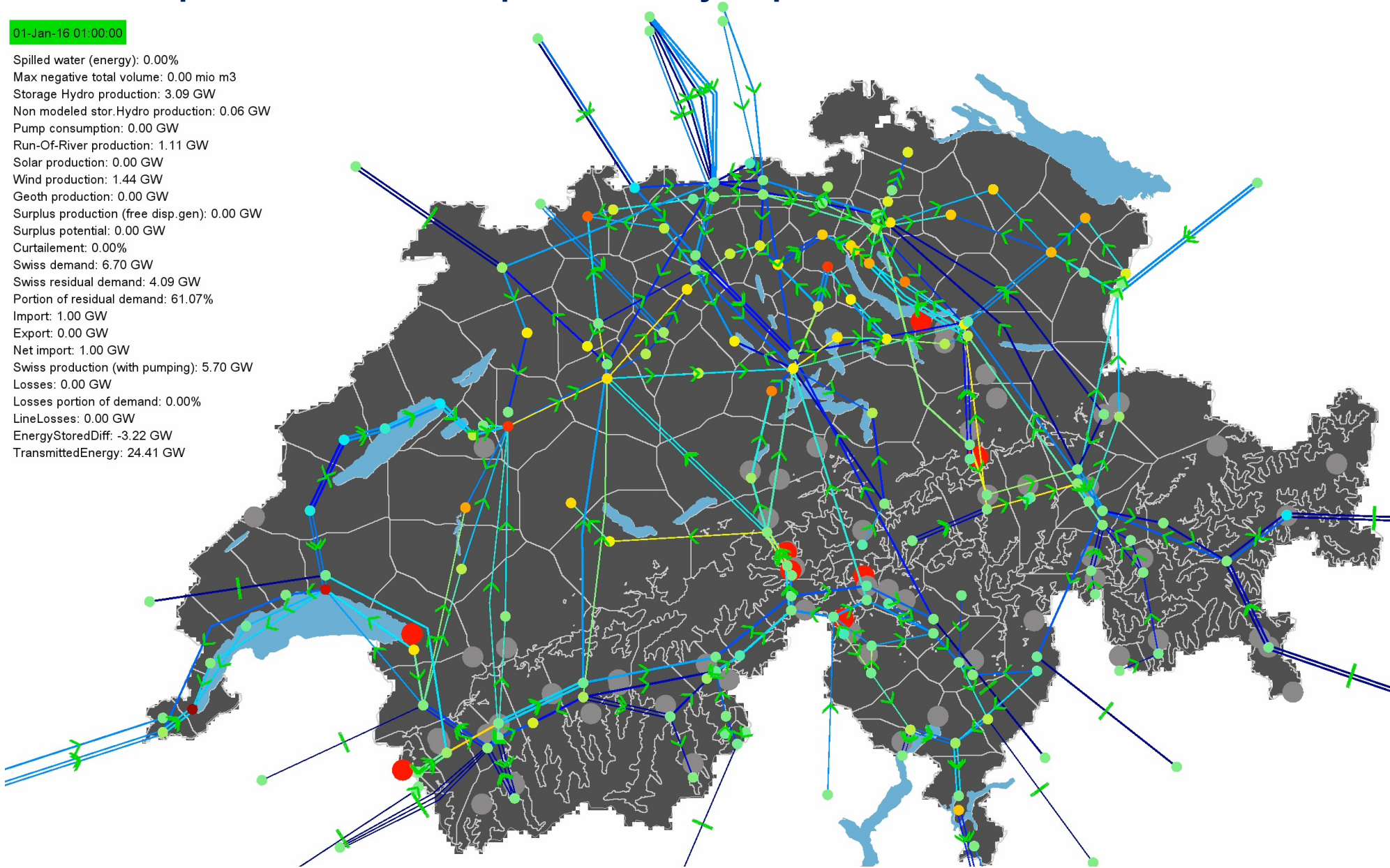
Losses: 0.00 GW

Losses portion of demand: 0.00%

LineLosses: 0.00 GW

EnergyStoredDiff: -3.22 GW

TransmittedEnergy: 24.41 GW

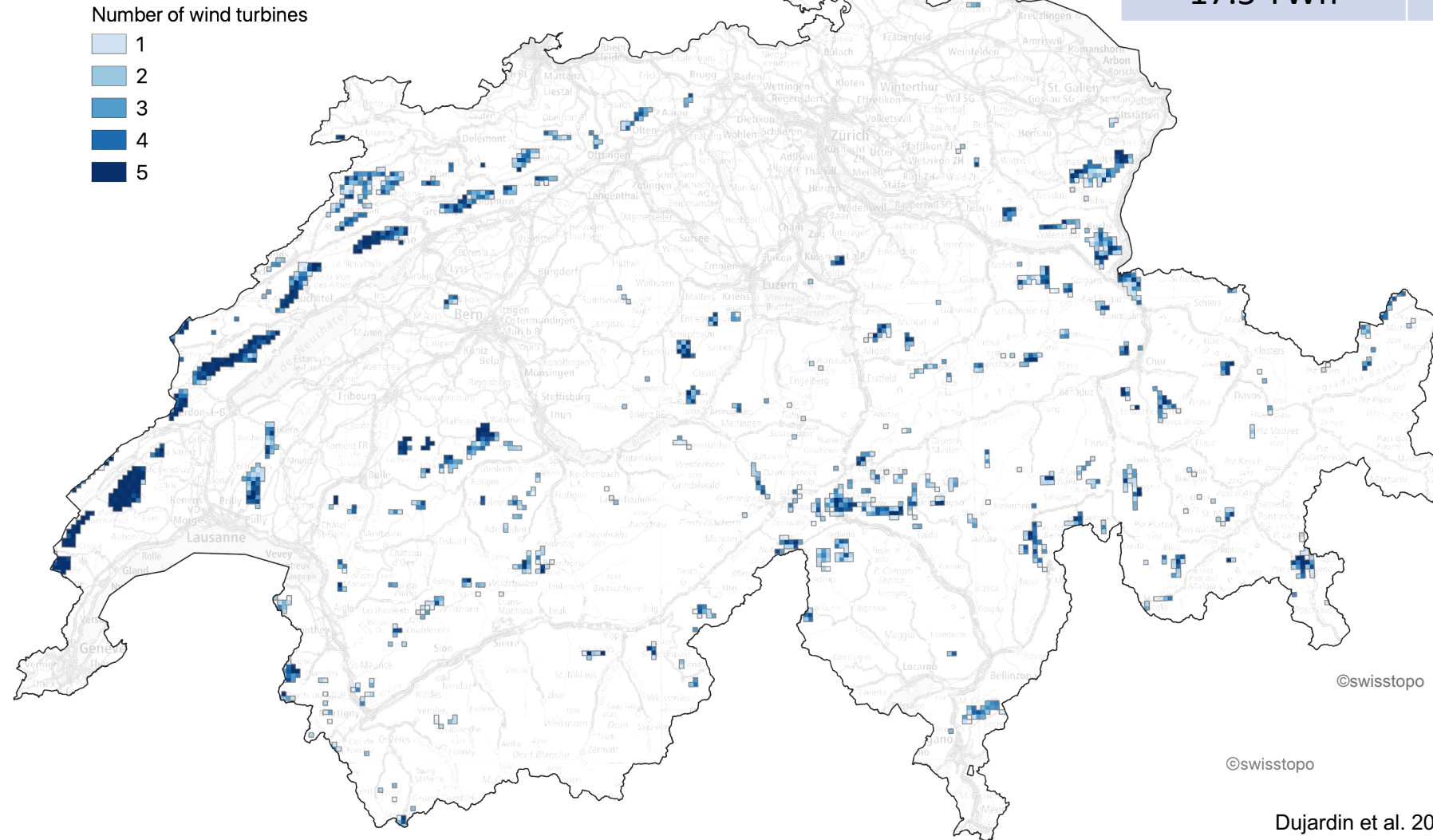


II. Wind power: an ideal complement to hydropower

Winter deficit

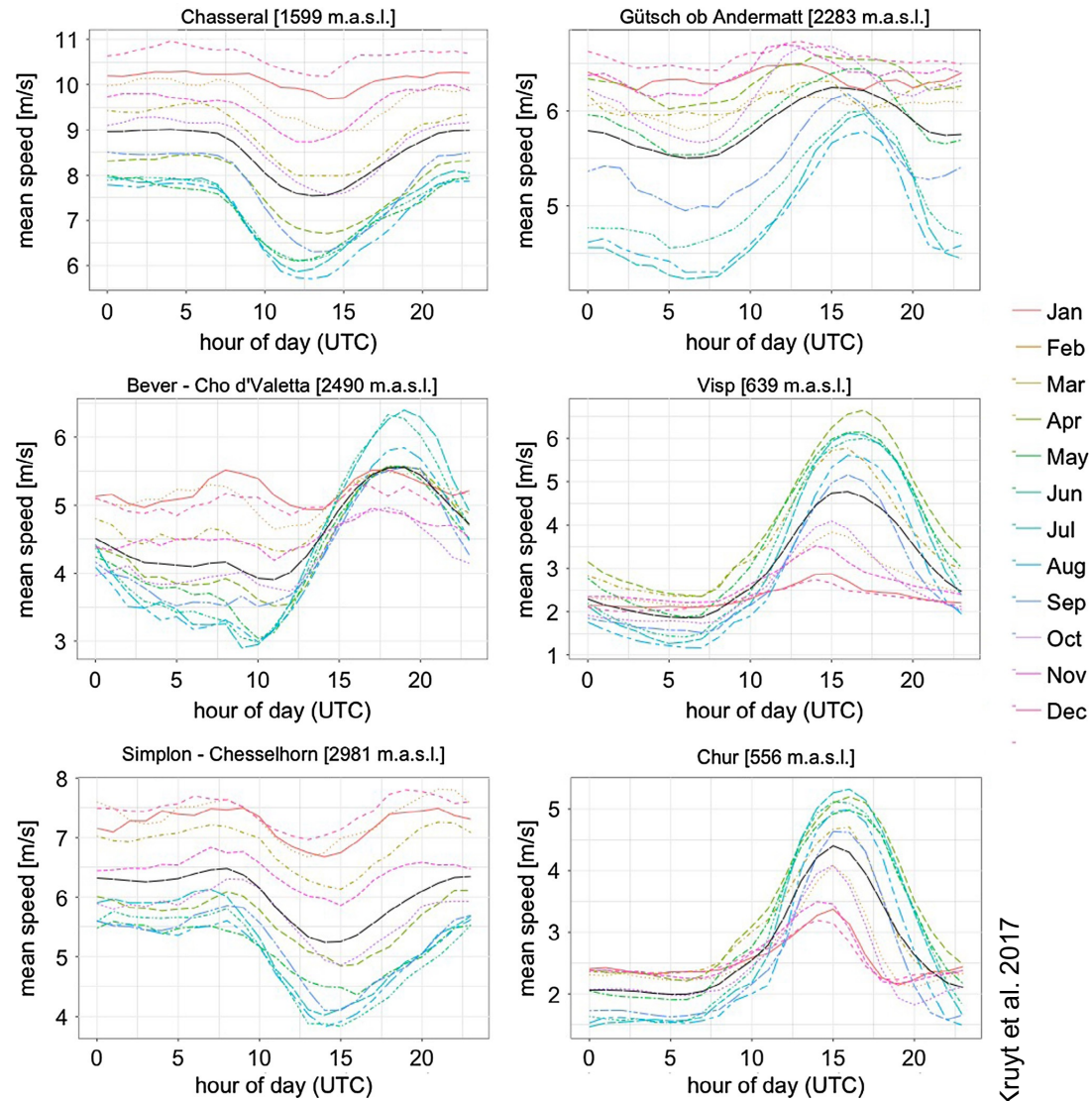
Urban PV	Opti PV + Wind
17.5 TWh	3.5 TWh

(year 2016)



Dujardin et al. 2021

II. Wind power: an ideal complement to hydropower



Kruyt et al. 2017

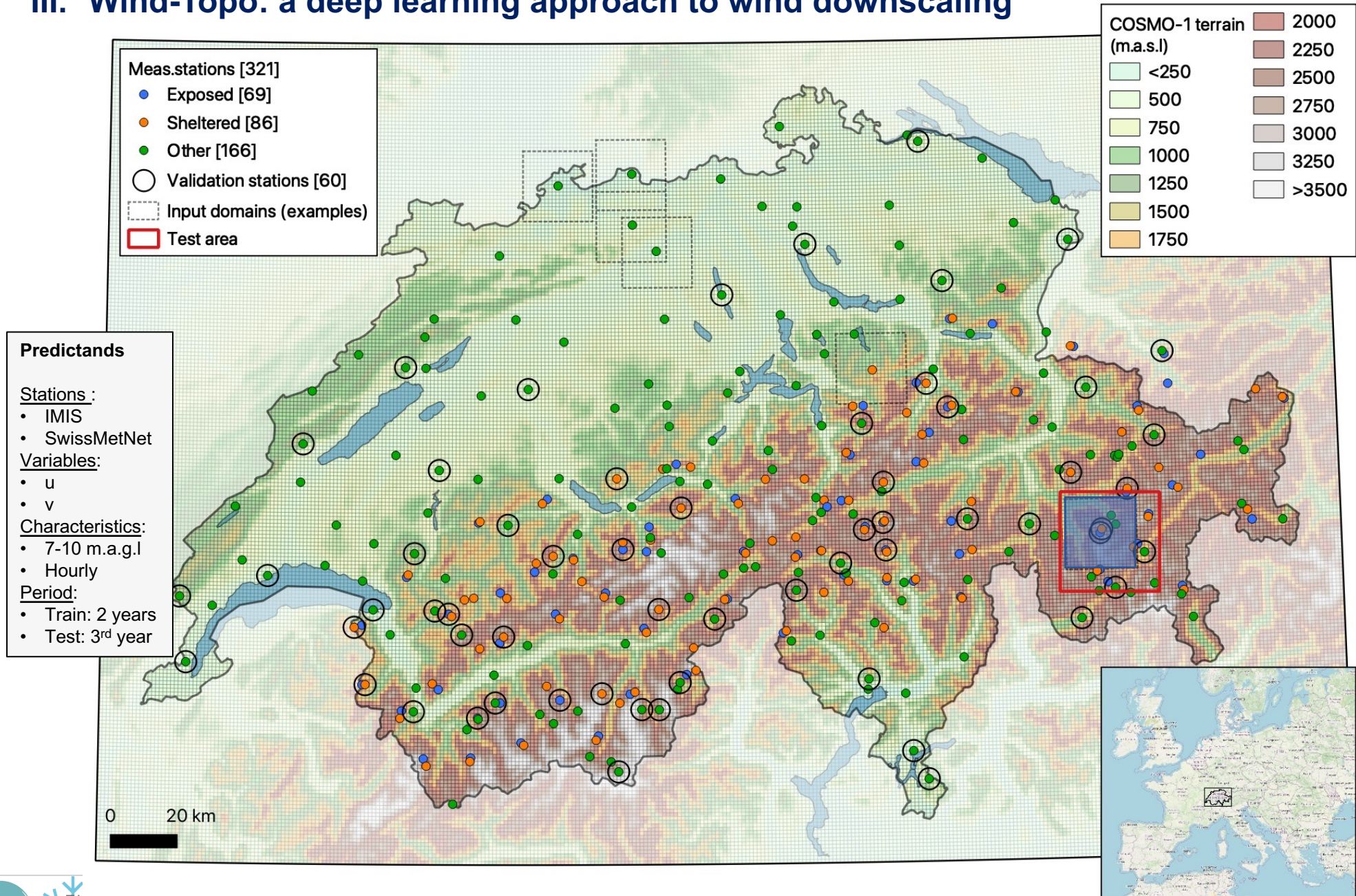
Complex topography → High heterogeneity

Small (sub-grid) scale effects like:

- Sheltering
- Ridge acceleration
- Thermally driven flows



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



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):

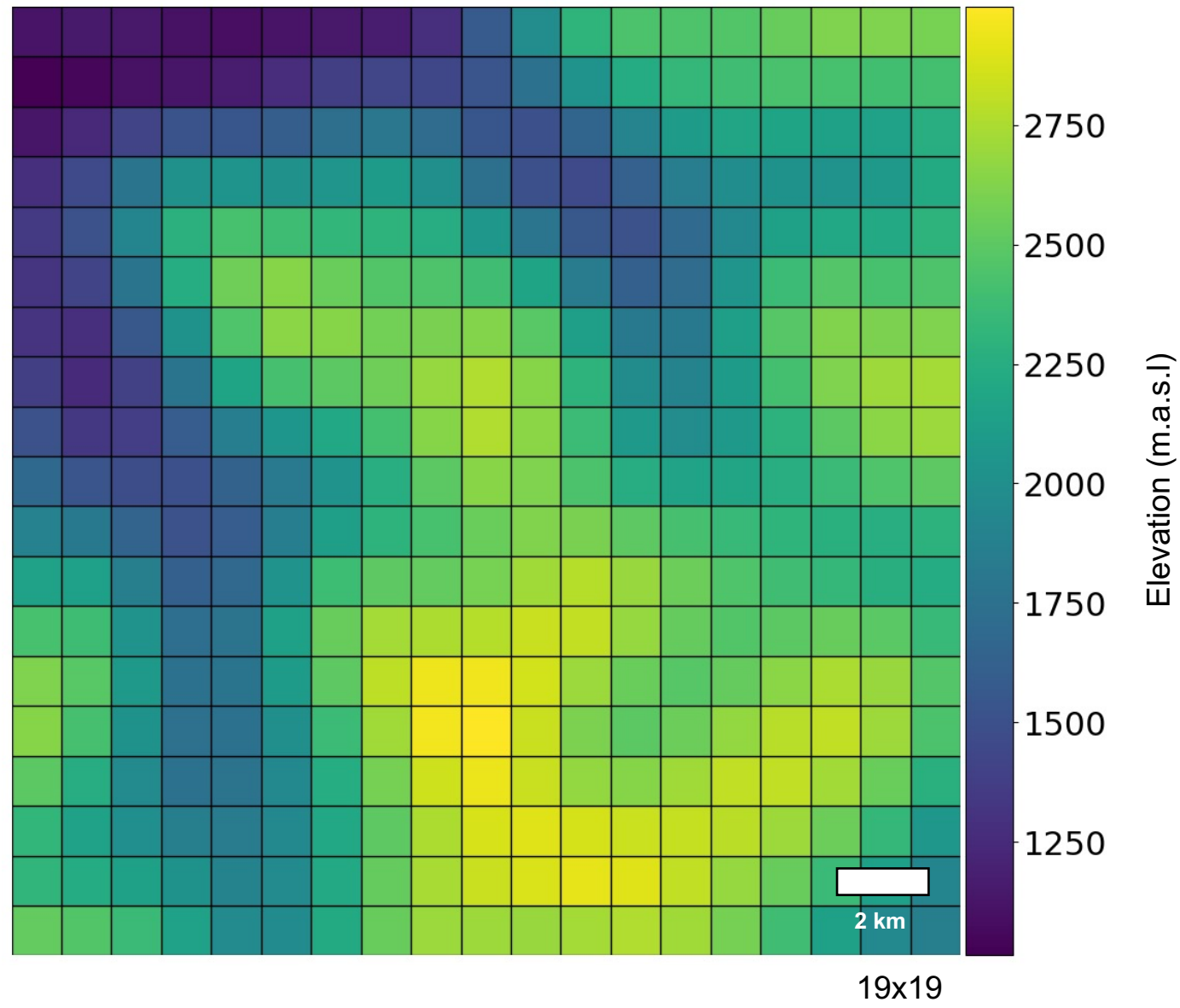
- Z_{cosmo} (1)
- u_{cosmo} (5)
- v_{cosmo} (5)
- w' (5) *
- $\Delta\theta / \Delta h$ (4) **
- q_s (1)

Period:

- Same times as measurements

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

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



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRMMS

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

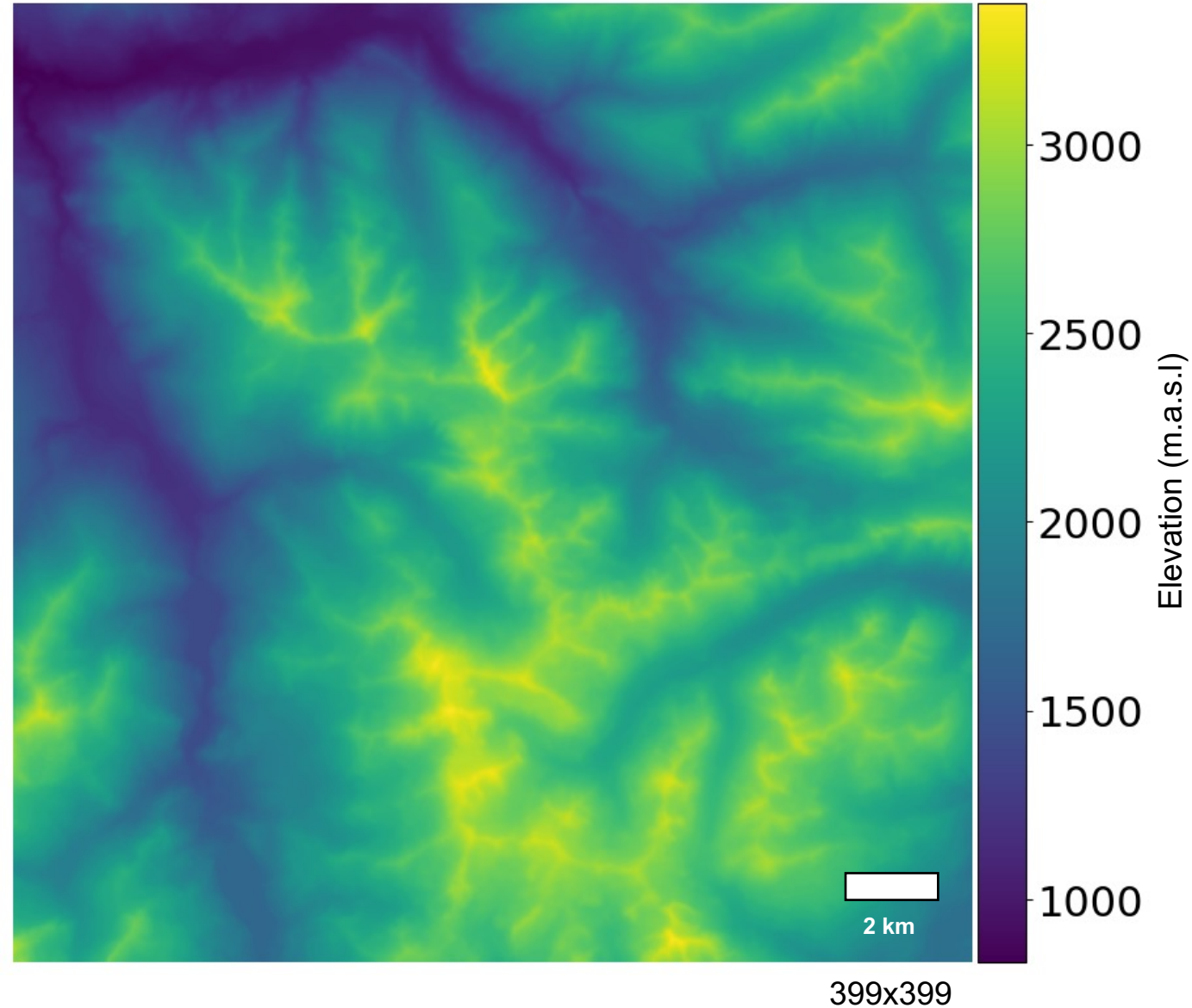
**Topographic data
(high-res predictor)**

Resolution:

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

Variables (# layers):

- Z_{topo} (1)
- slope (1)
- aspect (1)



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRM

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

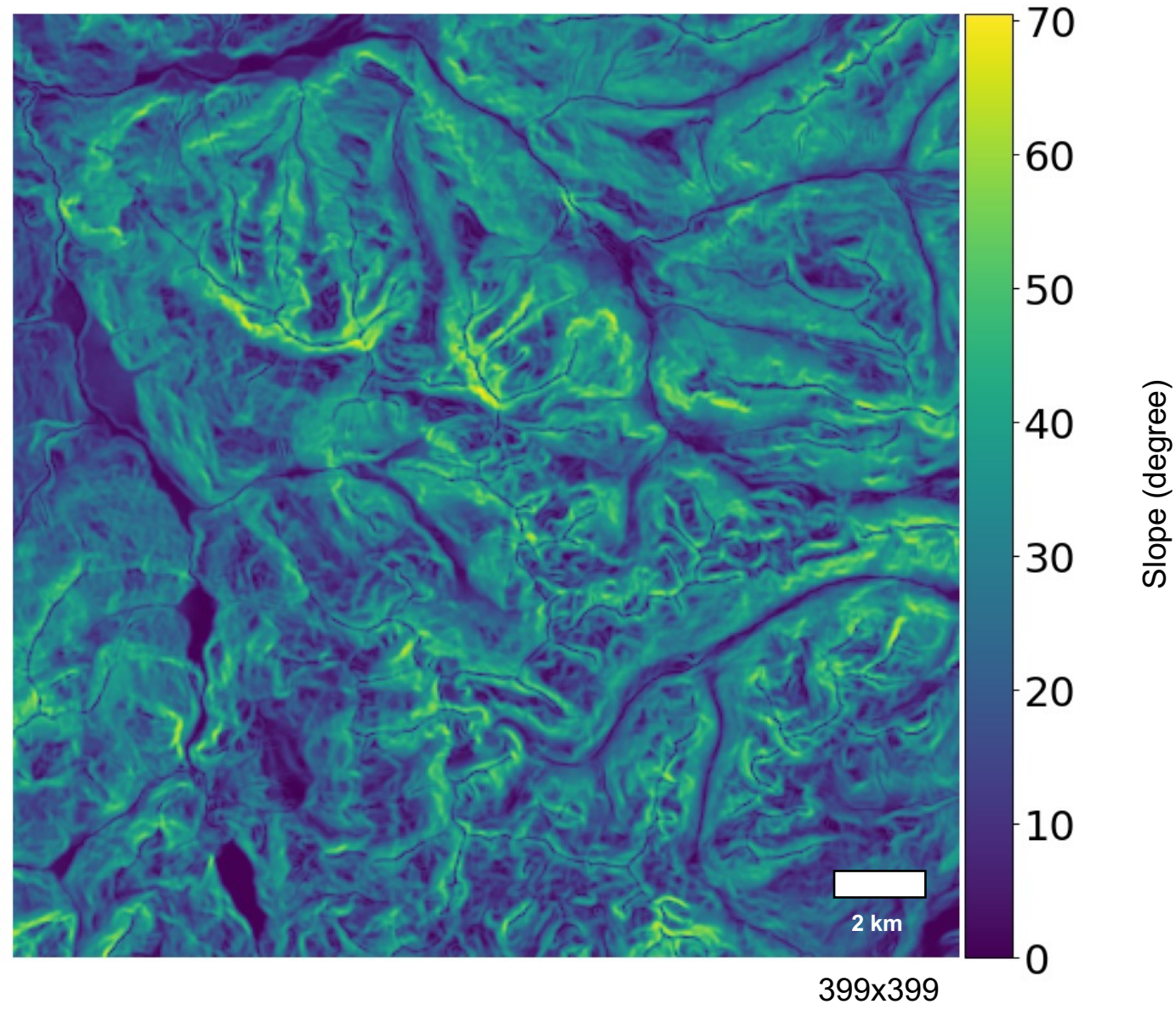
**Topographic data
(high-res predictor)**

Resolution:

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

Variables (# layers):

- Z_{topo} (1)
- **slope** (1)
- aspect (1)



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRM

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

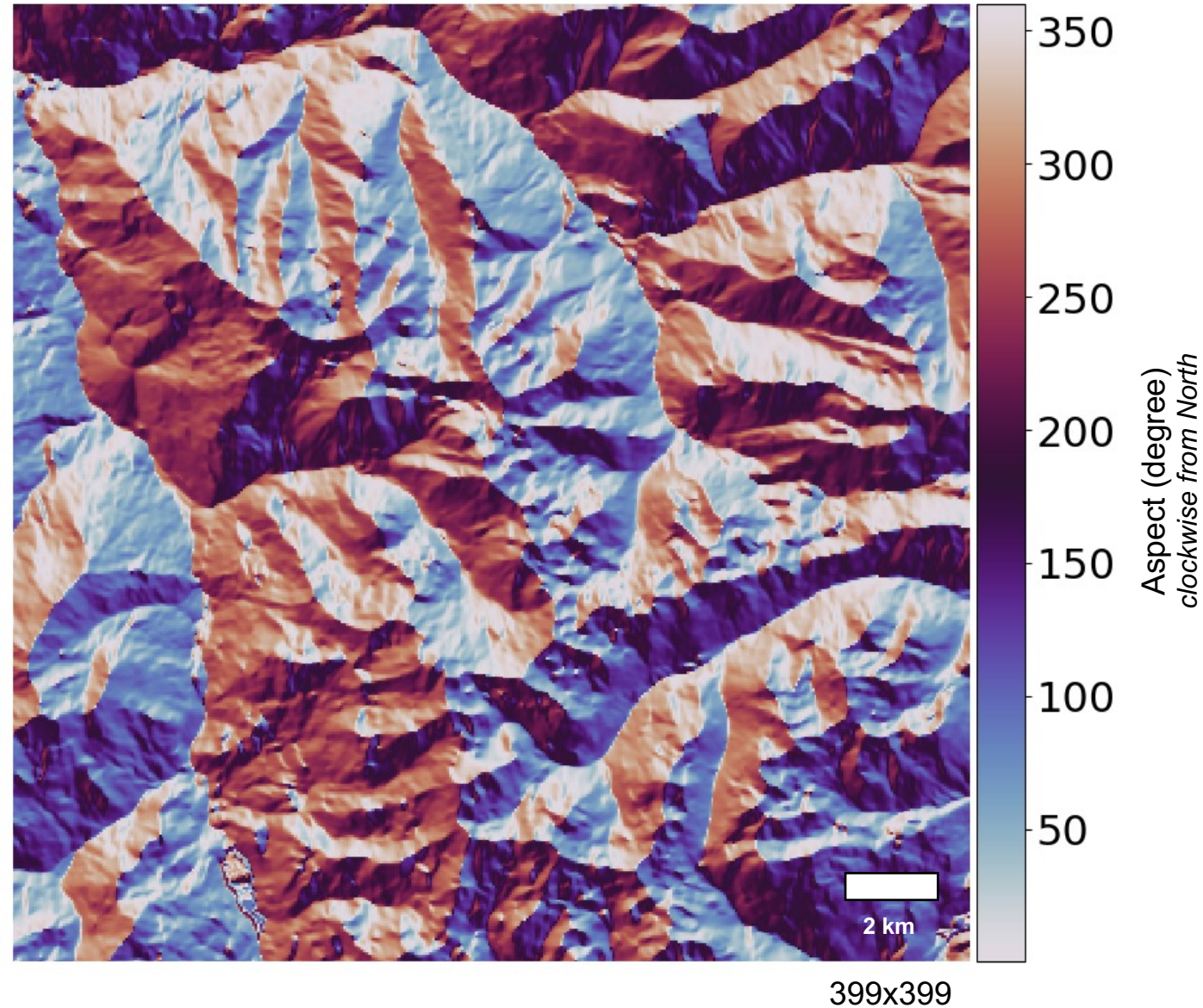
**Topographic data
(high-res predictor)**

Resolution:

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

Variables (# layers):

- Z_{topo} (1)
- slope (1)
- **aspect** (1)



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRM

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

Computation of time-dependent topographic descriptors

Needs:

- $u_{\text{cosmo}}, v_{\text{cosmo}}$
- slope
- aspect

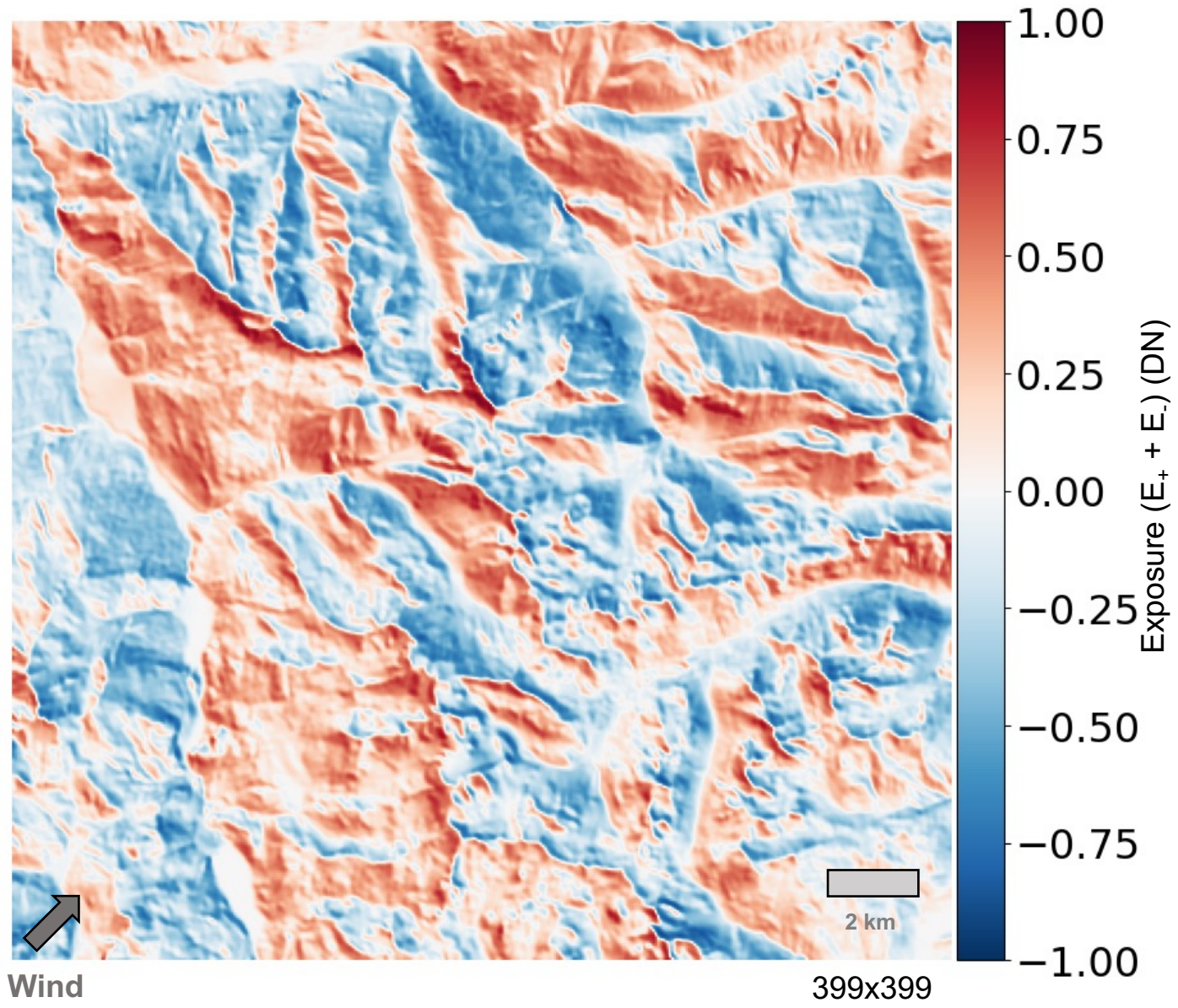
Outputs:

- 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,

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



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRM

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

Computation of time-dependent topographic descriptors

Needs:

- $u_{\text{cosmo}}, v_{\text{cosmo}}$
- slope
- aspect

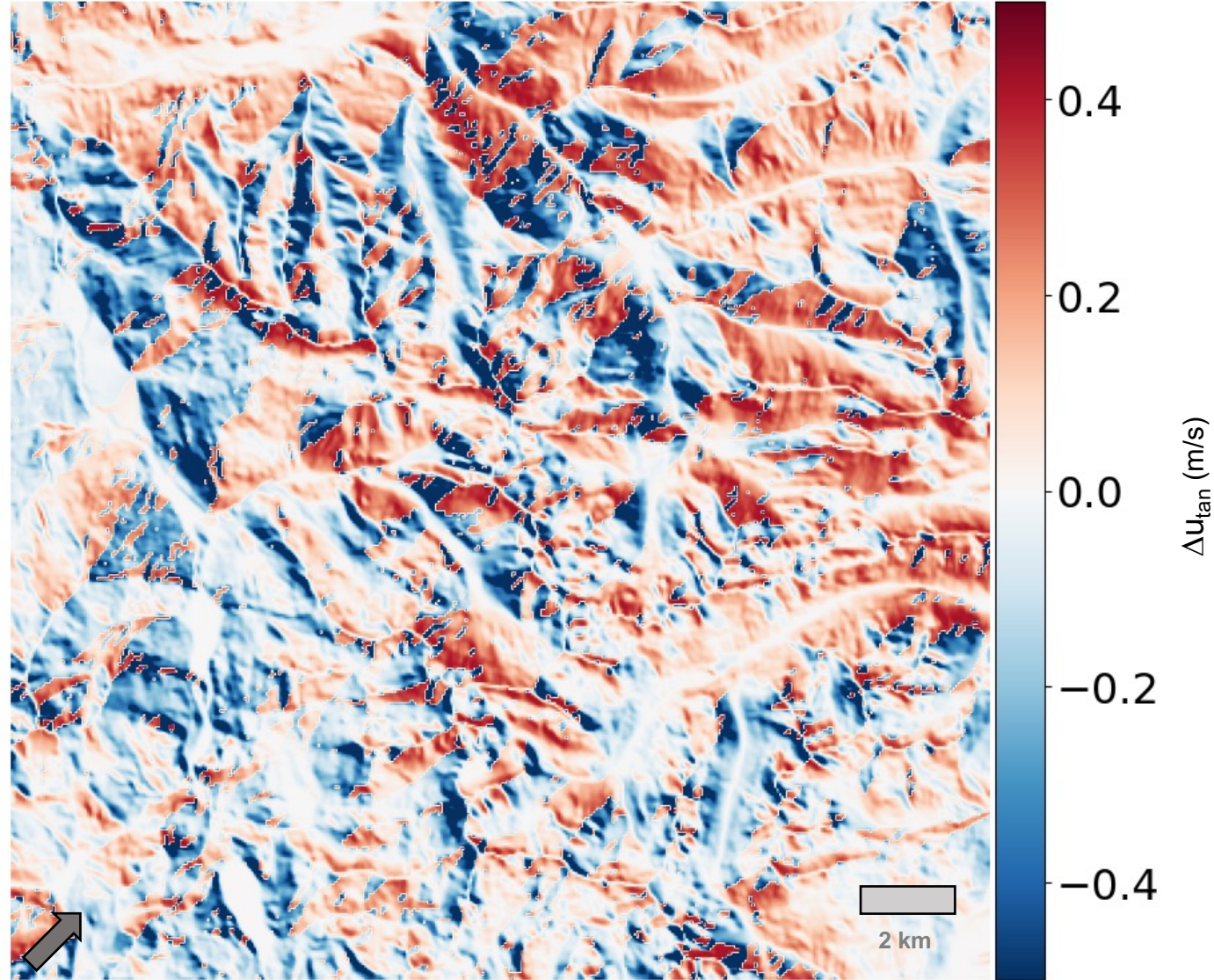
Outputs:

- E^+ (1)
- E^- (1)
- Δu_{tan} (1)
- Δv_{tan} (1)

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

where,

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



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

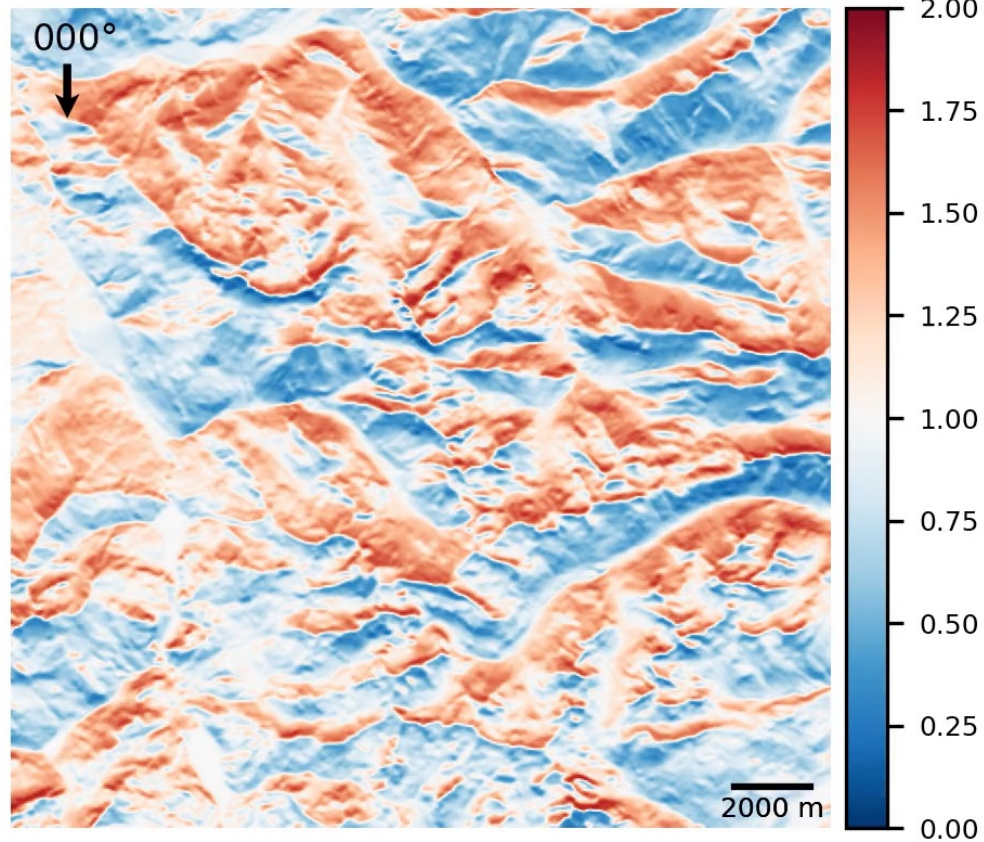
399x399

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

Example of exposure

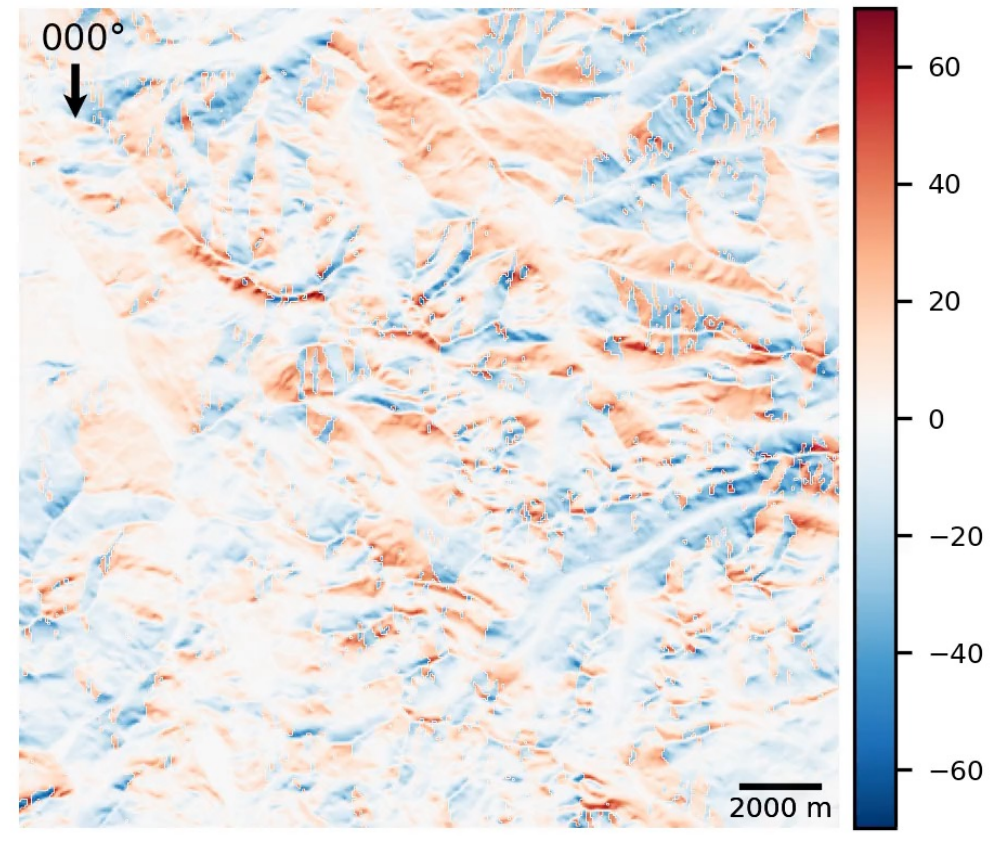
$$\begin{aligned}
 u &\rightarrow u + u E_+ + u E_- \\
 v &\rightarrow v + v E_+ + v E_-
 \end{aligned}$$



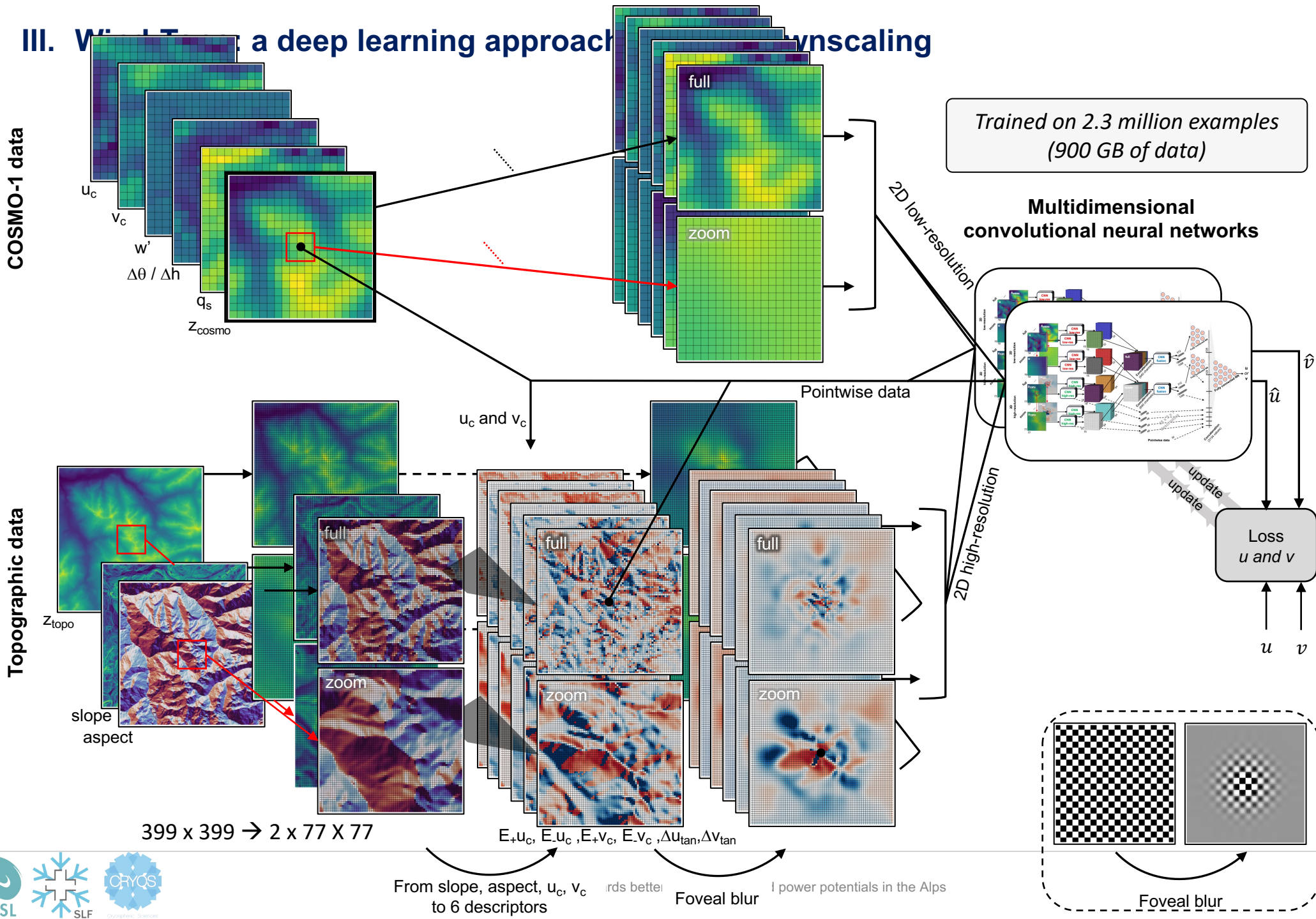
Example of deflection

$$\begin{aligned}
 u &\rightarrow u + \Delta u_{\tan} \\
 v &\rightarrow v + \Delta v_{\tan}
 \end{aligned}$$

Anti-clockwise deflection (degree)

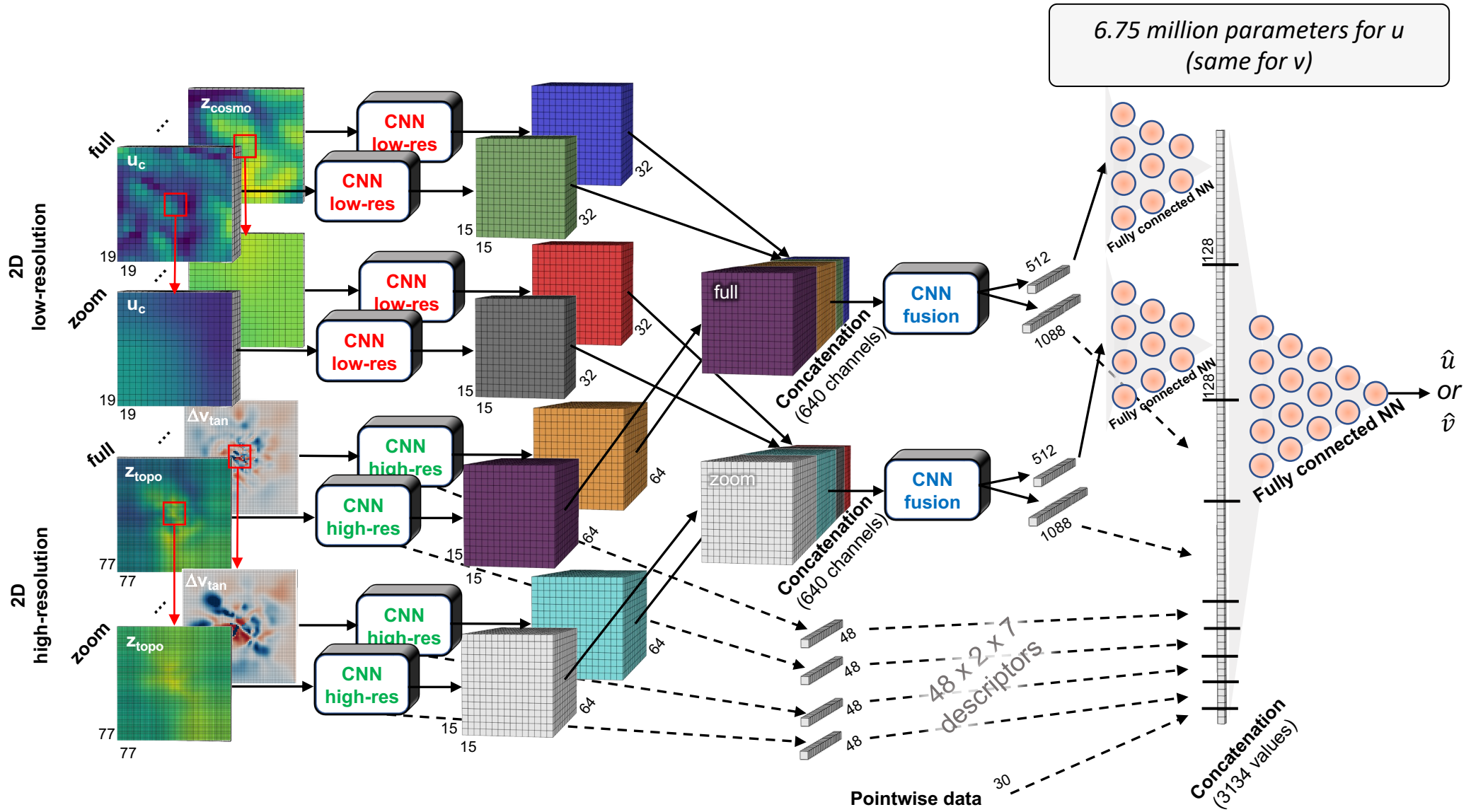


III. Wind-Topo: a deep learning approach for wind downscaling



Wind-Topo: Downscaling - Dujardin and Lehning - 2022 - QJRMIS

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

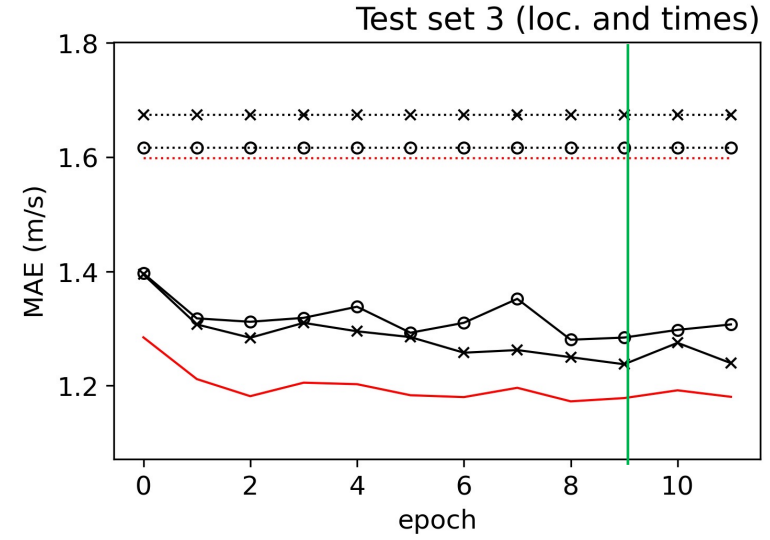
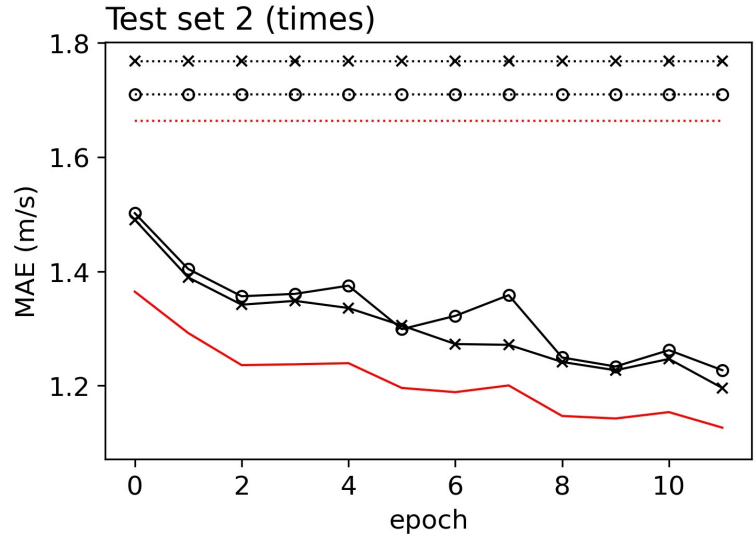
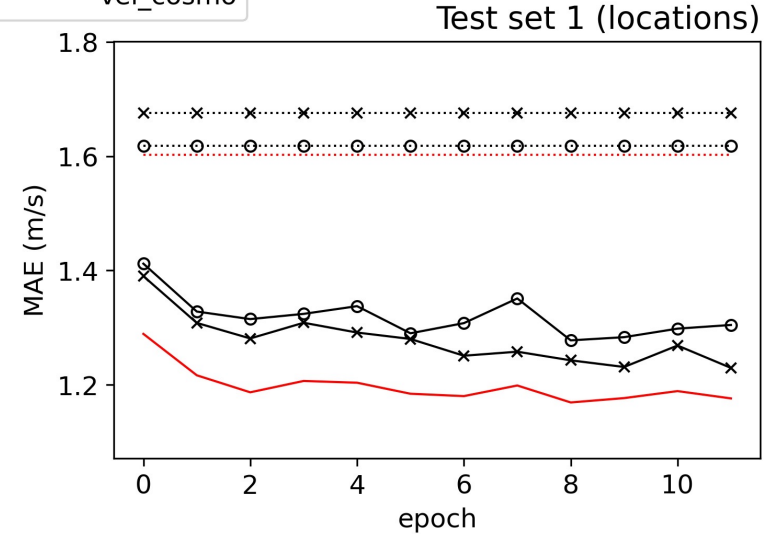
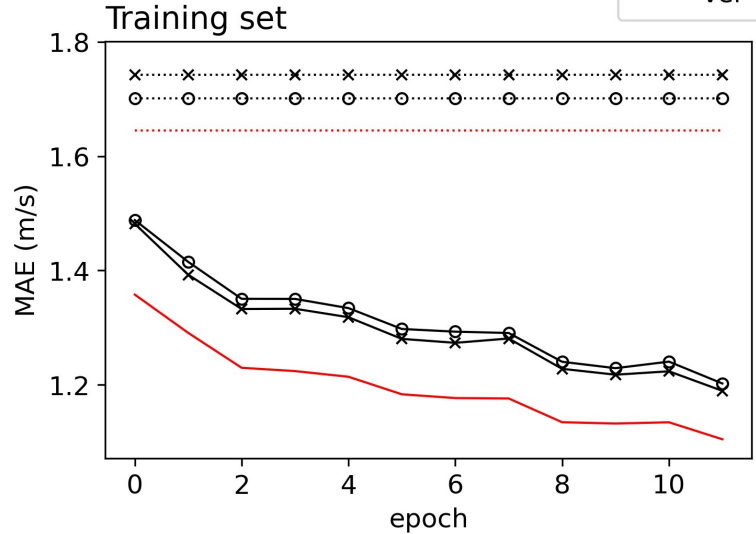


III. Wind-Topo: a deep learning approach to wind downscaling

Mean absolute errors



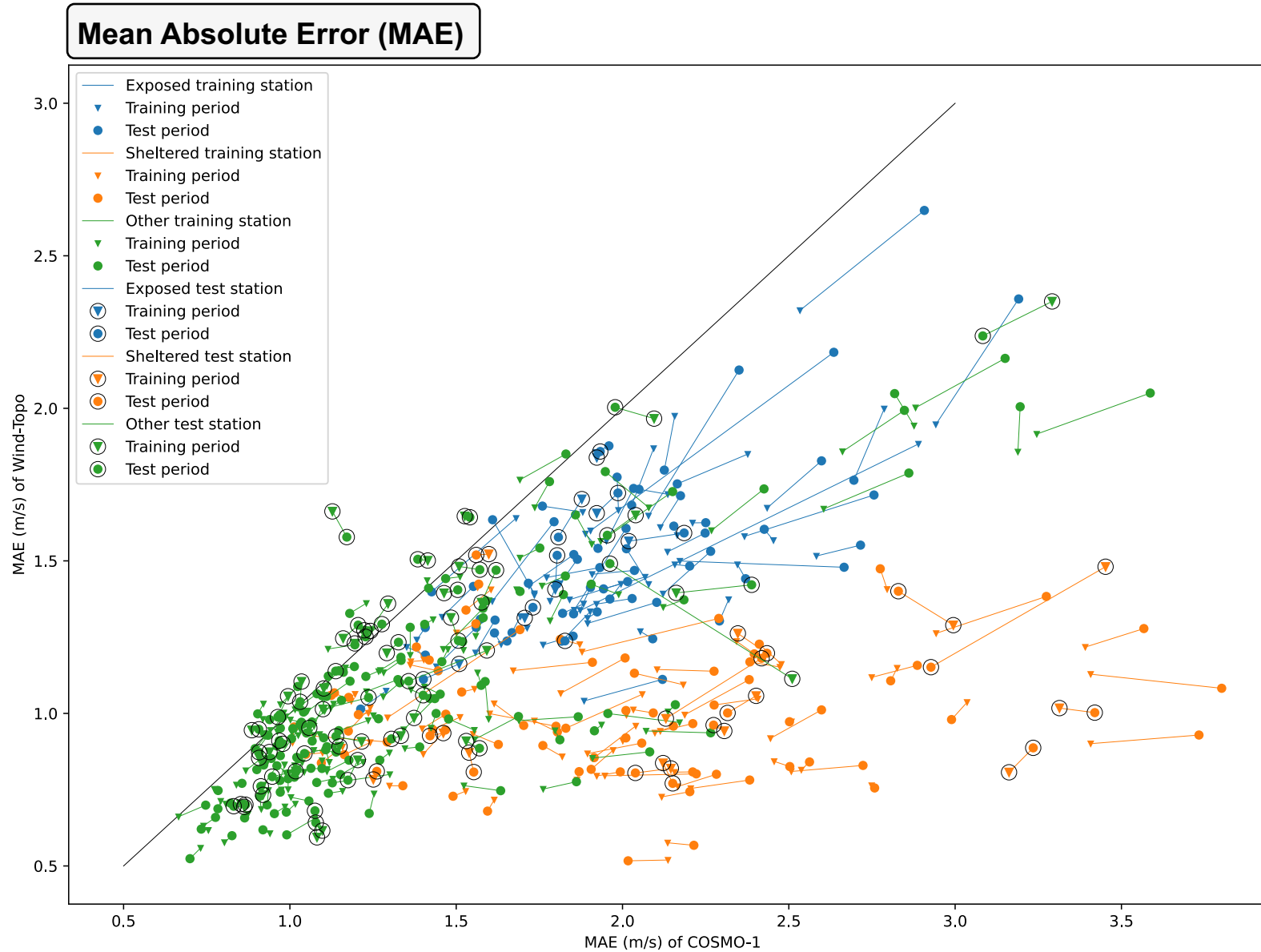
Training set:
 261 stations
 01 Oct. 2015 – 01 Oct. 2016
 and
 01 Oct. 2017 – 01 Oct. 2018
 Test set 3:
 60 stations
 01 Oct. 2016 – 01 Oct. 2017



1 epoch = 1 pass through the entire training set

Wind-Topo: Downscaling - Dujardin and Lehning - 2022 - QJRMIS

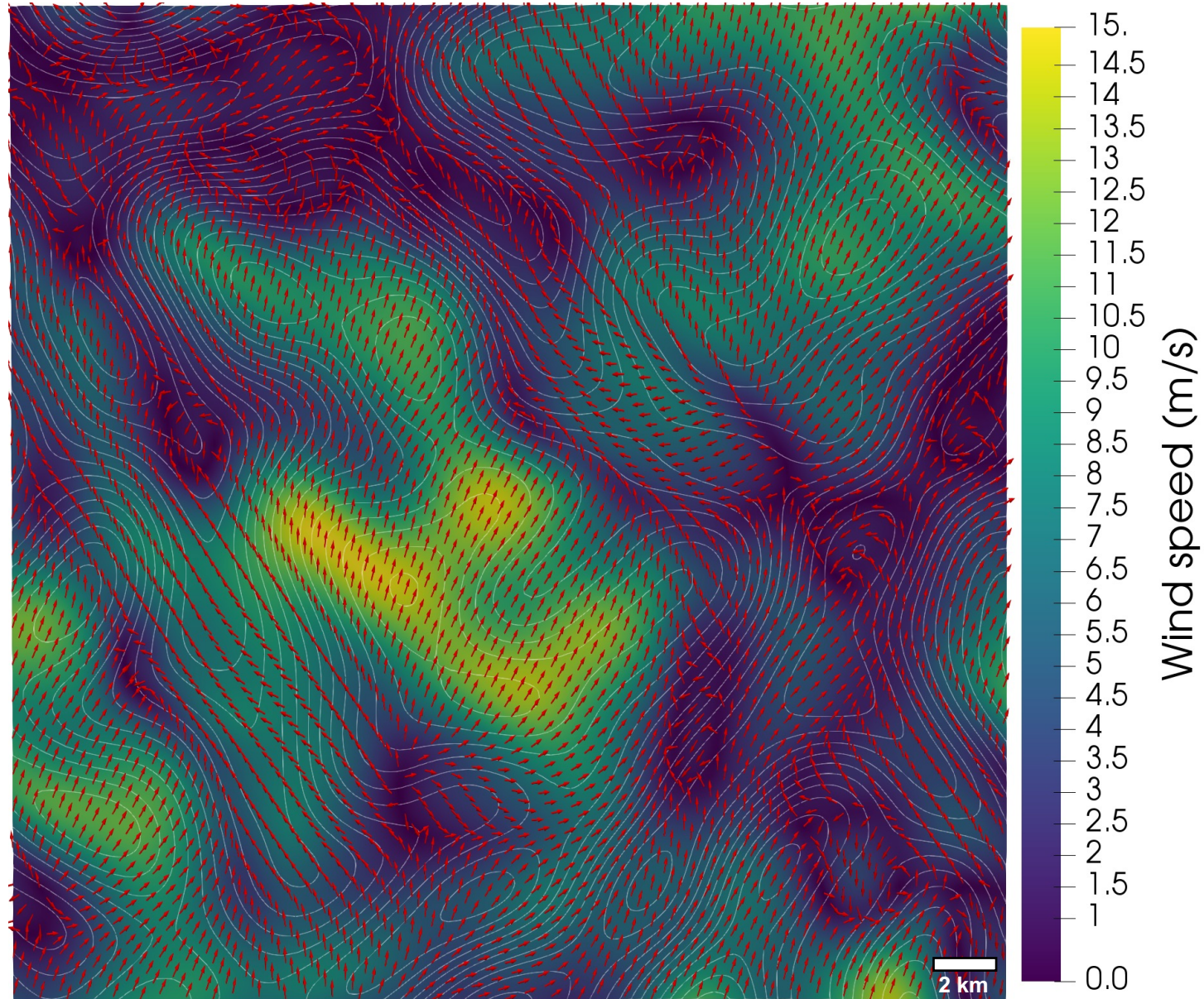
III. Wind-Topo: a deep learning approach to wind downscaling



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRMS

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

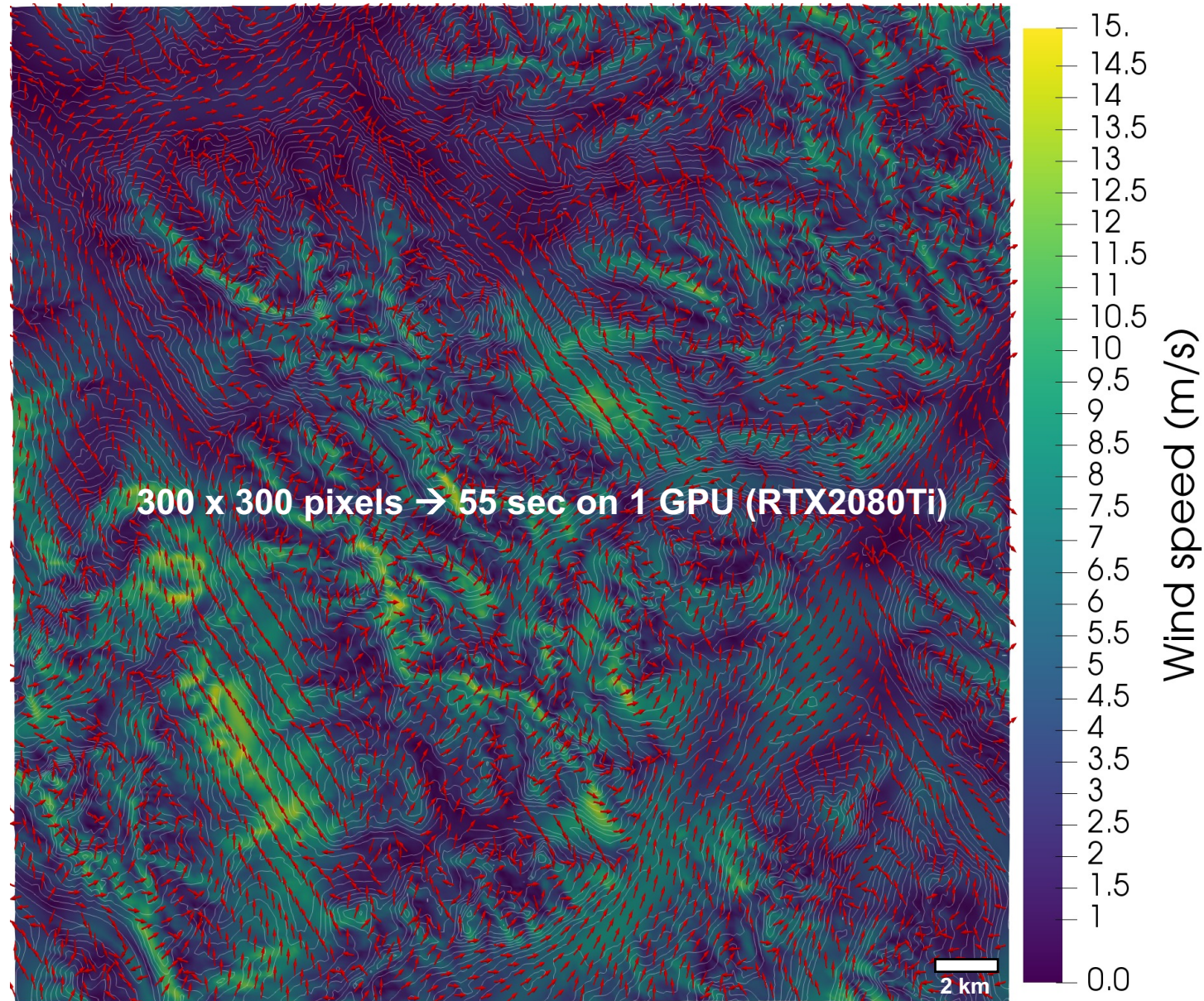
COSMO-1
at 20:00 23 Oct. 2016



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

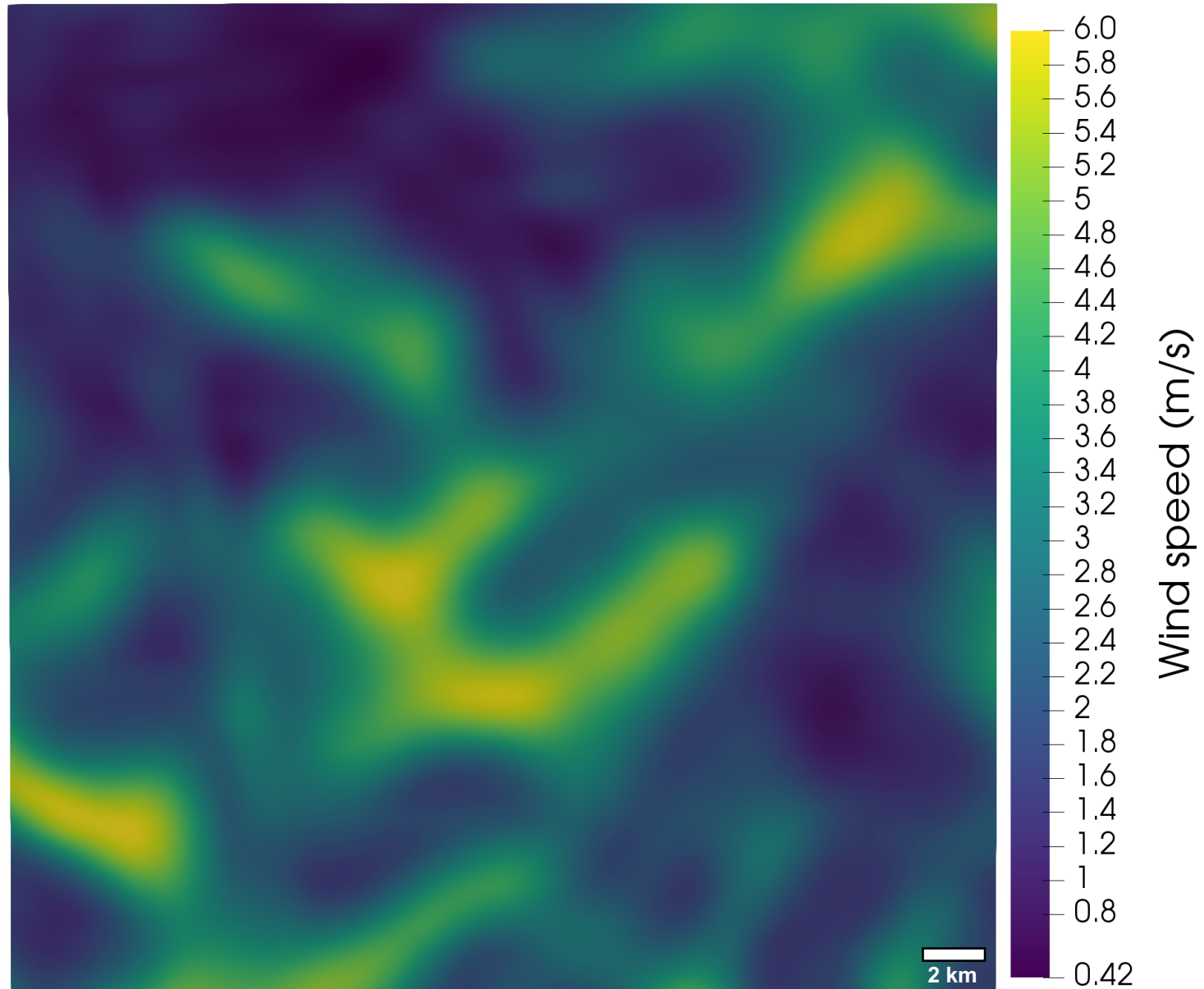
Wind-Topo
at 20:00 23 Oct. 2016



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRM

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

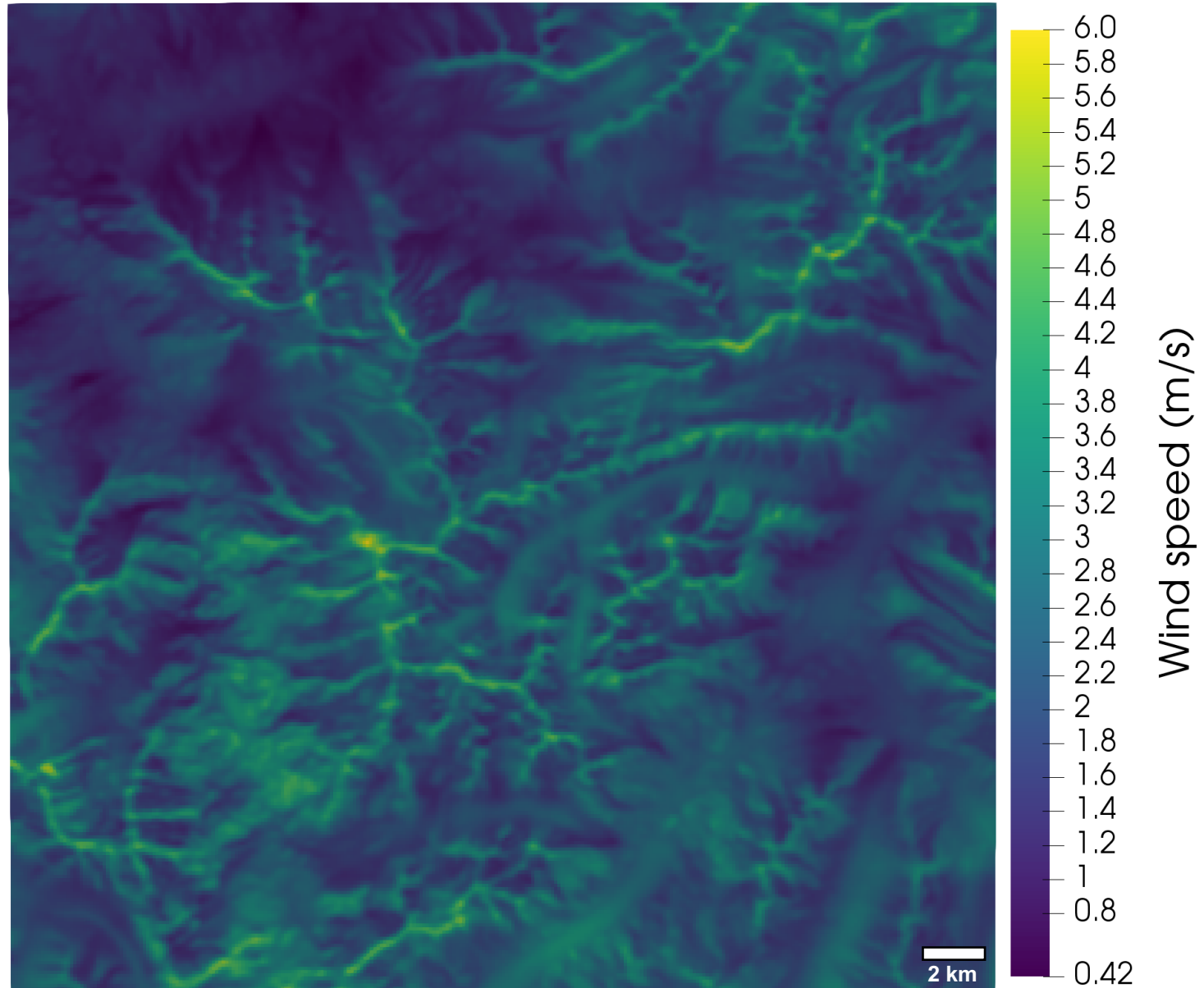
1 year hourly



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRMIS

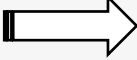
III. Wind-Topo: a deep learning approach to wind downscaling

1 year hourly



Wind-Topo: Downscaling ... - Dujardin and Lehning - 2022 - QJRM

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?

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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 Institute for Snow and Avalanche Research (SLF), Swiss Federal Institute for Forest, Snow and Landscape Research (WSL), Davos, Switzerland

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Funding information
 This work was supported by the Swiss Competence Center for Energy Research, Supply of Electricity

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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 2022; 1-21 | wileyonlinelibrary.com/journal/qj

Wind-Topo_model

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COMPLEX TERRAIN | CONVOLUTIONAL NEURAL NETWORKS | DOWNSCALING | HIGH RESOLUTION | MACHINE LEARNING | METEOROLOGY | SURFACE WINDS | TOPOGRAPHY

Description
 Wind-Topo is a statistical downscaling model for near surface wind fields especially suited for highly complex terrain. It is based on deep learning and was trained (calibrated) using the hourly wind speed and direction from 261 automatic measurement stations (IMIS and SwissMetNet) located in Switzerland. The periods 1st October 2015 to 1st October 2016 and 1st October 2017 to 1st October 2018 were used for training. The model was validated using 60 other stations on the period 1st October 2016 to 1st October 2017. Wind-Topo was trained using COSMO-1 data and a 53-meter Digital Elevation Model as input. This dataset provides all the necessary code to understand, use and incorporate Wind-Topo in a new downscaling scheme. Specifically, the dataset contains the architecture of Wind-Topo and its optimized parameters, as well as a python script to downscale uniform wind fields with a prescribed vertical profile for any given 53-meter DEM. Accompanies the publication "Wind-Topo: Dow.."

Data and resources
 Wind-Topo_v0.1.0
 Contains: all codes, installation procedure, technical documentation, an example of Digital Elevation Model of the Swiss Alps, the expected outputs of the code (downscaled wind...)
 ZIP: 426.62 MB, 7 Jan 2022 11:24, 16 Mar 2022 16:42

Citation
 Jérôme Dujardin, Michael Lehning (2022). Wind-Topo_model. Envidat. doi: 10.16904/envidat.301

Related Publications
 "Wind-Topo: Downscaling near-surface wind fields to high-resolution topography in highly complex terrain with deep learning" Dujardin and Lehning. Quarterly Journal of the Royal Meteorological Society, 2022. https://doi.org/10.1002/qj.4265

Dujardin > Wind-Topo

Wind-Topo Project ID: 153

downscaling wind subgrid topo... + 4 more

1 Commit | 1 Branch | 0 Tags | 436.5 MB Files | 436.7 MB Storage

Wind-Topo is a statistical downscaling model for near surface wind fields especially suited for highly complex terrain. It is based on deep learning and was trained with data from 261 stations. Dujardin and Lehning 2022 "Wind-Topo: Downscaling.."

main | wind-topo | History | Find file | Clone

version of Envidat and Wind-Topo publication (Dujardin and Lehning, 2022, QJRMS) | Dujardin authored 3 weeks ago | 134975a8

Thank you for your attention

2016-10-22 00:00:00

