Welcome to Fourier-Land

Deep-Learning based downscaling of near-surface winds and drifting snow using WRF simulations over synthetic topographies

Manuel Saigger*, Thomas Mölg (*: presenting, contact: manuel.saigger@fau.de)

Friedrich-Alexander-Universität Erlangen-Nürnberg

1. The Problem

- wind-driven redistribution affects snow accumulation on small scales in mountain areas [1]
- interactions between drifting snow and the atmosphere can influence local flow field [2]

→ high spatial resolution + coupling of drifting snow and wind needed to represent snowdrift

→ too expensive for (multi-)seasonal assessment for glaciers with classic numerical approach

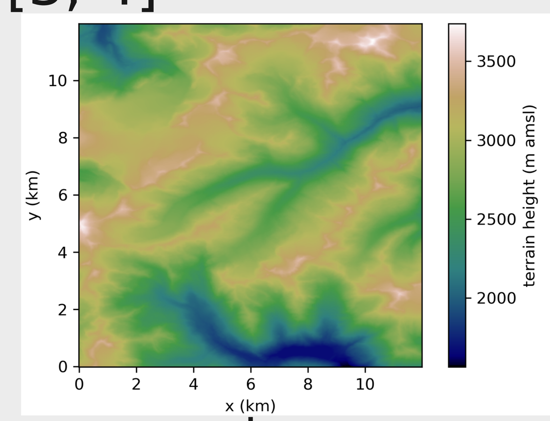
2. The Idea

- replace numerical simulation (WRF) of drifting snow with deep learning (DL) model
- build training data set of high-resolution WRF simulations
- run WRF in idealized setting
  → control what DL model is learning later
- WRF input (atmosphere, terrain, snow) representative for real-world conditions

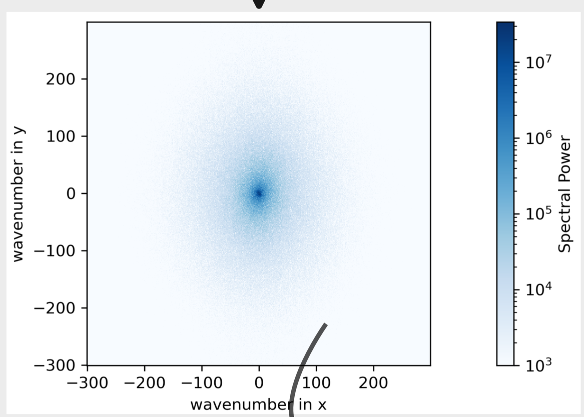
3. Creating Fourier-Land

Idea: synthetic topographies with similar spectral information as real terrain

real terrain spectra
e.g. applied in atmospheric science [3, 4]



Fourier Transform



$P \sim a\ \lambda^b$

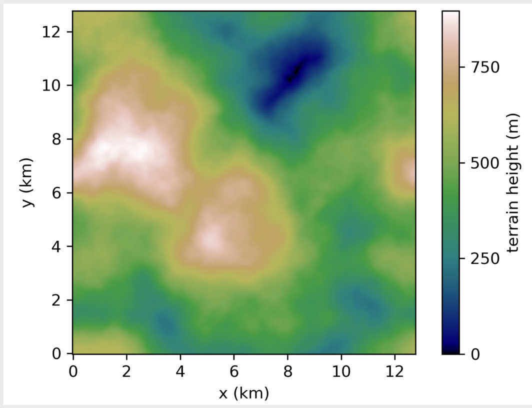
Alps : a ~ 15 ... 25
b ~ -1.5 ... -2.5

synthetic terrain
e.g. applied in engineering [5] or computer game design

Start from white noise

apply scaling

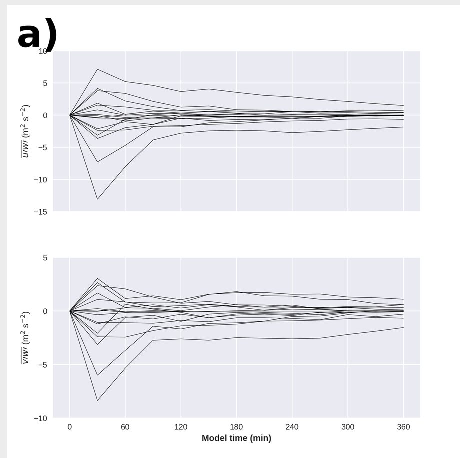
inverse Fourier Transform



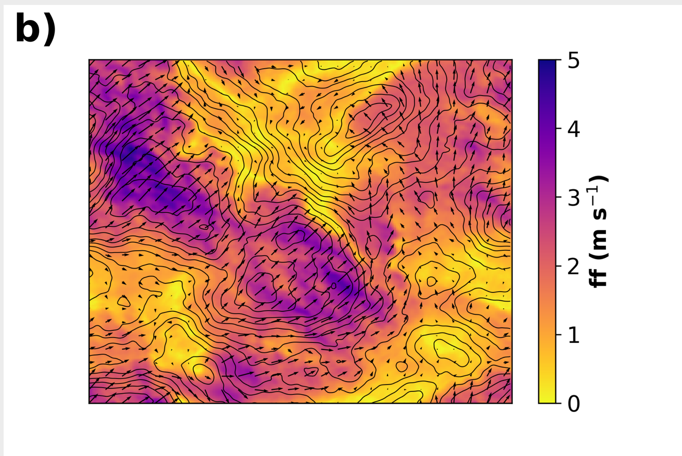
total data set:
72 topographies with 256x256 points,
Δx = 50 m

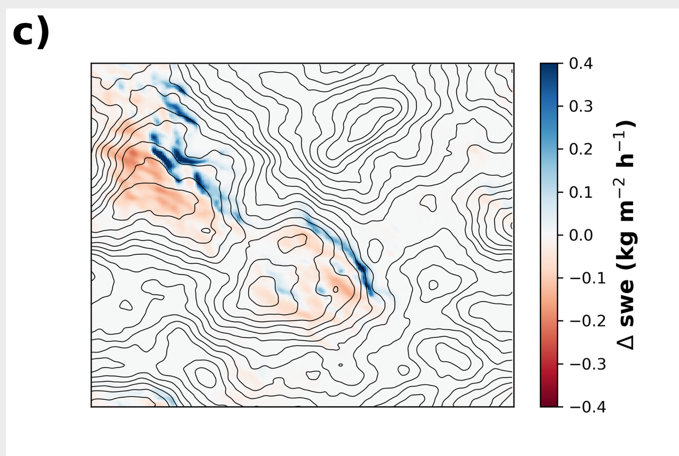
4. Training Data

- idealized WRF LES setup (Δx = 50 m) with coupled snow drift scheme [2], online flux averaging [6], and synthetic topographies
- initial conditions: height-constant profiles (preliminary reduced complexity in training data: $ff = 10\ m\ s^{-1}$, $N = 0.01\ s^{-1}$, $\rho_{snow} = 100\ kg\ m^{-3}$, variable input wind directions)
- periodic boundary conditions
- run simulation until momentum fluxes stabilize
- use stabilized fields as training data



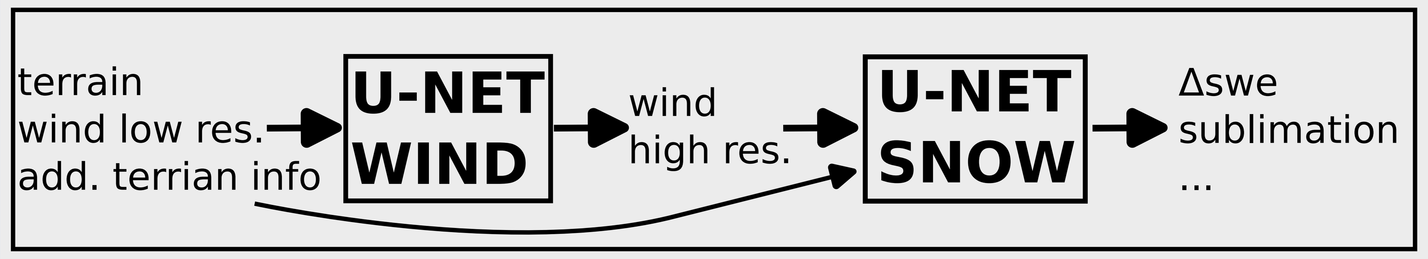
a) 30 min average vertical momentum flux at 16 points equally distributed over the domain at second vertical layer.
b) Average flow field at 10 m above the ground (wind arrows and wind speed), averaged for model time 4 to 6 h, input wind direction is 230°
c) Average snow mass change rate due to drifting snow, averaged for model time 4 to 6 h

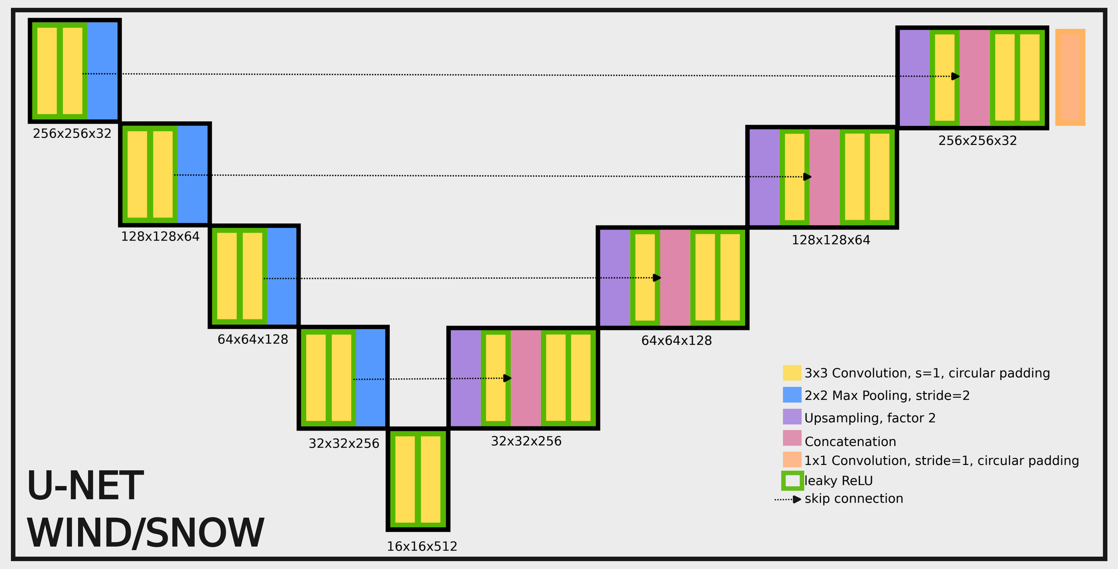




5. DL Downscaling

basic architecture: U-Net [7]
stacking U-Nets:

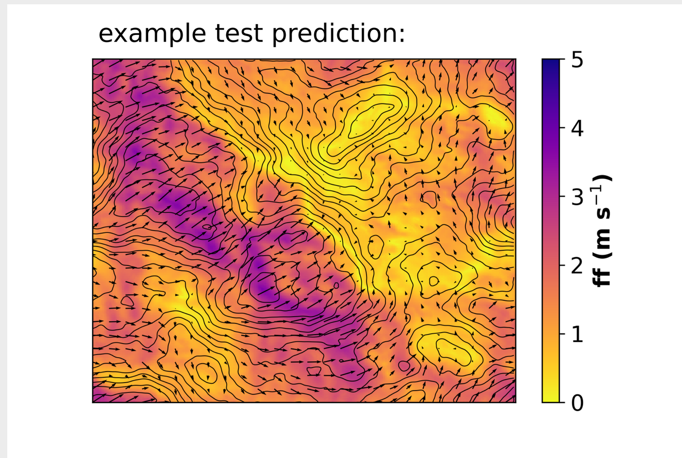


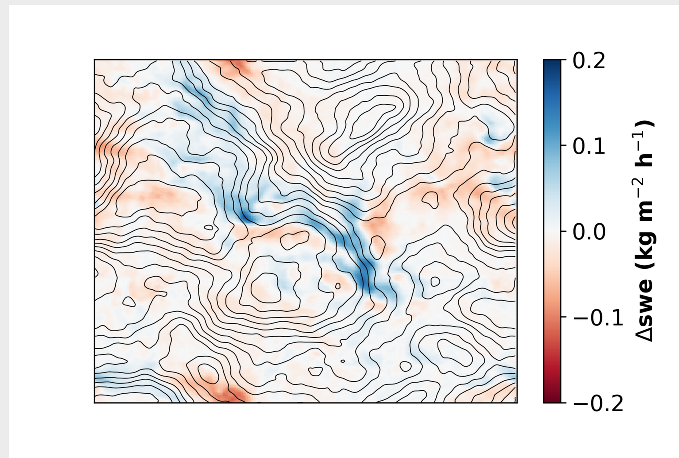


data split: 56 - 4 - 12

performance on test data:
$RMSE(ff) = 0.98\ m\ s^{-1}$
$bias(ff) = -0.51\ m\ s^{-1}$
$RMSE(dd) = 38.8°$

Optimzer	SGD
Learning rate	0.01, with lr. decay
Normalization	mean - std
Loss Function	MSE
Batch Size	4
Epochs	500





6. Future Plans

- more complexity in training data
- mass conservation constraint in U-NET SNOW
- couple to glacier mass balance model
- run with real-world atmospheric input

→ Influence of drifting snow on glacier mass balance?

References

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[6] Göbel, M. et al.: Numerically consistent budgets of potential temperature, momentum, and moisture in Cartesian coordinates: application to the WRF model, Geoscientific Model Development, doi:10.5194/gmd-15-669-2022, 2022.
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