Downscaling vertical profiles of turbulent atmospheric variables using deep learning

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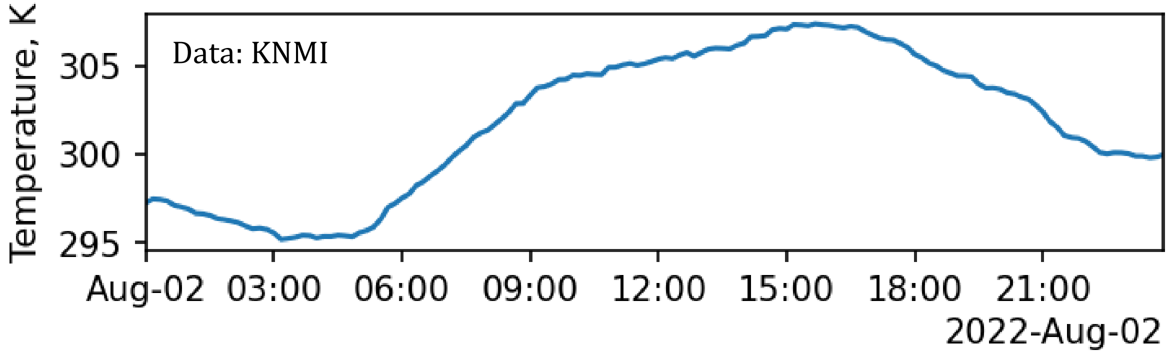
What is turbulence, and why do we care about it?

Reynolds (1883)

Turbulence = small-scale fluctuations around mean

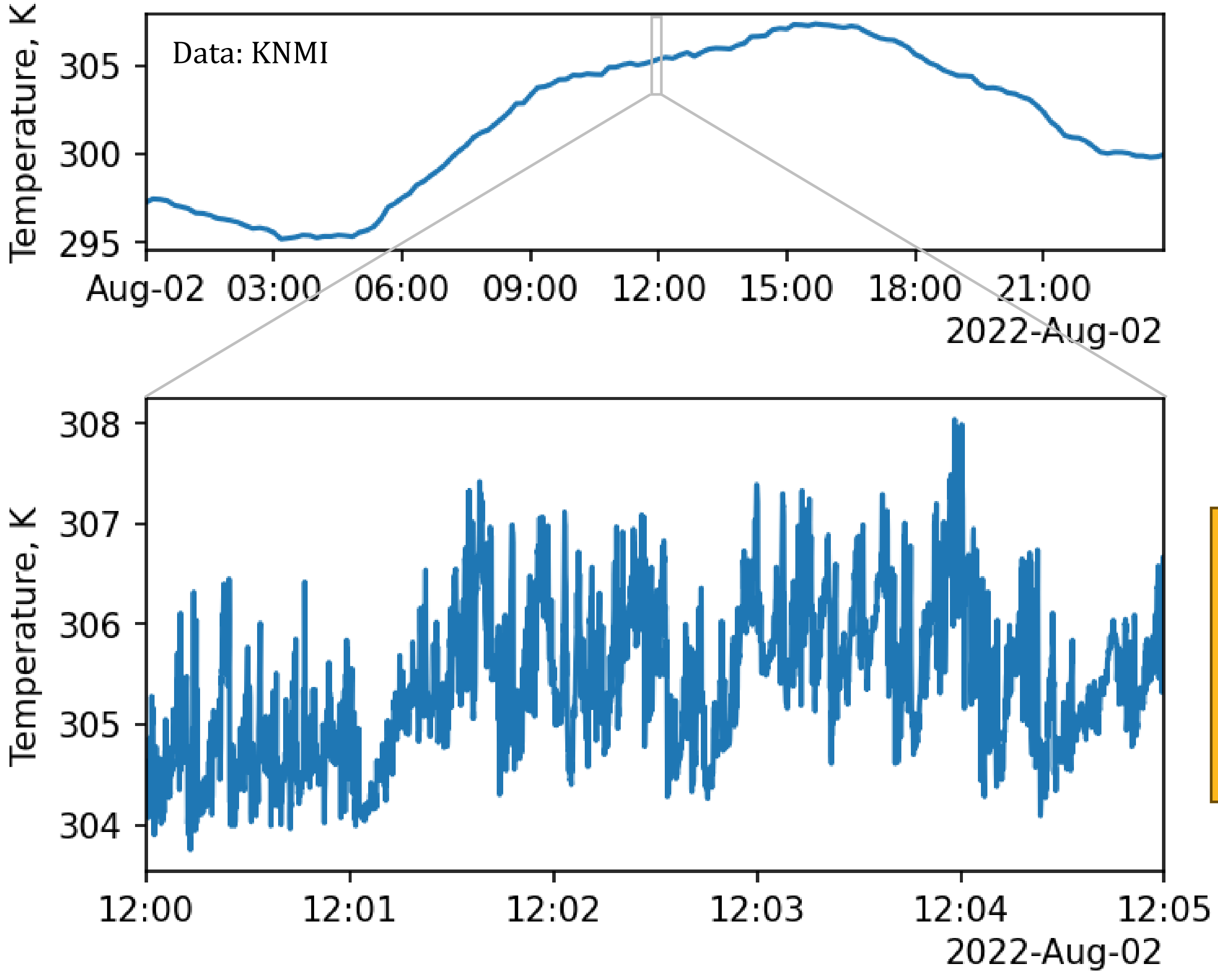
10 min average



Well-captured in AIWP

Turbulence = small-scale fluctuations around mean

10 min average



0.1s instantaneous

Well-captured in AIWP

Turbulence statistics
(variances, covariances, ...)
have so far received little attention in AIWP

High-res (*) profiles of turbulence statistics needed in many applications

(*): $\overline{\Delta z}_{\mathrm{BL}} \approx 50\mathrm{m}$ / $\overline{\Delta z}_{\mathrm{FA}} \approx 500\mathrm{m}$

Clear Air Turbulence

Credit: Lufthansa

Pollution dispersion


Credit: Martin Vorel

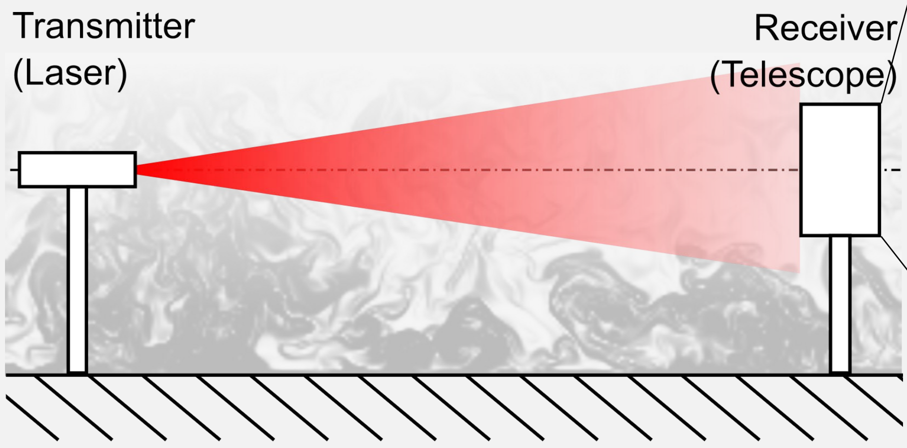
Optical Turbulence

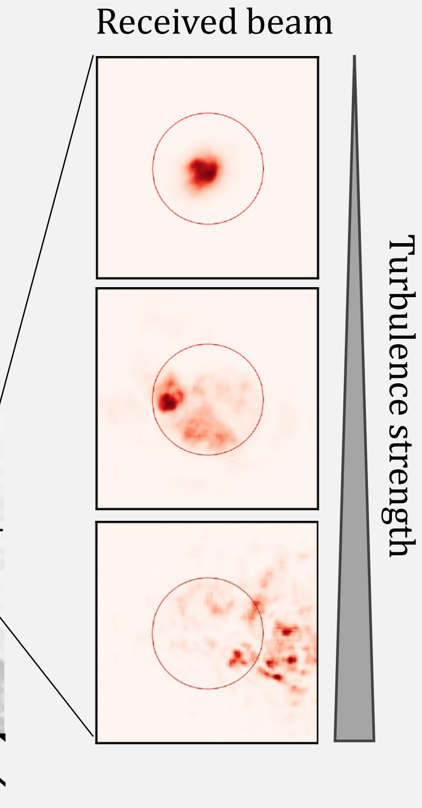

Credit: TU Delft

Laser Satellite Communication


Credit: ELT

Optical Astronomy



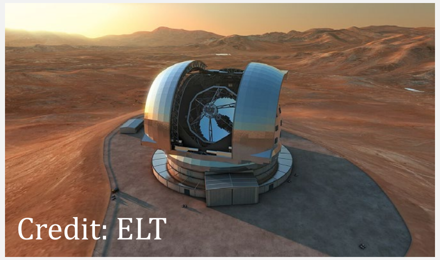


Turbulence background: Katherine Fador, MPI Hamburg

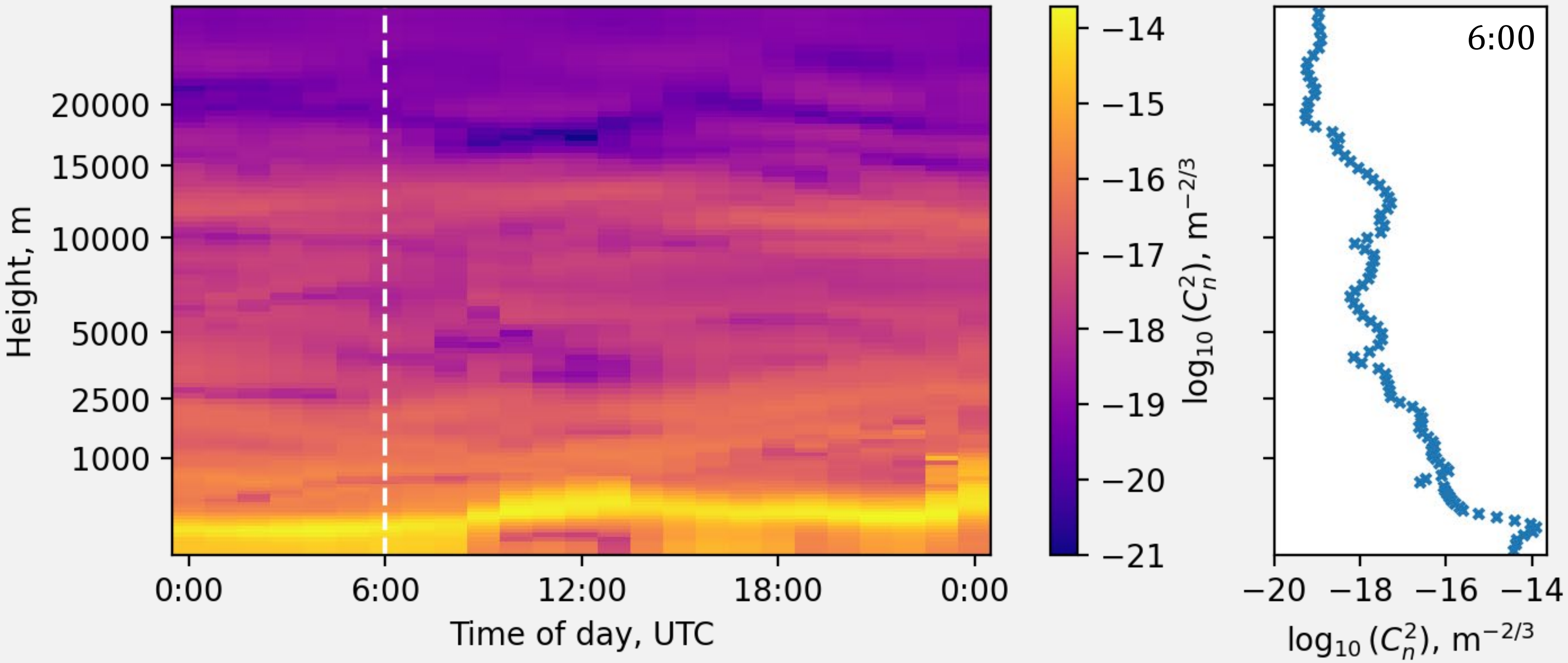
High-res (*) optical turbulence profiles (C_n^2) needed…

(*): $\overline{\Delta z}_{\mathrm{BL}} \approx 50\mathrm{m}$ / $\overline{\Delta z}_{\mathrm{FA}} \approx 500\mathrm{m}$

Laser Satellite Communication



Optical Astronomy



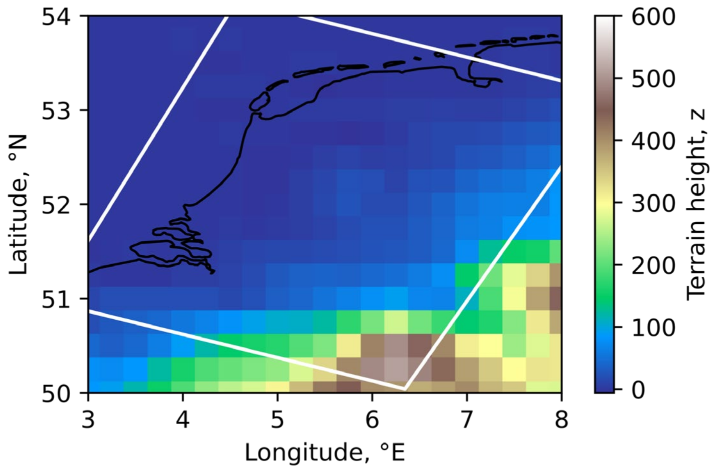
Goal: Estimate C_n^2 profiles from ERA5

Methodology

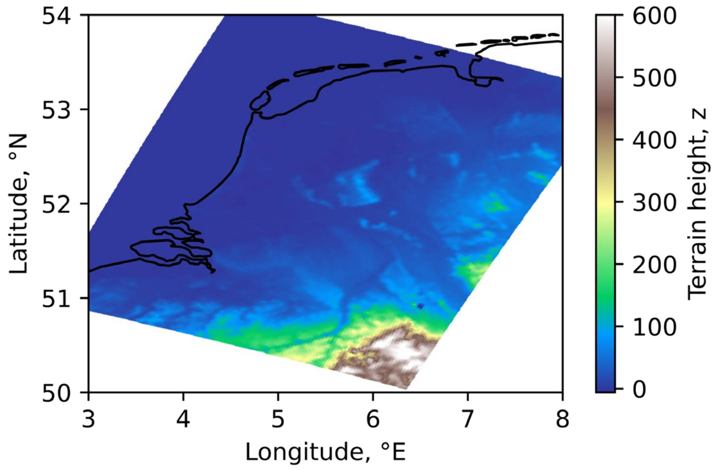
Vertical profile regression and super resolution

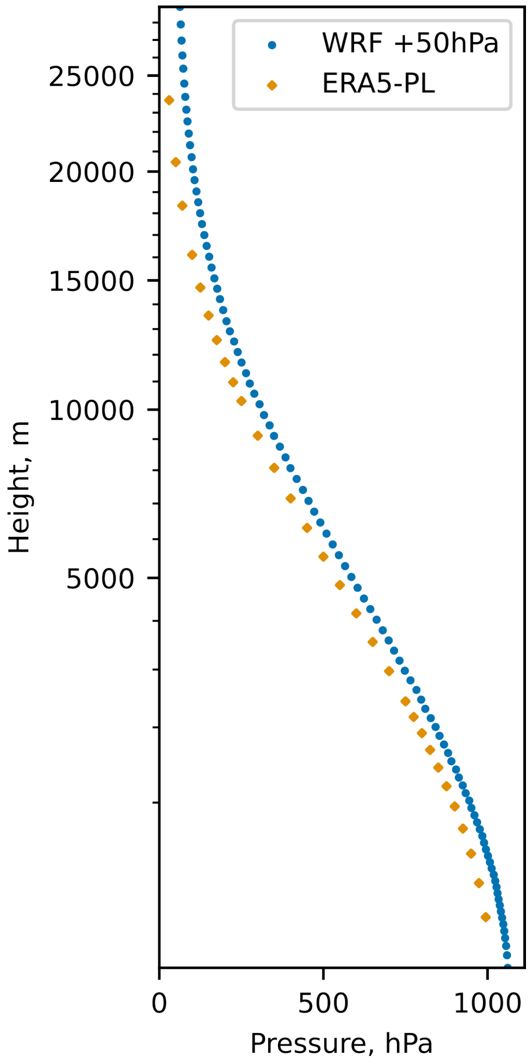
Datasets

ERA5 Pressure Levels, 0.25° x 0.25°



Mesoscale Weather Model (WRF), 2km x 2km

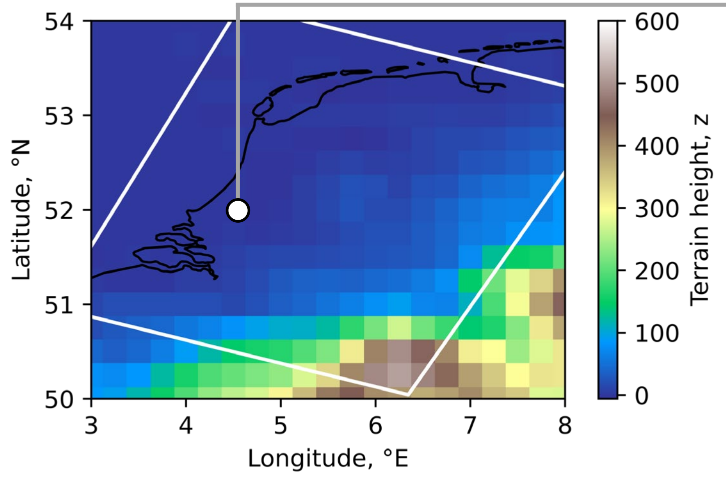




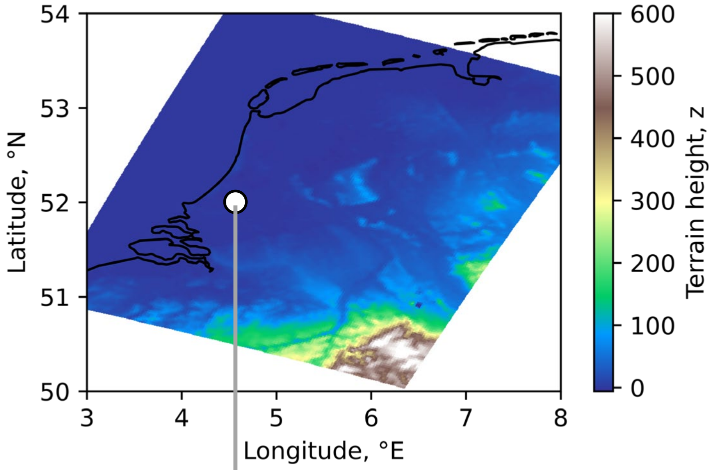
ERA5 PL:
- 30 levels
- $\overline{\Delta z_{BL}} \approx 230\text{m}$
- $\overline{\Delta z_{FA}} \approx 1100\text{m}$

WRF:
- 100 levels
- $\overline{\Delta z_{BL}} \approx 60\text{m}$
- $\overline{\Delta z_{FA}} \approx 425\text{m}$

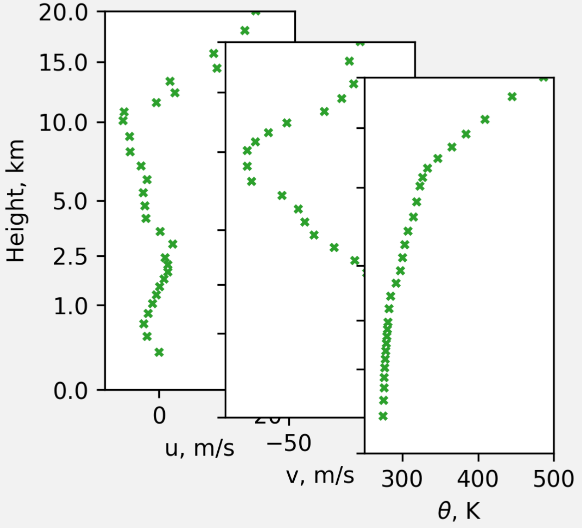
ERA5 Pressure Levels, 0.25° x 0.25°
(30 levels / $\overline{\Delta z}_{BL} \approx 230$m / $\overline{\Delta z}_{FA} \approx 1100$m)



Mesoscale Weather Model (WRF), 2km x 2km
(100 levels / $\overline{\Delta z}_{BL} \approx 60$m / $\overline{\Delta z}_{FA} \approx 425$m)



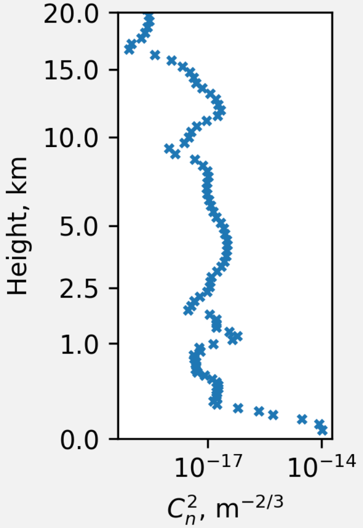
X: low-res input profiles + surface features



+ vert. gradients
+ pressure
+ z

+ sfc. sensible hf
+ sfc. latent hf
+ sfc. pressure
+ sfc. friction velocity
+ ...

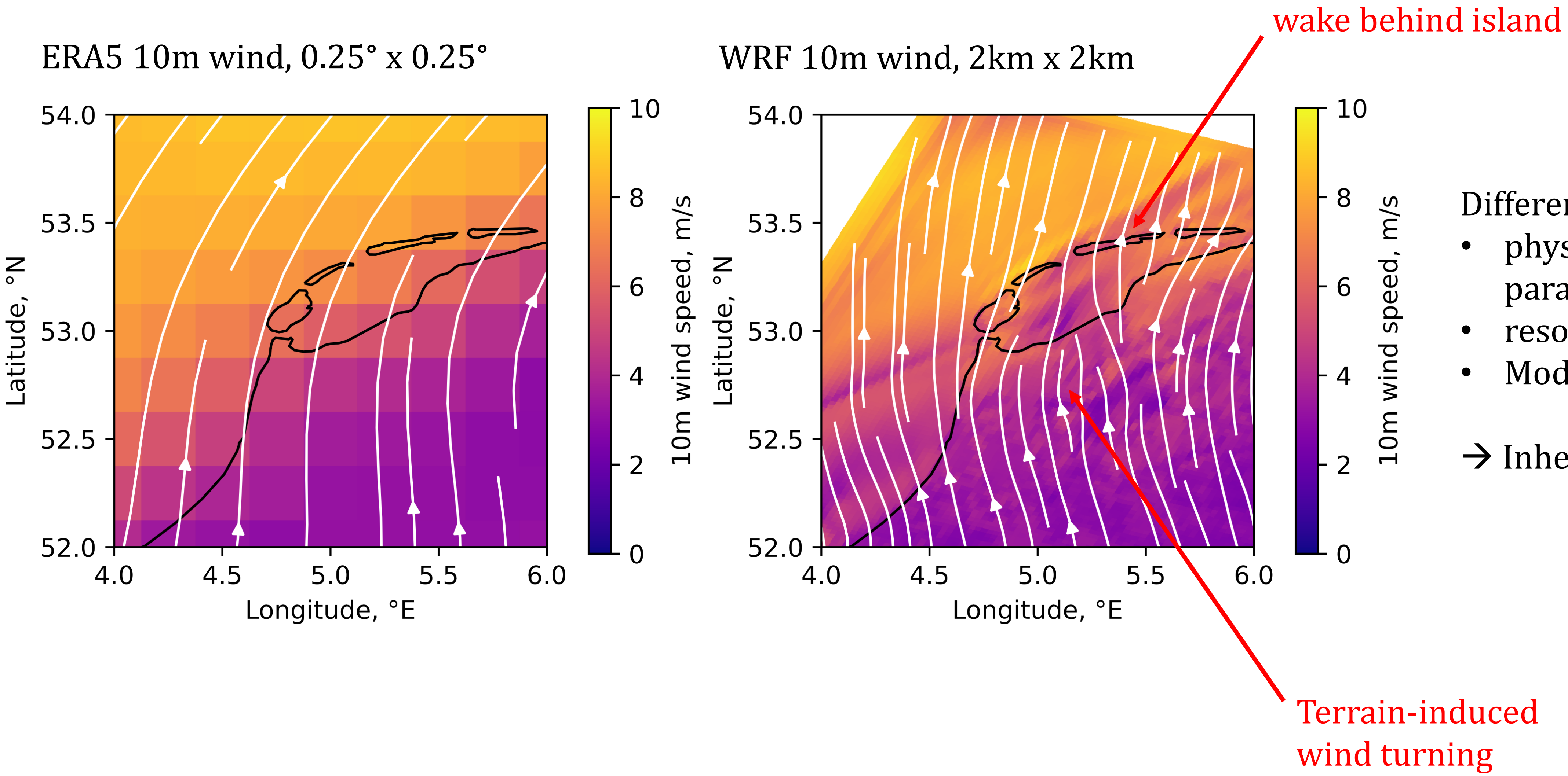
y: high-res C_n^2 profile



Task: 1D regression and super resolution

But: not just deblurring. Inherent dataset differences!

TU Delft



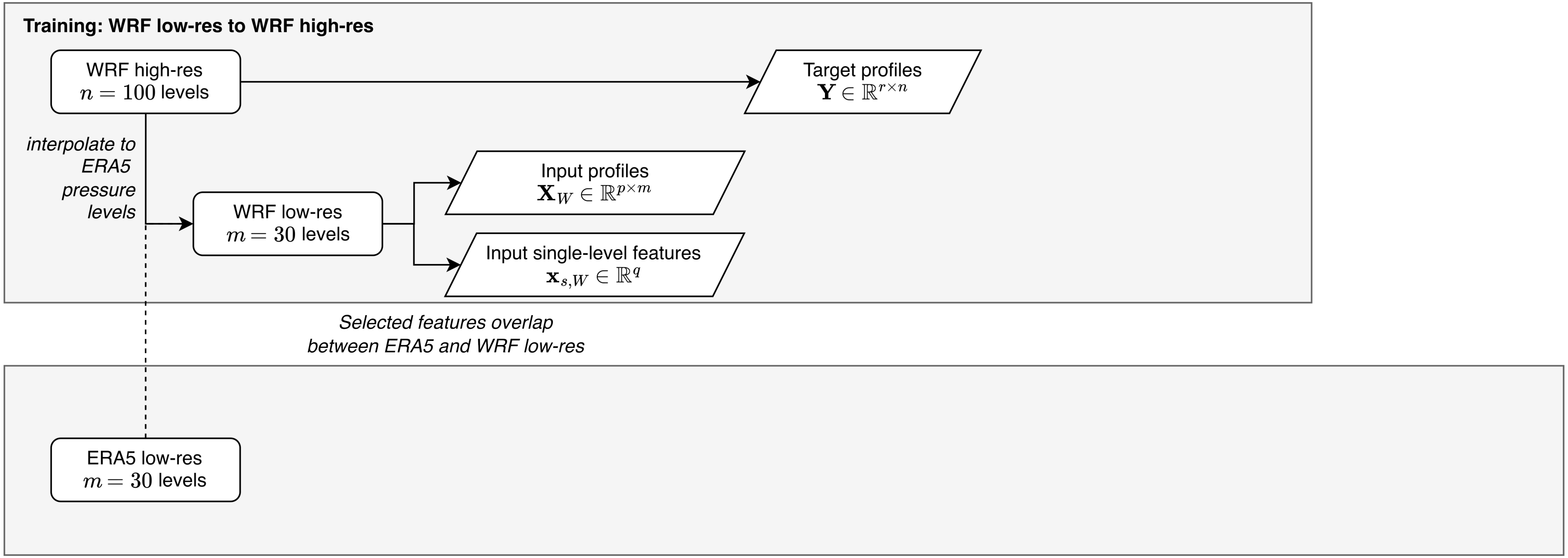
Differences due to
- physics parameterizations
- resolution
- Model drift

→ Inherent

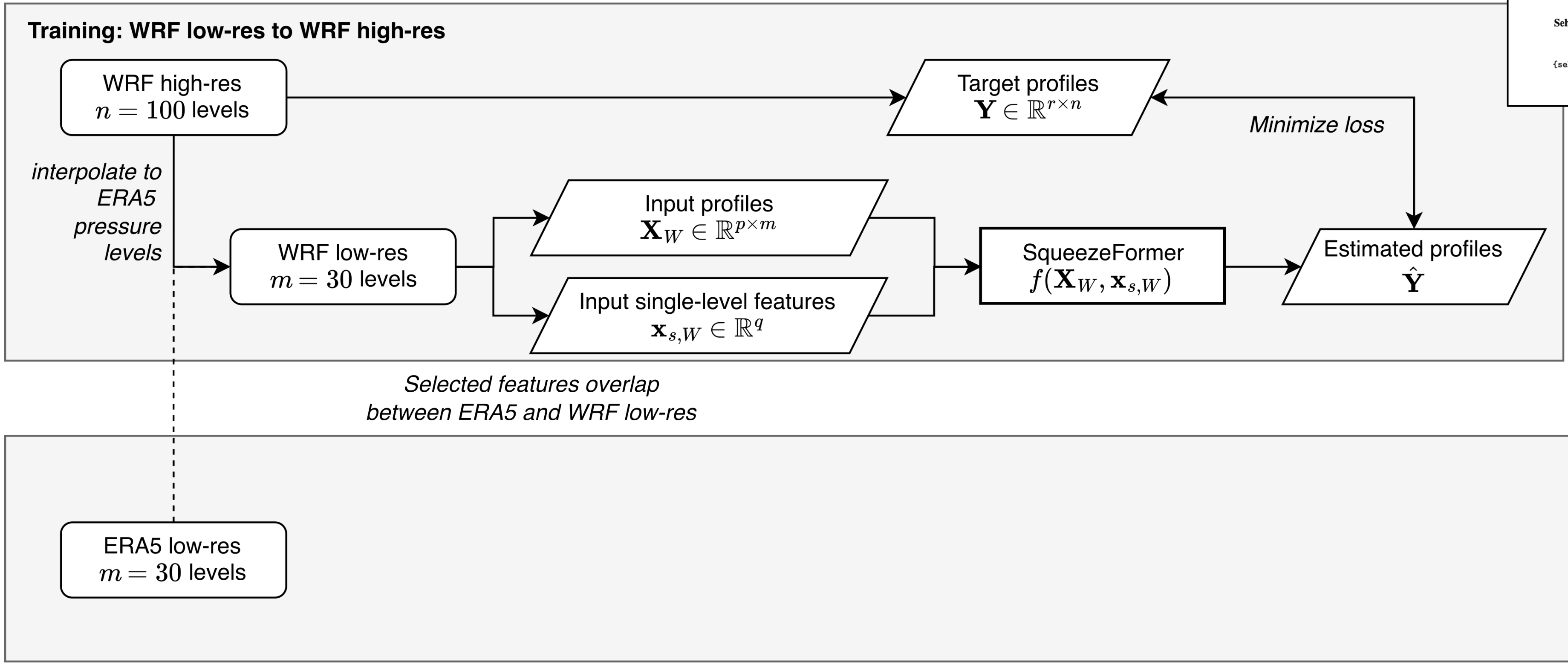
Address through decoupled training

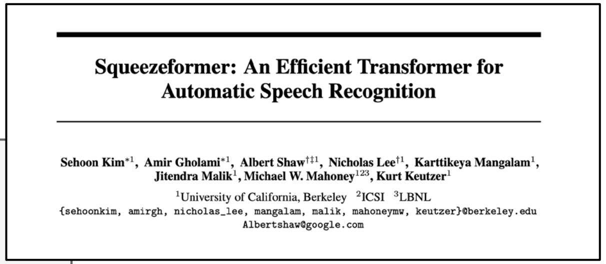
Address through decoupled training

Address through decoupled training



Address through decoupled training




Squeezeformer: An Efficient Transformer for Automatic Speech Recognition

Sehoon Kim*[1], Amir Gholami*[1], Albert Shaw†‡[1], Nicholas Lee†[1], Karttikeya Mangalam[1], Jitendra Malik[1], Michael W. Mahoney[123], Kurt Keutzer[1]

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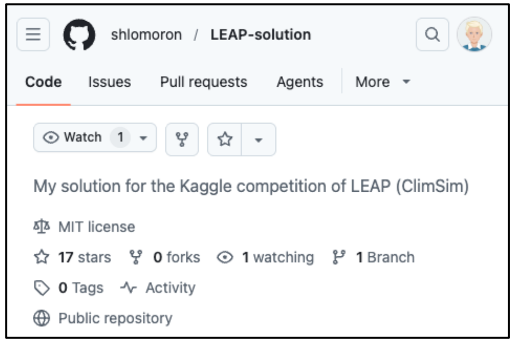
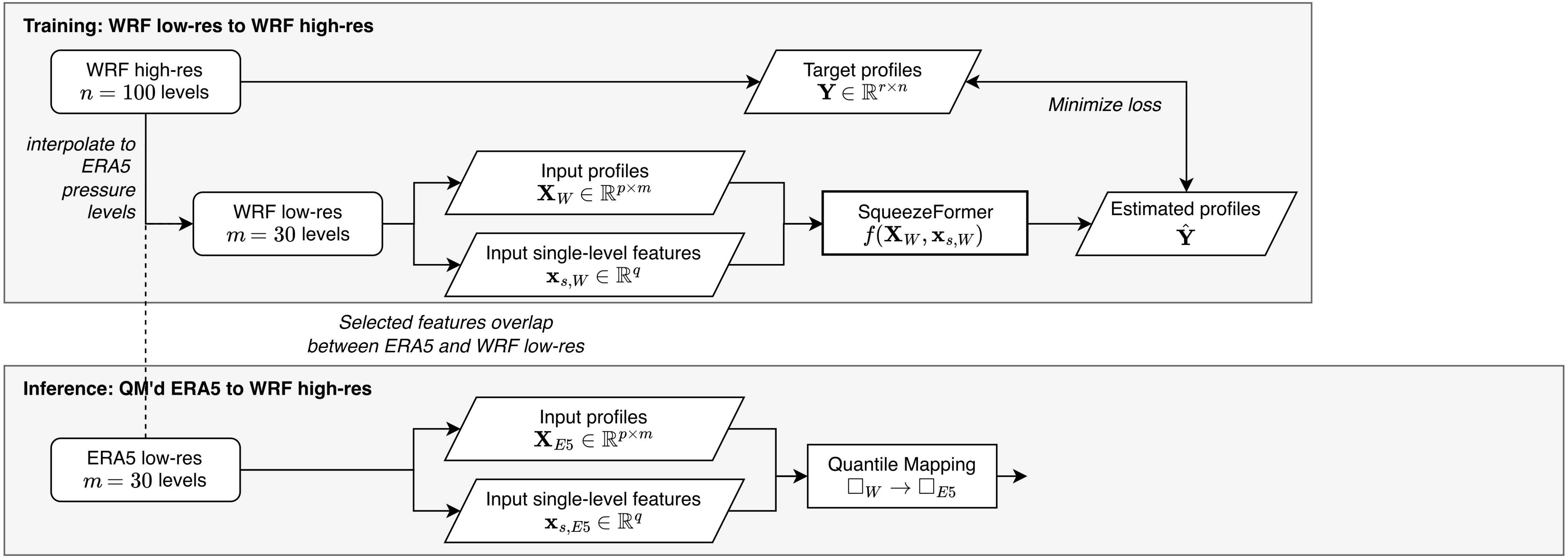
{sehoonkim, amirgh, nicholas_lee, mangalam, malik, mahoneymw, keutzer}@berkeley.edu

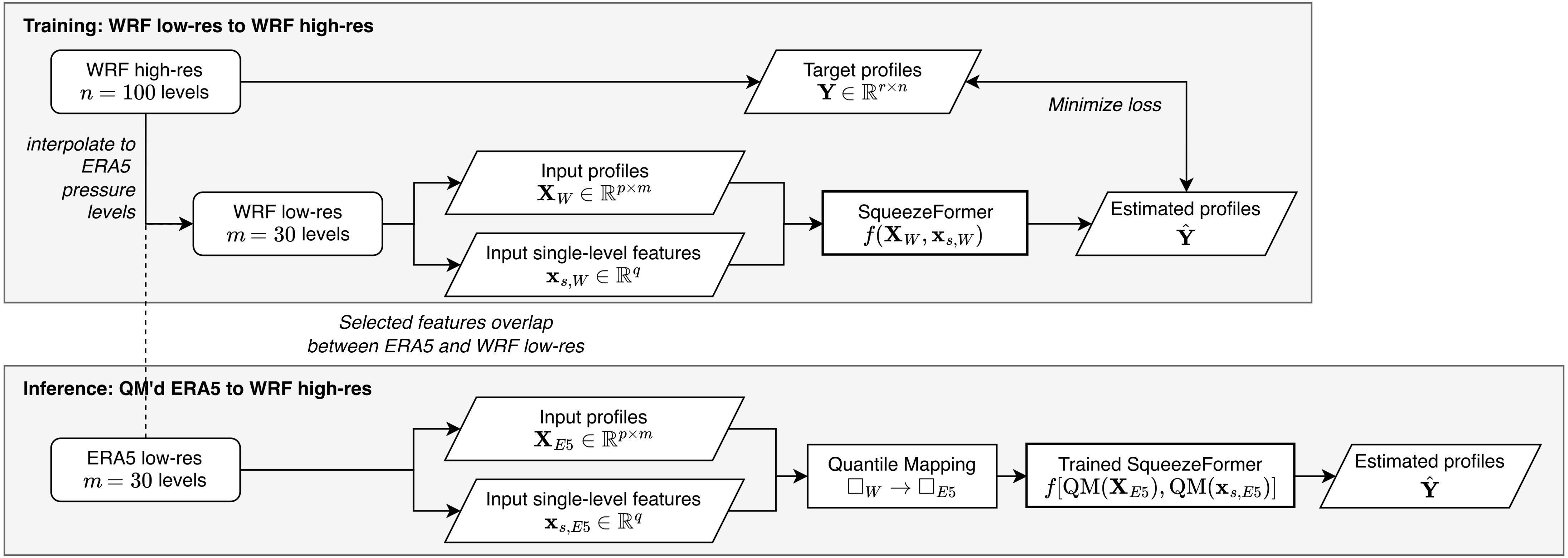
Albertshaw@google.com



Address through decoupled training

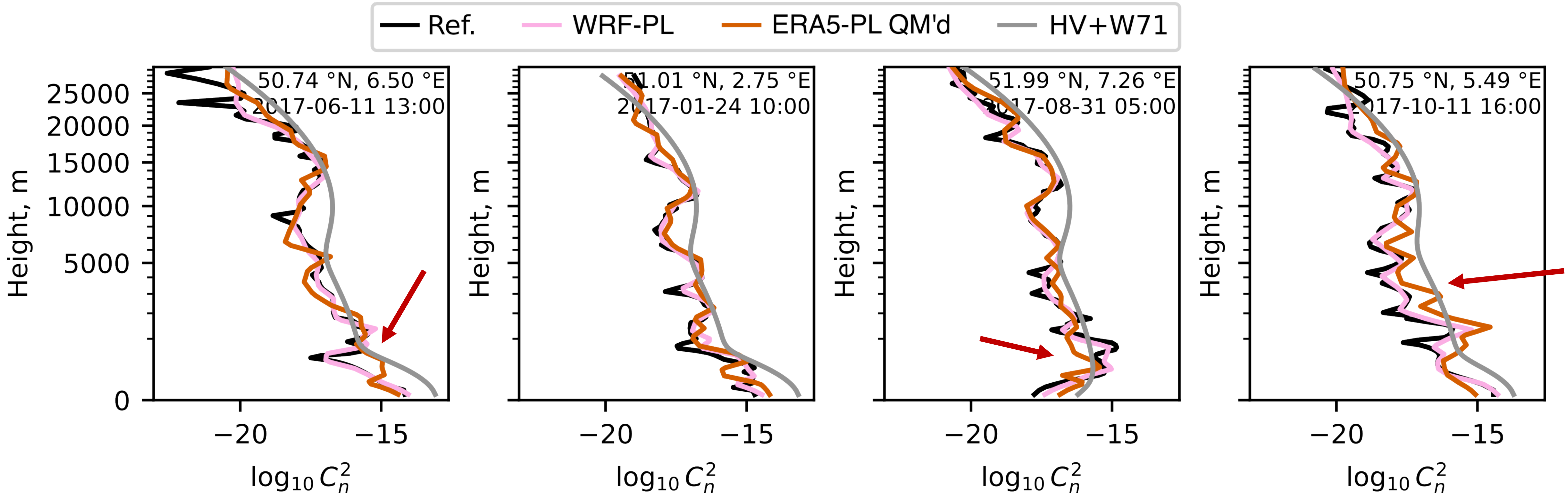


Address through decoupled training



Results

Estimated profiles are realistic but smoothed

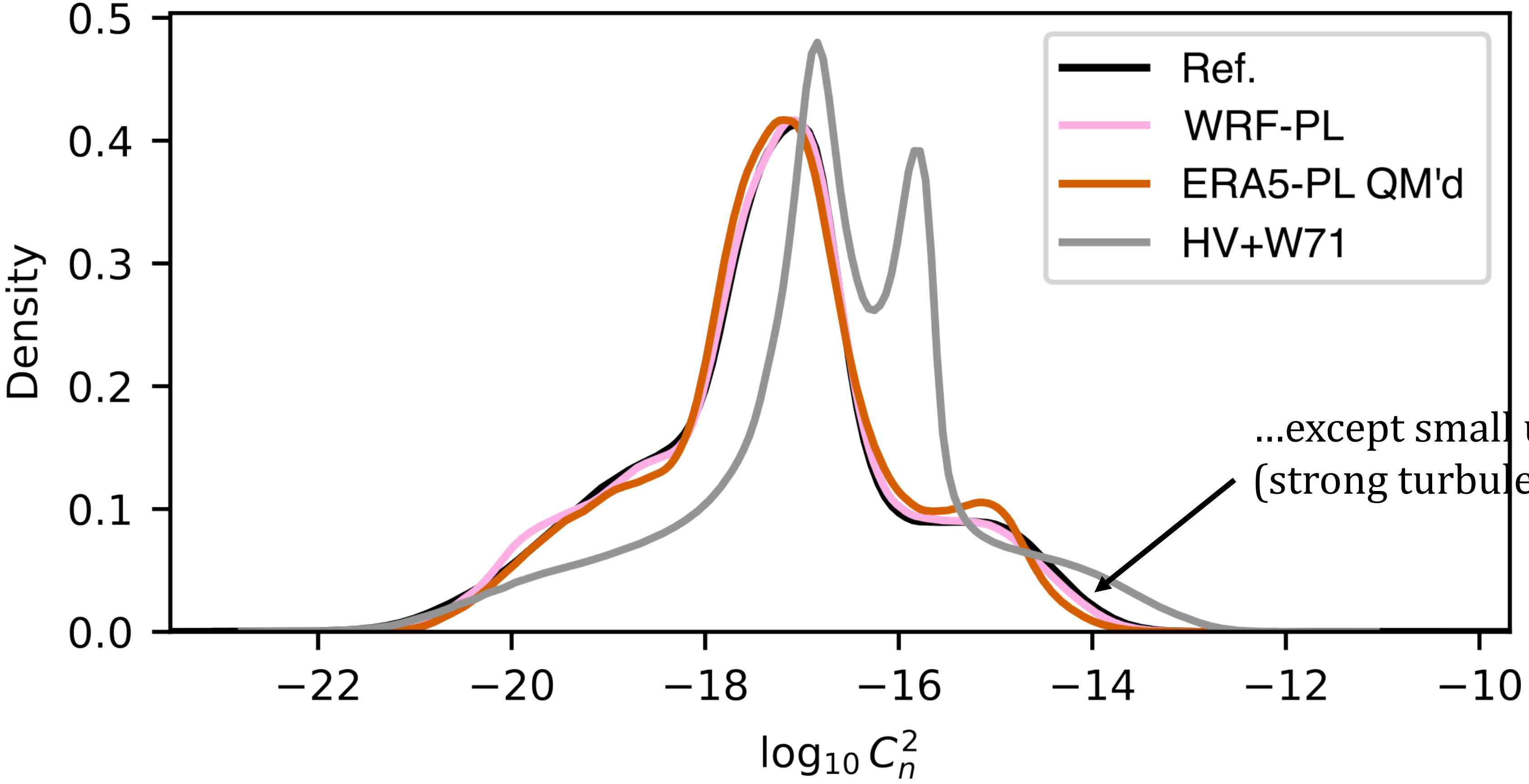


Hufnagel-Valley analytical baseline

$$C_n^2(z) = f\left[\int M(z)dz\right] \exp(-z) + c_2 \exp(-z/1.5) + c_3 \exp(-z/0.1)$$

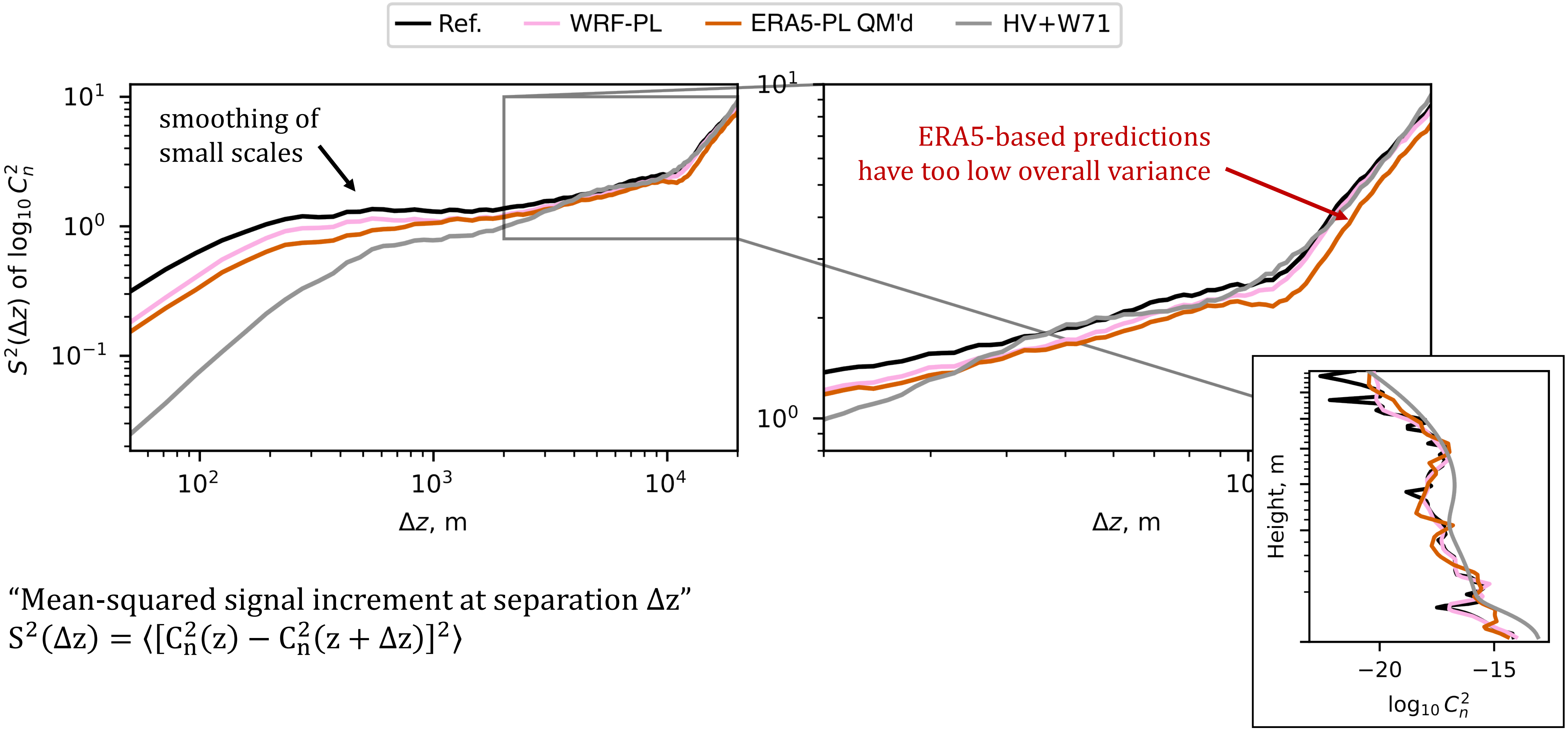
Dataset mismatch makes direct evaluation of ERA5-based estimates difficult

Distributions match well…



…except small underestimation of tail (strong turbulence)

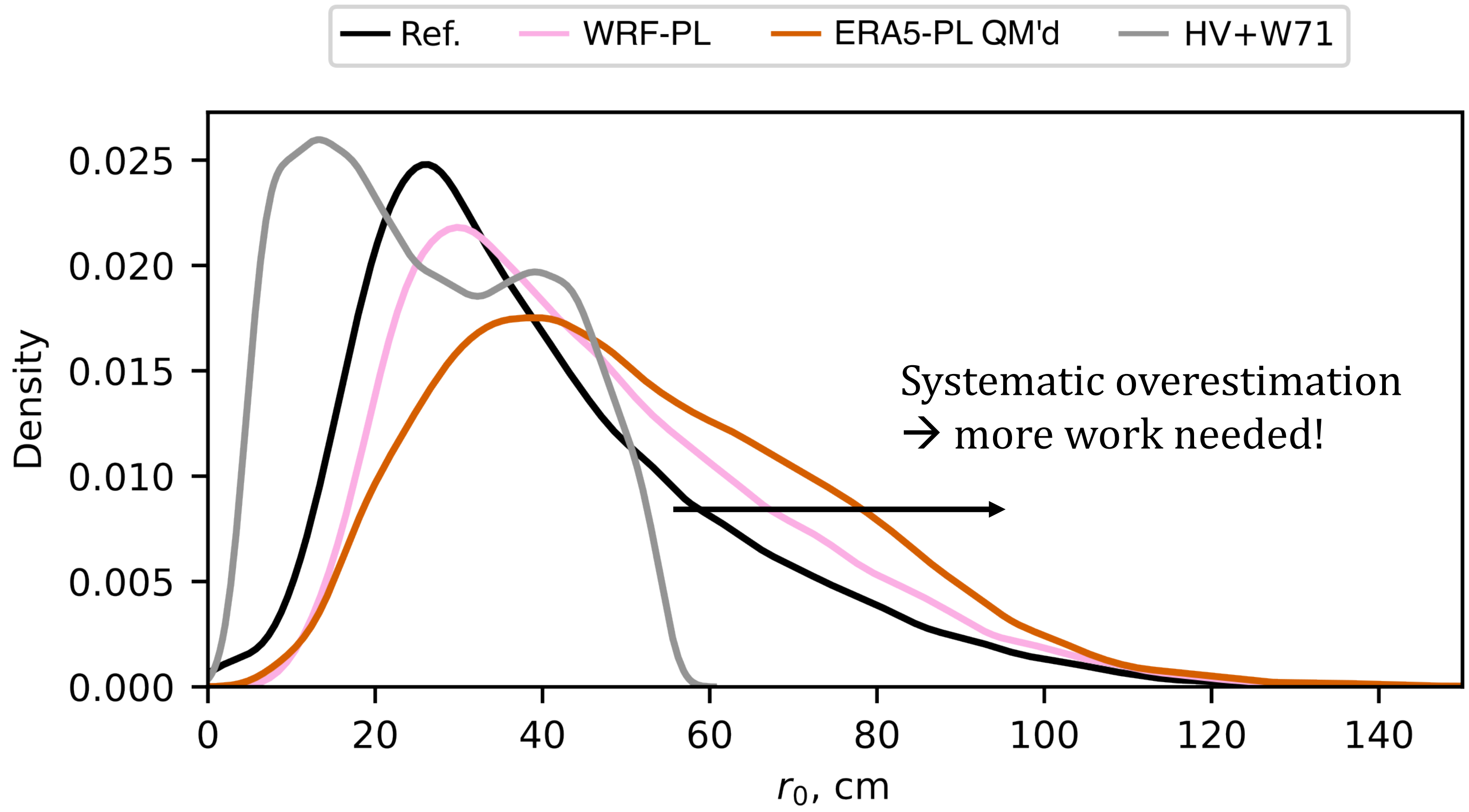
Smoothing shows as earlier drop of structure function

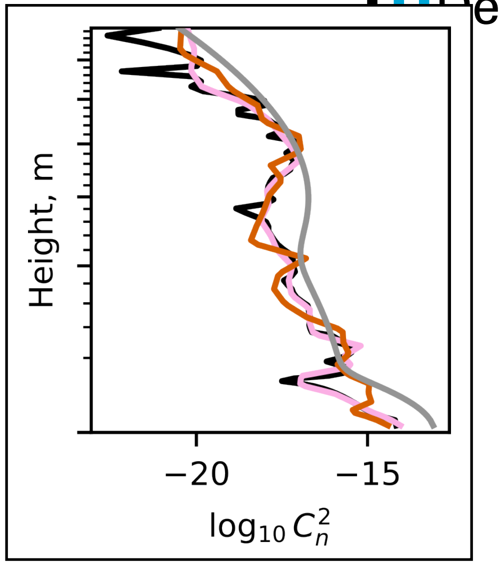


"Mean-squared signal increment at separation Δz"

$$S^2(\Delta z) = \langle [C_n^2(z) - C_n^2(z + \Delta z)]^2 \rangle$$

Profile smoothing and displacement propagate into column-integrated parameters





$$r_0 \sim \left(\int_0^H C_n^2(z) dz \right)^{-3/5}$$

Similar to
- Integrated water vapor
- Liquid water path
- Aerosol optical depth
- ...

Conclusion and Outlook

Conclusion

Overall promising! Applicable to other (turbulent) profiles.

- Yields realistic profiles
- Smoothing acceptable for profiles, but causes bias in integrated quantities
- Decoupled training yields more realistic profiles (not shown, see paper)
- Still, dataset differences challenging

Next steps

- Probabilistic training with CRPS loss
- Different domain adaptation techniques
- Hybrid models? (dynamical core + DL)

@everyone: turbulence is important :)!


OTProf: estimating high-resolution profiles of optical turbulence (C_n^2) from reanalysis using deep learning

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(Dated: April 10, 2026)

Accurate high-resolution vertical profiles of optical turbulence (C_n^2), which reflect local meteorology and topography, are crucial for ground-based optical astronomy and free-space optical communication. However, measuring these profiles or generating them with numerical weather models requires substantial operational or computational effort. In this work, we present OTProf, a deep-learning method that estimates high-resolution C_n^2 profiles from widely available coarse-resolution ERA5 reanalysis data. We evaluate the approach in the Netherlands and compare it with the commonly used Hufnagel-Valley model. Overall, OTProf reproduces the vertical structure of C_n^2 more accurately than Hufnagel-Valley and yields more accurate estimates of the Fried parameter r_0 and the scintillation index σ_I^2. As typical in machine learning, the C_n^2 predictions are slightly smoothed compared to reference data, especially in cases of rare strong turbulence. This smoothing affects the integrated parameters, sometimes leading to overly optimistic r_0 and σ_I^2 values. Despite this limitation, OTProf offers a more accurate, efficient, and physically consistent alternative to traditional analytical models and computationally expensive mesoscale models.

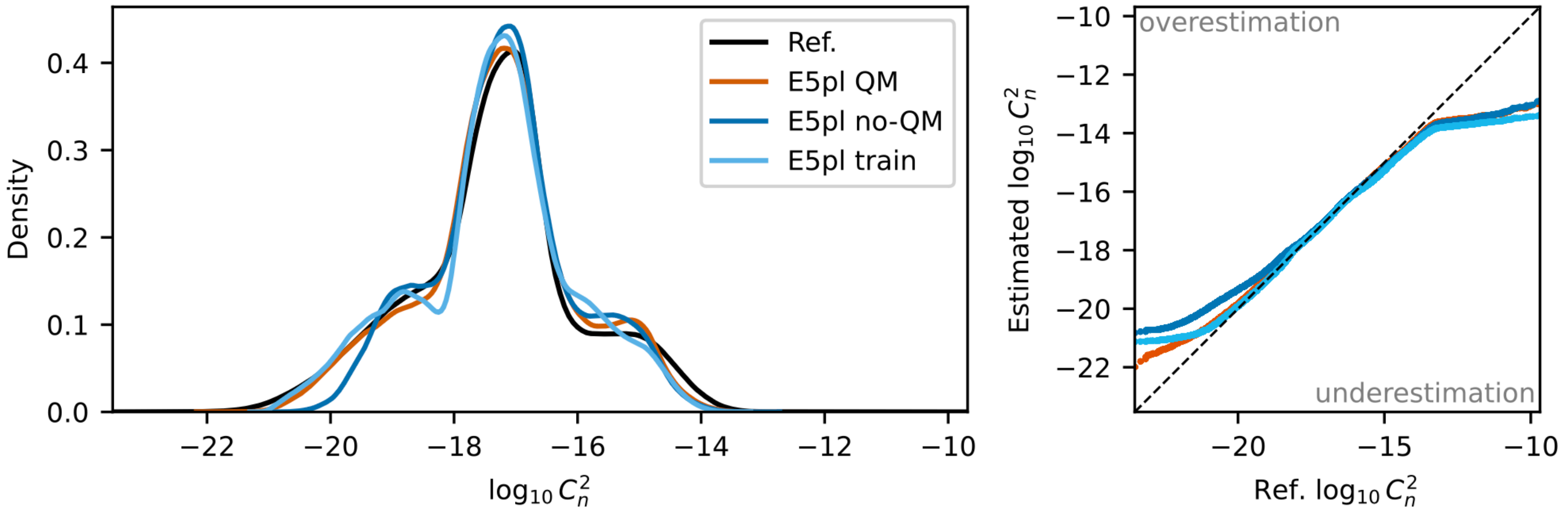
I. INTRODUCTION

https://arxiv.org/abs/2604.09346

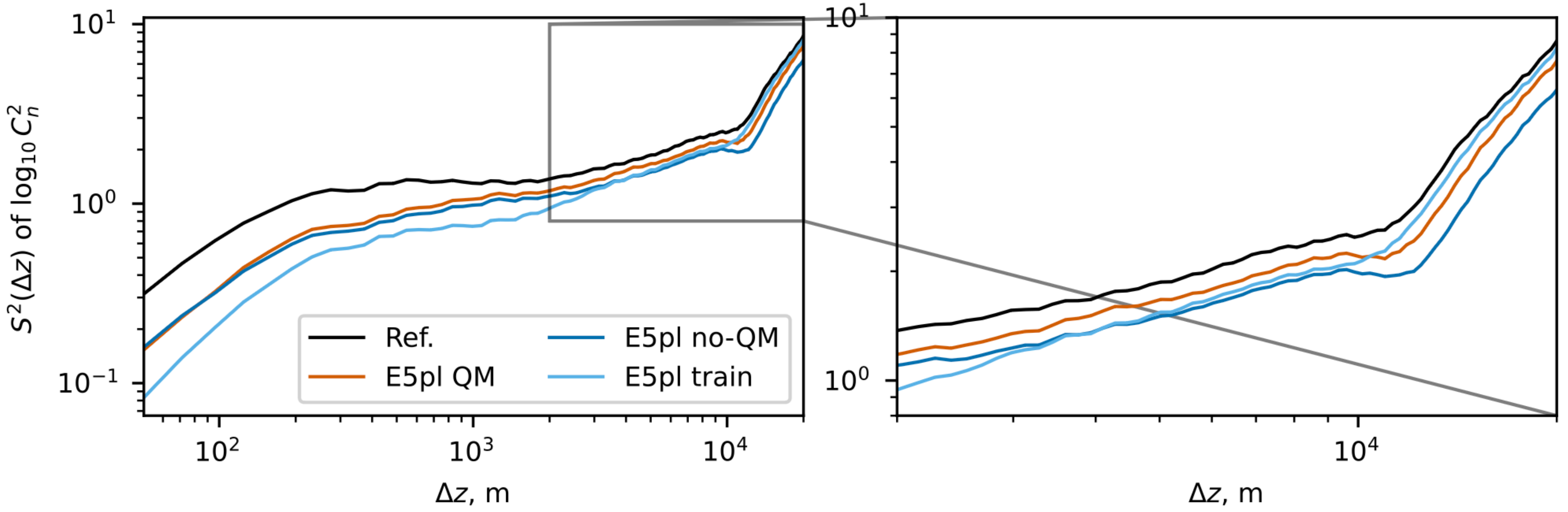
Thank you!

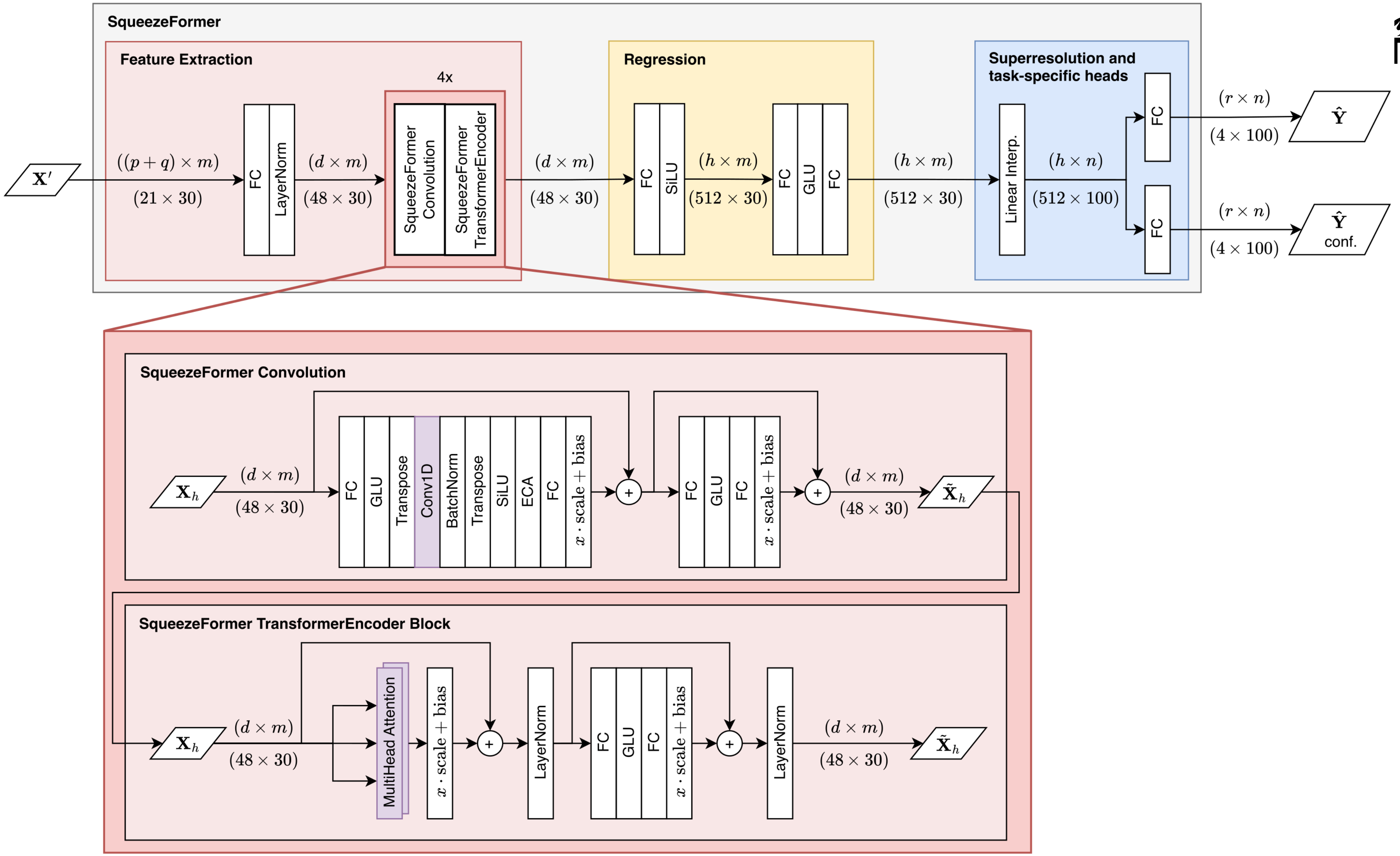
Questions?

(b) Histograms and quantile-quantile plots of $\log_{10} C_n^2$ predictions against WRF-based reference profiles.

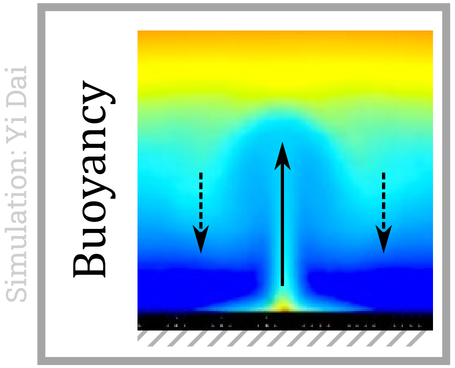


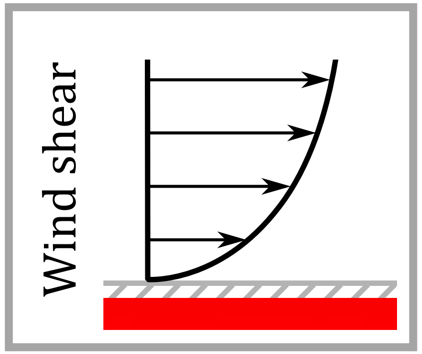
(c) Vertical second-order structure functions of $\log_{10} C_n^2$.




SqueezeFormer
Feature Extraction
$\mathbf{X}'$
$((p+q)\times m)$
(21×30)
FC
LayerNorm
$(d\times m)$
(48×30)
4x
SqueezeFormer Convolution
SqueezeFormer TransformerEncoder
$(d\times m)$
(48×30)
Regression
FC
SiLU
$(h\times m)$
(512×30)
FC
GLU
FC
$(h\times m)$
(512×30)
Superresolution and task-specific heads
Linear Interp.
$(h\times n)$
(512×100)
FC
FC
$(r\times n)$
(4×100)
$\hat{\mathbf{Y}}$
$(r\times n)$
(4×100)
$\hat{\mathbf{Y}}$ conf.
SqueezeFormer Convolution
$\mathbf{X}_h$
$(d\times m)$
(48×30)
FC
GLU
Transpose
Conv1D
BatchNorm
Transpose
SiLU
ECA
FC
$x\cdot\mathrm{scale}+\mathrm{bias}$
+
FC
GLU
FC
$x\cdot\mathrm{scale}+\mathrm{bias}$
+
$(d\times m)$
(48×30)
$\tilde{\mathbf{X}}_h$
SqueezeFormer TransformerEncoder Block
$\mathbf{X}_h$
$(d\times m)$
(48×30)
MultiHead Attention
$x\cdot\mathrm{scale}+\mathrm{bias}$
+
LayerNorm
FC
GLU
FC
$x\cdot\mathrm{scale}+\mathrm{bias}$
+
LayerNorm
$(d\times m)$
(48×30)
$\tilde{\mathbf{X}}_h$

(Optical) turbulence is driven by buoyancy and wind shear





Turbulence

- Velocity field fluctuations
- Temperature fluctuations
- Humidity fluctuations
- Density field fluctuations
- Refractive index fluctuations

2nd order temperature structure function

$$C_T^2 = \langle [T'(x) - T'(x+r)]^2 \rangle / r^{2/3}$$

Gladstone relationship

$$C_n^2 \sim C_T^2 + C_{Tq} + C_q^2$$