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Numerical Weather Prediction at MeteoSwiss

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New ensemble-only forecasting system with high-resolution data assimilation cycle for the Alpine region

COSMO-1E

- 11 members at 1.1 km mesh size
- 8x per day up to +33/45 hours
- grid points: 1170 x 786 x 80
- ICs: KENDA-1 analysis
- LBCs: IFS ENS (HRES for control)
- Model perturbations: SPPT

COSMO-2E

- 21 members at 2.2 km mesh size
- 4x per day up to +120 hours
- grid points: 582 x 390 x 60
- ICs: upscaled KENDA-1 analysis
- LBCs: IFS ENS
- Model perturbations: SPPT

KENDA-1

first guess (FG) ensemble every hour

- 40 + 1 members at 1.1 km mesh size
- grid points: 1170 x 786 x 80
- LBCs: IFS HRES + IFS ENS perturbations (+1 day lead time)
- SPPT, latent heat nudging

hourly LETKF analysis

Cray CS-Storm cluster

- 3 cabinets divided into two logical partitions: production + R&D
- 12+6 compute nodes with
  - 2 Intel Skylake (8 cores) CPUs
  - 8 NVIDIA Tesla V100 GPUs
- 10+10 post-processing and 3+3 login nodes with 2 Intel Skylake (20 cores) CPUs
- node assignment to partitions exchangeable within 10 min
- Time-to-solution for COSMO 5.08, single precision:
  - COSMO-1E: 50 min (for +33h)
  - COSMO-2E: 40 min
  - KENDA-1 FG: 9 min
  - LETKF: 8 min

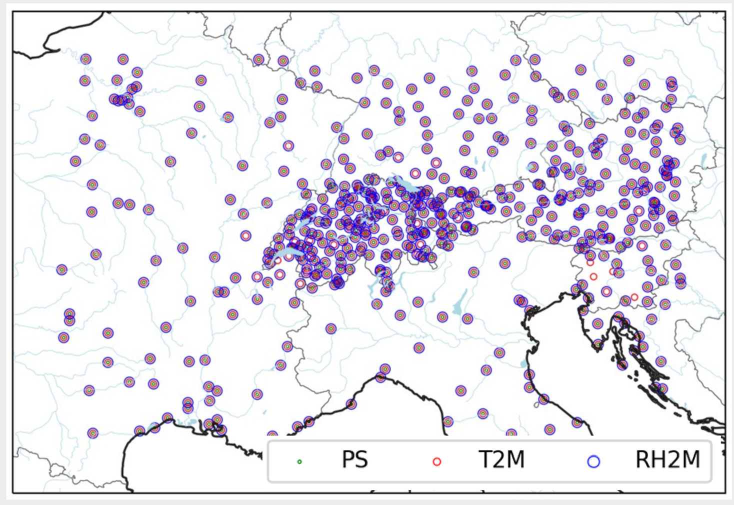
Assimilation of surface temperature and moisture to improve fog forecasts

Difficulties with fog forecasts

COSMO fog forecasts often suffer from an incorrect thermodynamical boundary layer structure due to insufficient constraints by near-surface observations. To improve this situation, assimilation experiments using T2m and RH2m in the KENDA-1 system have been carried out.

Experimental Setup

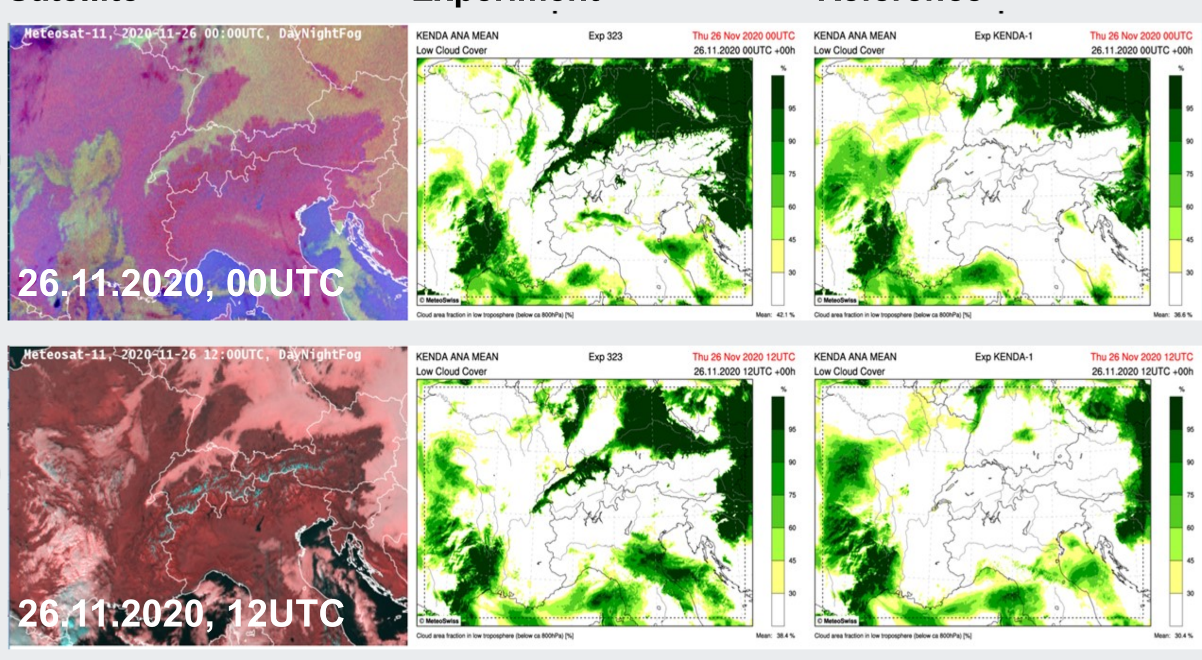
- Reference: KENDA-1 with operational observations (Surface pressure, TEMP, AIREP, Wind Profiler, Radar precipitation)
- Experiment: As reference but including T2m and RH2m observations
- Period: 21.11.-21.12.2020



Locations of actively assimilated surface observations

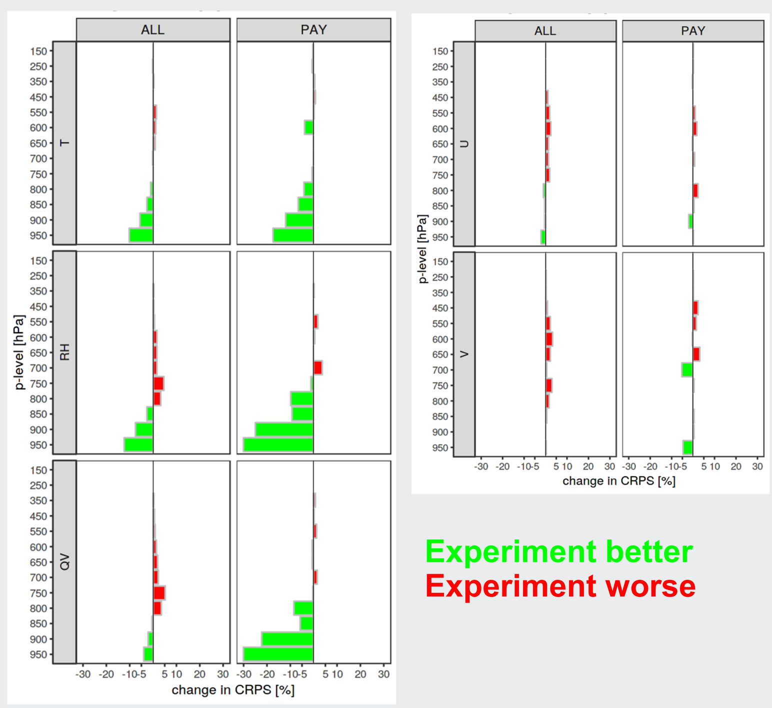
Results

Impact on analysis mean cloudiness



Cloudiness as observed by satellite (right) and analysed by KENDA-1 (middle and right)

Impact on forecasts



CRPS decrease (%) against ALL TEMP in domain and PAYerne

Summary

- Successful assimilation of T2m and RH2m
- Improves thermodynamical structure of near-surface atmosphere
- Improves fog and low stratus in stable situations
- Impact into forecast time lasts up to +24h

Outlook

- Introduce in operations during fall/winter
- Investigate summer period

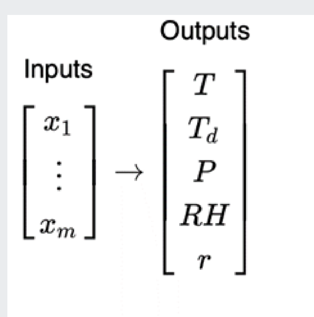
Physics-constrained deep learning for post-processing of surface temperature and humidity

A simple experiment to demonstrate how we can prescribe specific physical processes in our Deep Learning models, thus ensuring the **physical consistency** of the output while integrating **meteorological expertise**.

Unconstrained approach

- Neural Network (NN) predicts target variables directly

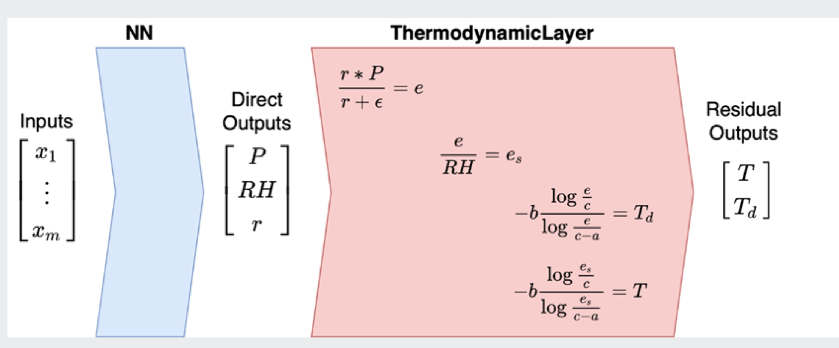
Problem: violations of physics are possible, e.g., if the NN model predicts $T < T_d$



Constrained approach

- Inspired by framework from Beucler et al. (2021)
- Optimizable NN predicts subset of variables
- Remaining variables are derived from **analytical (thermodynamic) equations**, implemented as an additional custom layer of the NN model
- Optimization based on all five variables, such that relationships between them are strictly respected while reducing the error for all of them simultaneously.

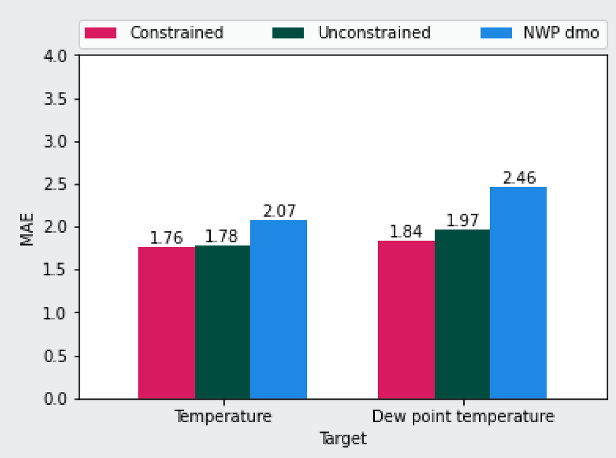
No violation of physics.



Results

Experiment: local post-processing of a station in Magadino (MAG)

- hourly observations from 2015 to 2020



Comparable performance (Mean Absolute Error), with added value of physical consistency.

Violations in independent test set predictions:

- Constrained: 0.0 %
- Unconstrained: 2.5%
- NWP: 0.0 %

References:

Beucler, T., Pritchard, M., Rasp, S., Ott, J., Baldi, P., & Gentine, P. (2021). Enforcing Analytic Constraints in Neural Networks Emulating Physical Systems. *Physical Review Letters*, *126*(9), 098302. https://doi.org/10.1103/PhysRevLett.126.098302

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