

A global EMOS postprocessing for temperature and precipitation forecasts for any location in Switzerland

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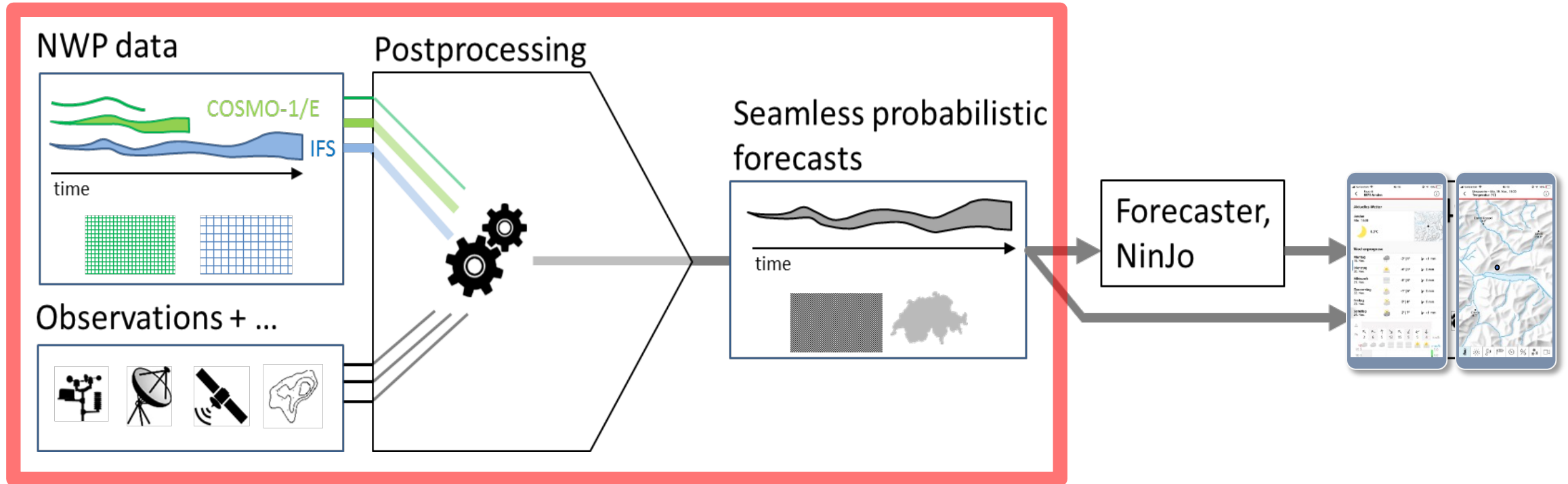
Development of Forecasting - Federal Office of Meteorology and Climatology, MeteoSwiss

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Motivation

MeteoSwiss Project «PostProcVeri»



- Calibrated, spatial («at any point in space»), seamless and probabilistic forecasts
- 4 key variables (temperature, precipitation, wind and cloud cover)

Postprocessing of NWP forecasts

Global Ensemble Model Output Statistics

- **Correction of NWP errors in mean and spread.**
- **Probabilistic and calibrated weather forecasts for arbitrary points in space**

Extension of the well-established traditional EMOS framework (Gneiting et al. 2005) by static predictor variables
=> global EMOS, or gEMOS.

Target distribution depends on considered variable:

- for temperature = gaussian
- for precipitation = censored (at 0) logistic (applied to sqrt-transformed precipitation)

Example gEMOS_Temperature:

$$\begin{array}{lcl} & \text{Additional Dynamic} & \text{Static Predictor} \\ & \text{Predictor Variables or Models} & \text{Variables} \\ \text{mea} & = a + b_1x_1 + \underbrace{b_2x_2 + b_3x_3 + \dots}_{\text{Additional Dynamic}} & + \underbrace{b_4x_4 + b_5x_5 + \dots}_{\text{Static Predictor}} \\ \text{std} & = \text{sqrt}(c + d_1s_1 + \underbrace{b_2x_2 + b_3x_3 + \dots}_{\text{Additional Dynamic}} & + \underbrace{b_4x_4 + b_5x_5 + \dots}_{\text{Static Predictor}}) \\ & \text{with predictors } x_1 \text{ (e.g. ens. } T_{\text{mea}} \text{) , } s_1 \text{ (ens. } T_{\text{std}} \text{), } x_2, (T_{\text{COSMO-1}}), x_3, x_4, \dots & \\ & \text{and coefficients } a, b_1, b_2, c_1, d, \dots . & \end{array}$$

Optimization of coefficients by CRPS minimization using lead-time dependent NWP-observation pairs.

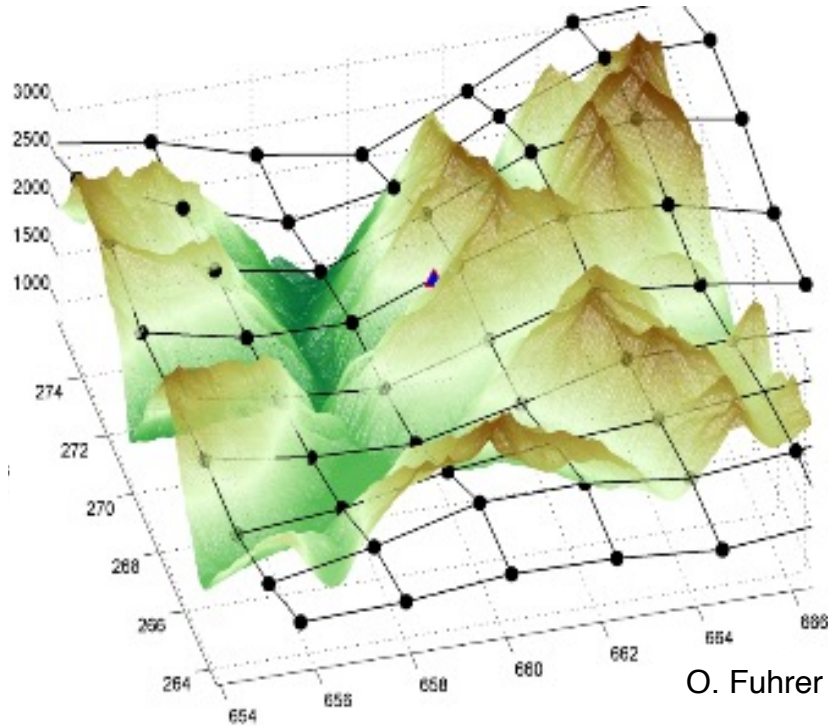
- for temperature = rolling window of 30 days
- for precipitation = seasonal training using all available data (currently 3 seasons = ~270 days)

(Swiss) Challenges

Complex Topography

Local-scale processes, unresolved even by high-resolution NWP models

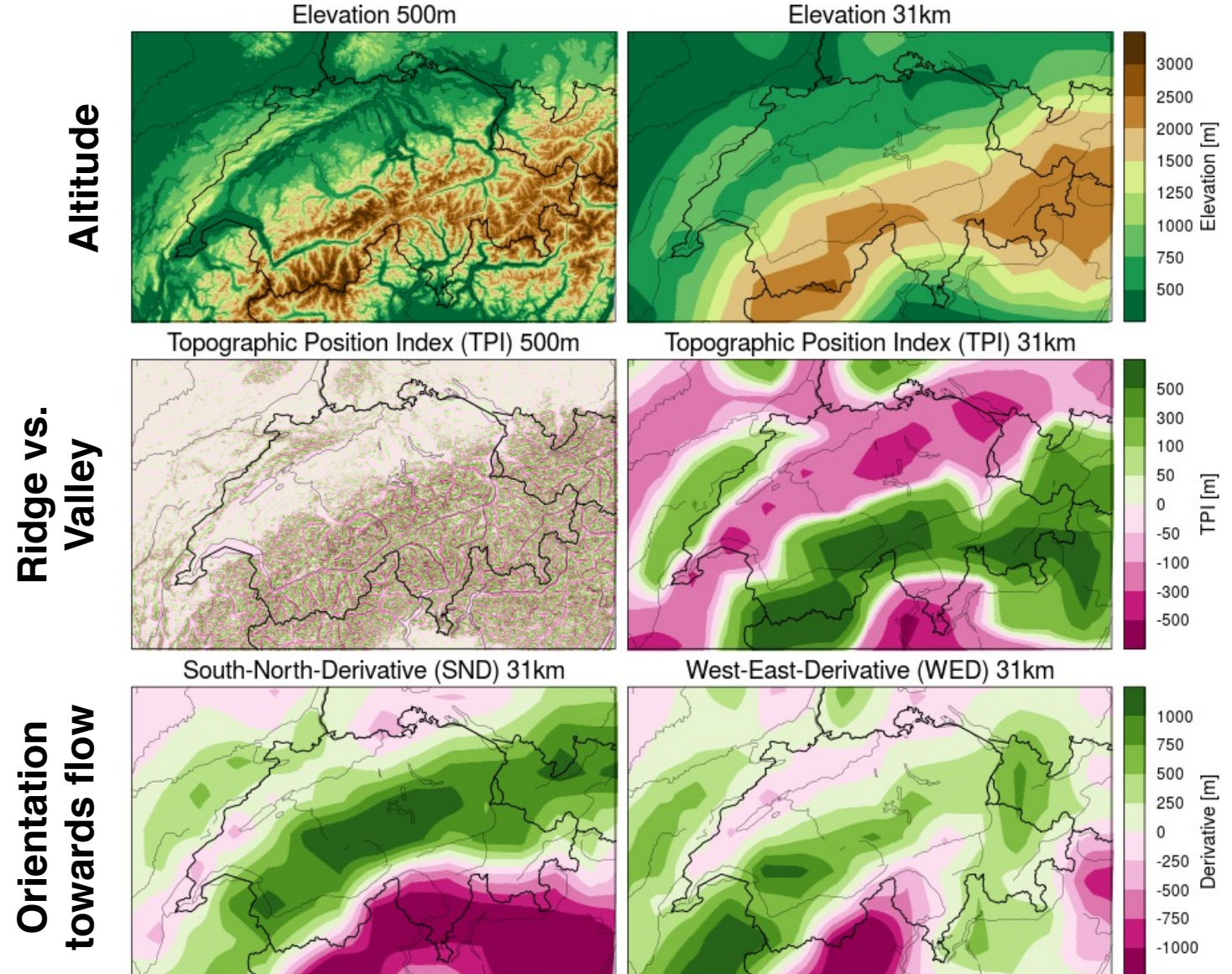
COSMO 2km output in the Swiss Alps



Static Predictor Variables

Topographical Information

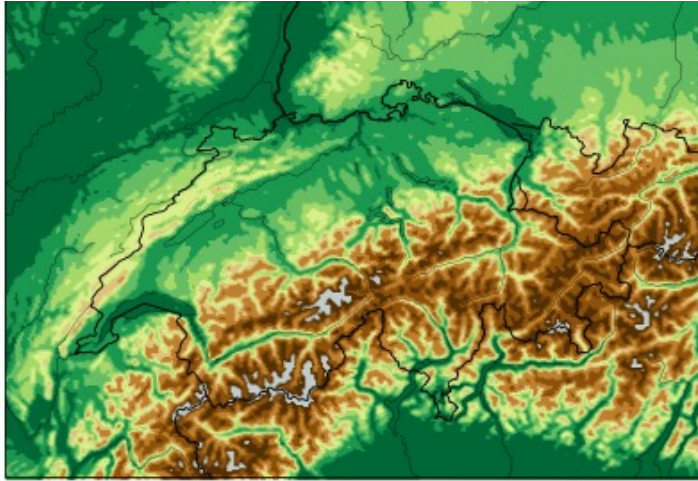
at different scales (local & large-scale)



NWP models

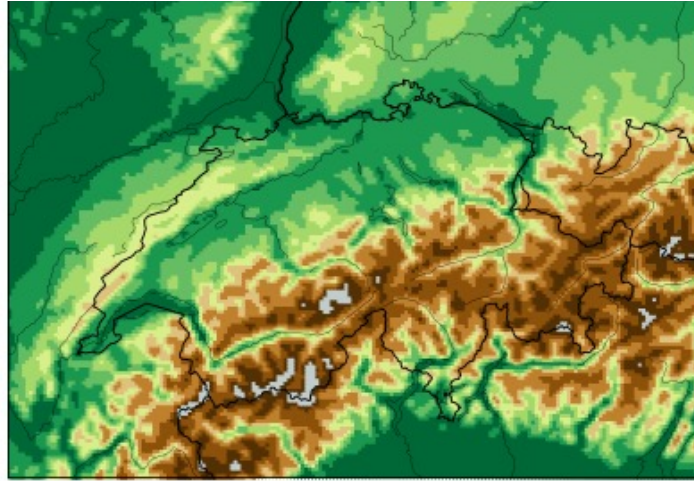
COSMO-1

n = 1, 1.1km, +33/45h, init.freq. 3h



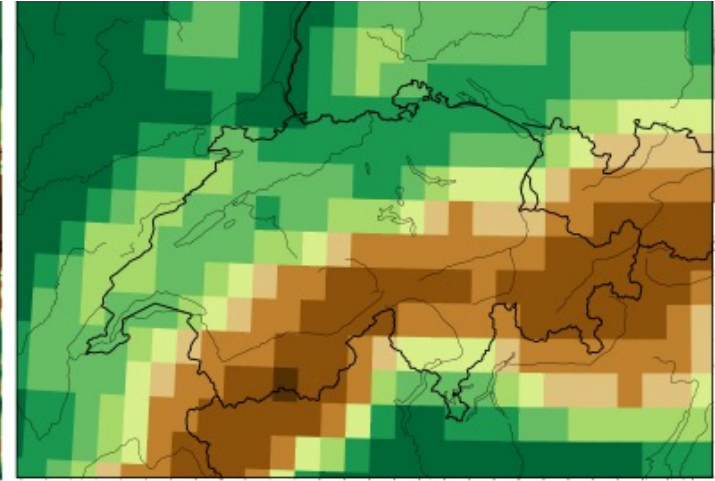
COSMO-2E

n = 21, 2.2km, +120h, init.freq. 12h

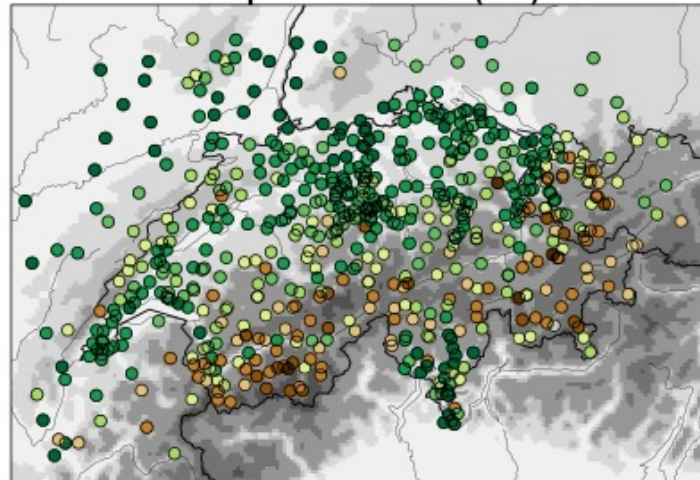


ECMWF-IFS

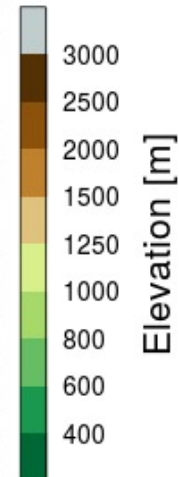
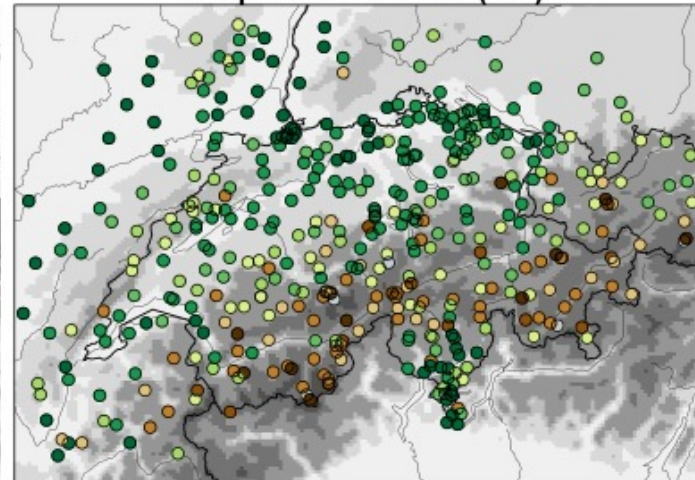
n = 51, 18km, +360h, init.freq. 12h



Precipitation Stations (623)

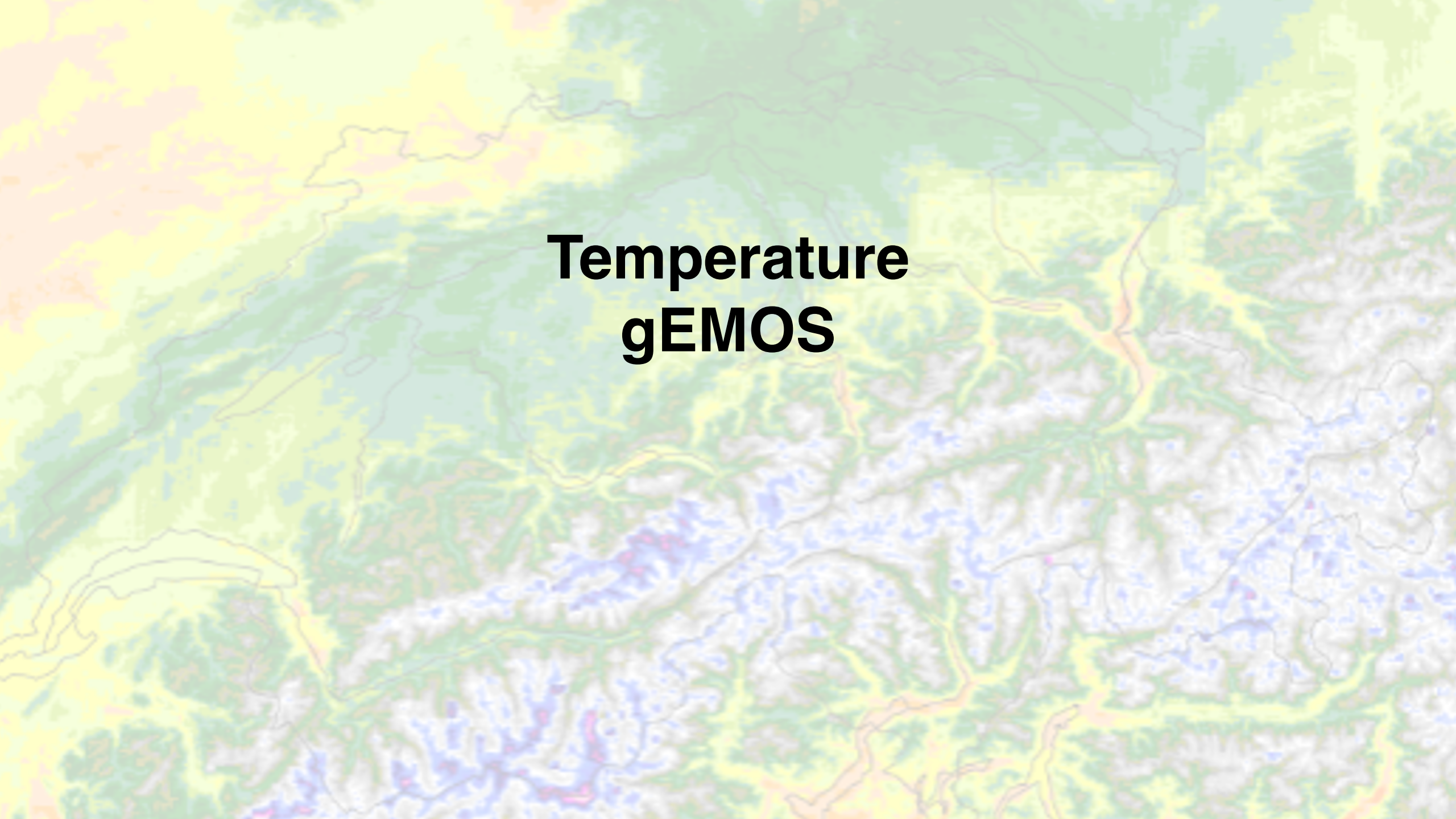


Temperature Stations (440)



Observational
Reference Data

> 4 year NWP model archive from 2016-today

The background is a topographic map of a mountainous region. It features brown contour lines indicating elevation. The map is color-coded with various shades: light green and yellow in the upper left, transitioning to darker green and blue in the center, and then to light blue and white in the lower right. There are also some orange and red patches, possibly indicating specific geological or temperature-related features. The overall texture is somewhat pixelated or blocky.

Temperature gEMOS

Details of Temperature gEMOS

Dynamical Predictors

COSMO-1

- Temperature

COSMO-E

- Ens. mean temperature
- Ens. st.dev. Temperature
- Ens. mean atmospheric boundary layer height (BLH)

ECMW-IFS

- Ens. mean temperature
- Ens. st.dev. Temperature

Static Predictors

At local- (~0.5km) and large-scale (~ 30km):

- Topographic position index (TPI)
- Elevation

Target Distribution

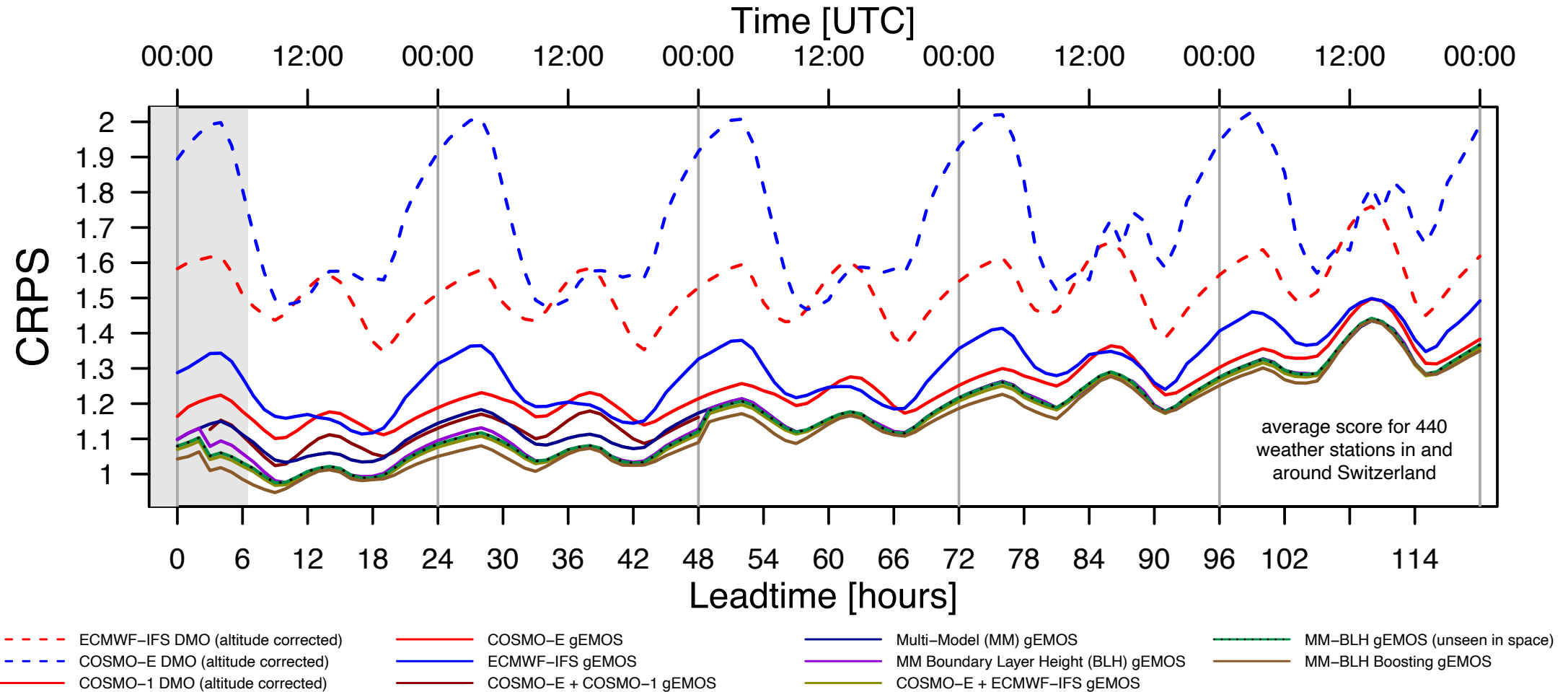
Gaussian

gEMOS set-up

- Simple versions of single-NWP-model gEMOS (single model).
- Multi-model versions of gEMOS.
- Multi-model version including all models and BLH
 - Mimicking an operational setting with lagged availability of NWP models.
 - COSMO-1 = 03UTC, COSMO-E = 00UTC, IFS = 12UTCprevious_day
- Simple linear models and versions with predictor-interaction tested (later did not show improvement of forecast skill).
- «Boosting» (linear and with interaction) using a selected (expert-judged) predictor-set showed slight improvement over best-performing method, but requires further investigation!

Verification of Temperature Predictions

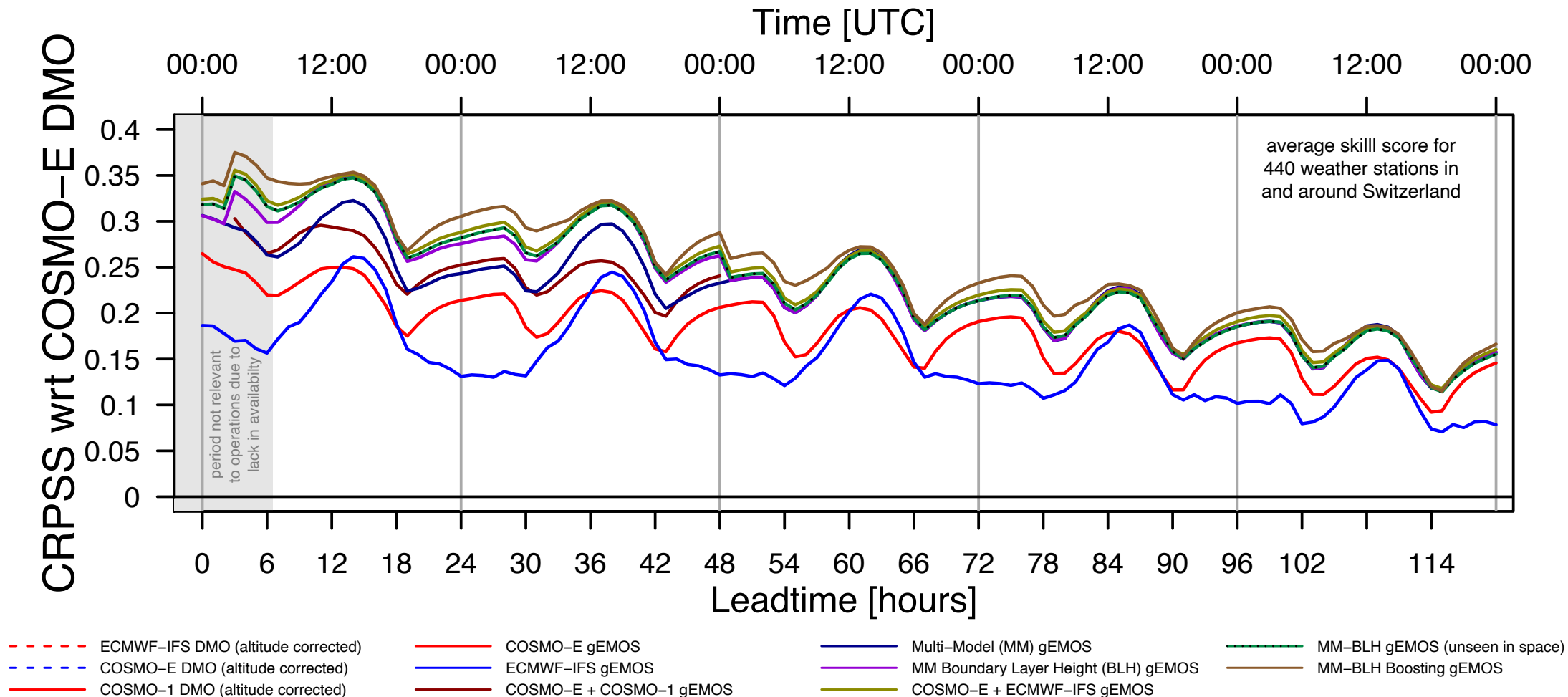
Continuous Ranked Probability Score (CRPS)



- *gEMOS improves forecasts substantially with respect to direct model output (DMO).*
- *Post-processed coarse-resolution NWP (IFS, blue line) outperforms high-resolution DMO output (COSMO-E, red dashed line).*
- *Multi-model combination and additional predictors improve performance substantially (see other colors in legend).*

Skill Improvement by Temperature gEMOS

Continuous Ranked Probability Skill Score (CRPSS)



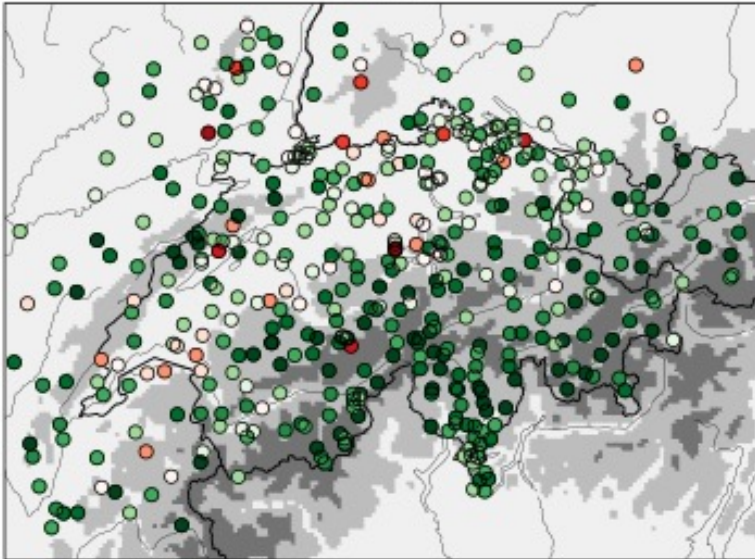
- *gEMOS improves forecasts substantially (compared to **altitude corrected** COSMO-E), even for simple strategies using IFS only.*
- *Multi-model combination further improves skill.*
- *More complex set-ups are able to even further improve on forecast quality (in particular including Boundary Layer Height as predictor).*

Skill Improvement by Temperature gEMOS

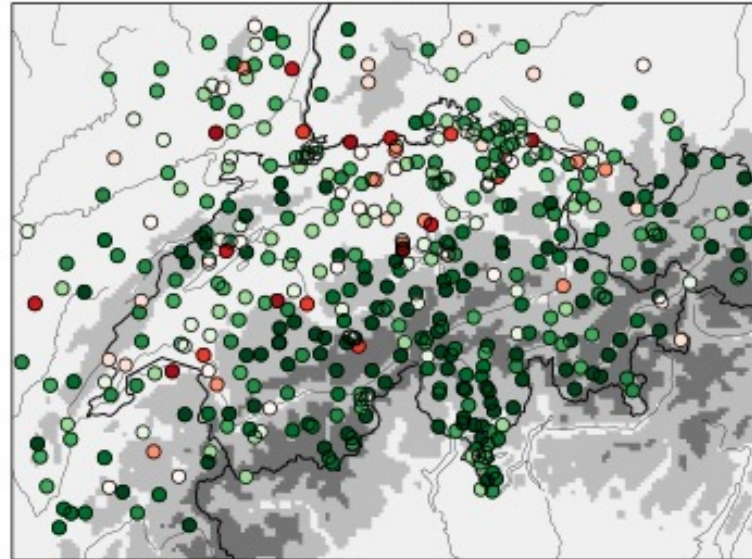
Day 1 (leadhours 7 to 30)

CRPSS vs. COSMO-E (altitude corrected) – gEMOS MM-BLH (cross-validated in time and space)

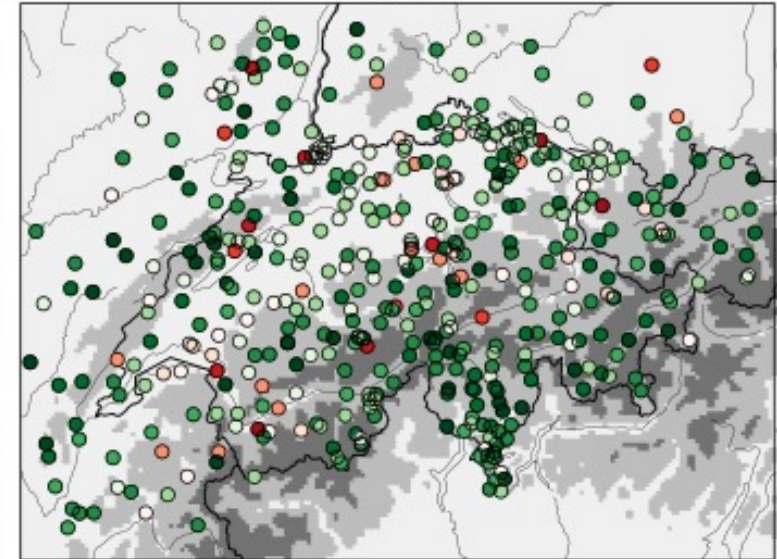
ANN



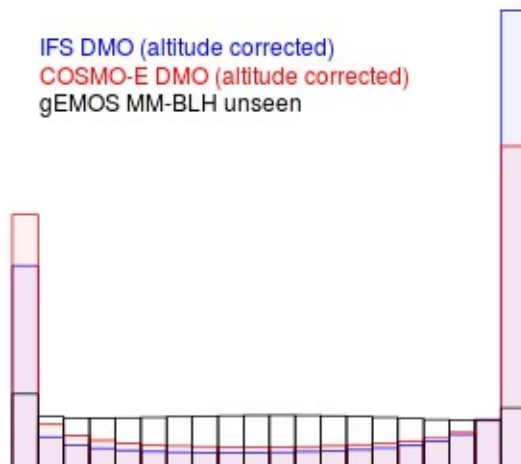
DJF



JJA



PIT histogram



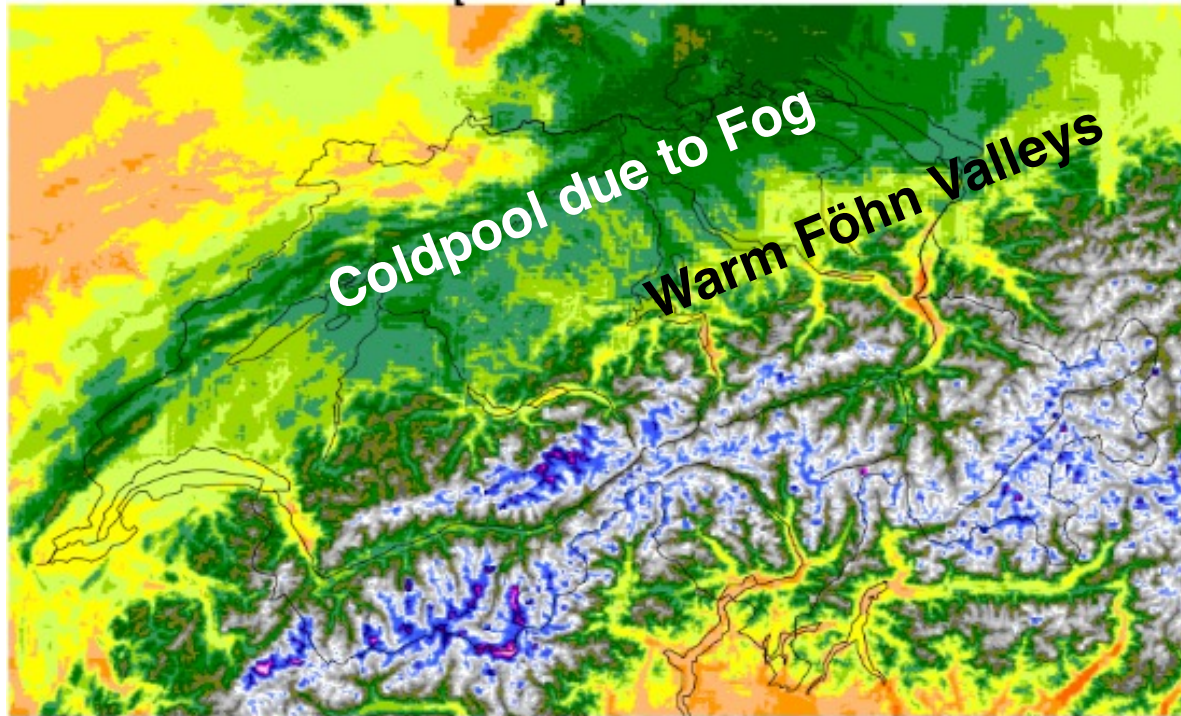
Cross-validated (space and time) evaluation

- Improvement at large majority of sites, independent season, evaluation of «any-point» aspect of gEMOS (locations unseen).
- Few stations with deterioration, where DMO is already skillful and where static predictors might not ideally represent local-scale conditions. *To be improved by additional / suitable predictors.*

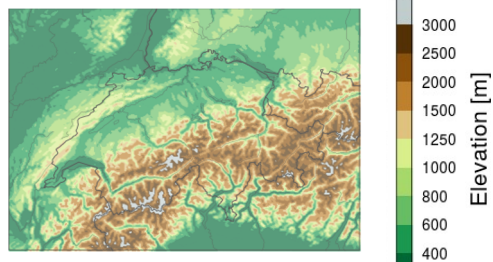
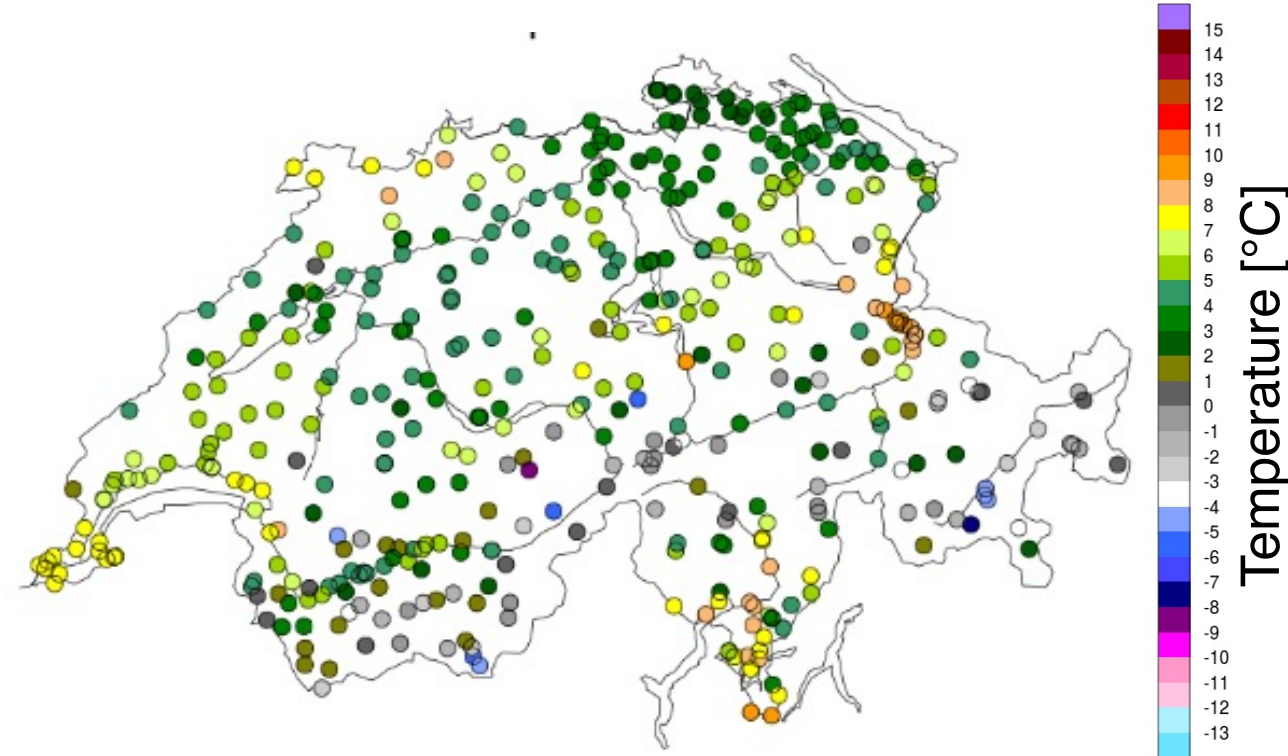
PIT Histogram visualizes the good calibration of gEMOS (flat distribution) with respect to altitude corrected direct model output from COSMO and IFS.

Exemplary Temperature Prediction from gEMOS

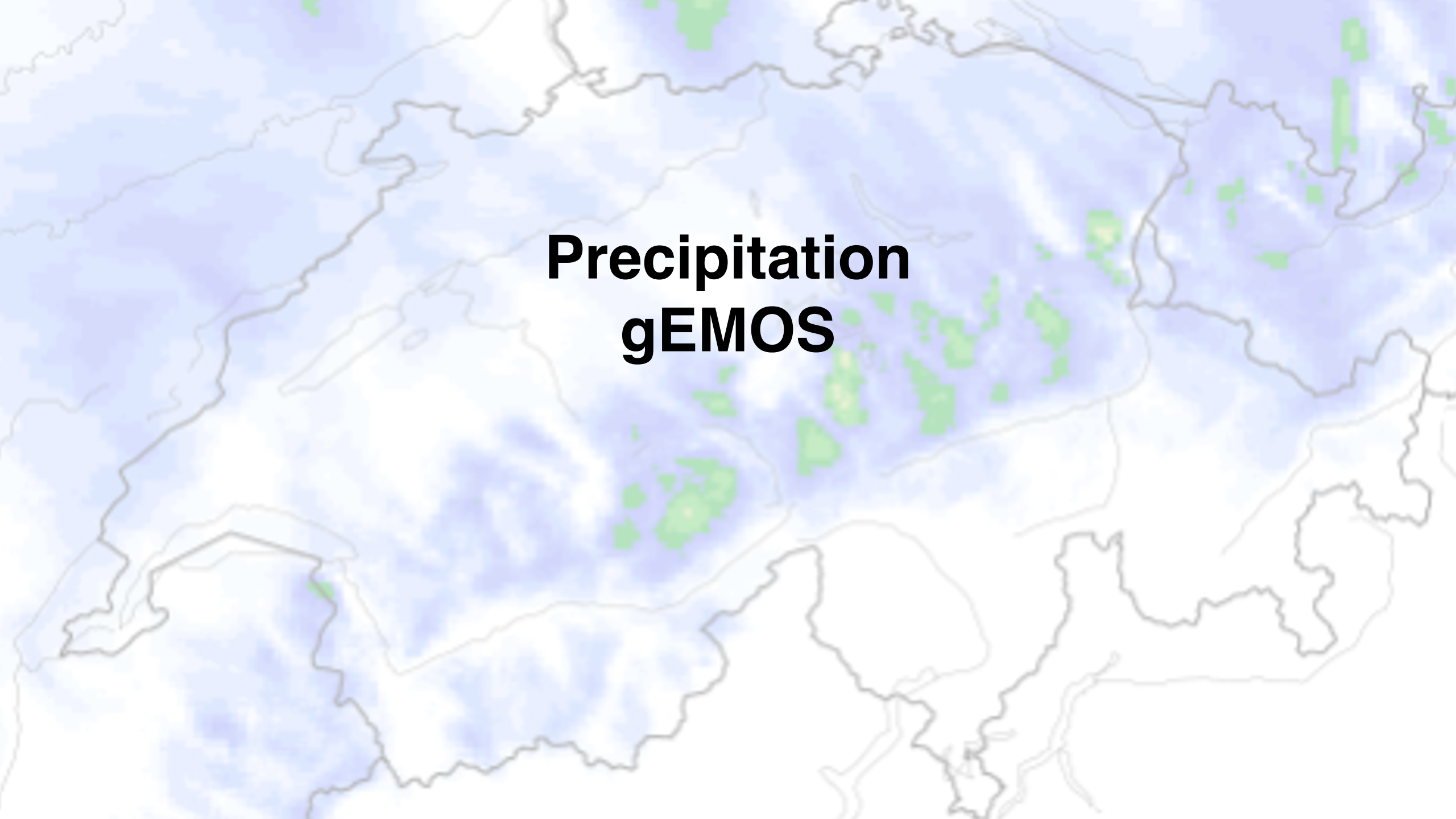
«Spatial or at-arbitrary-points»



«Station Specific»



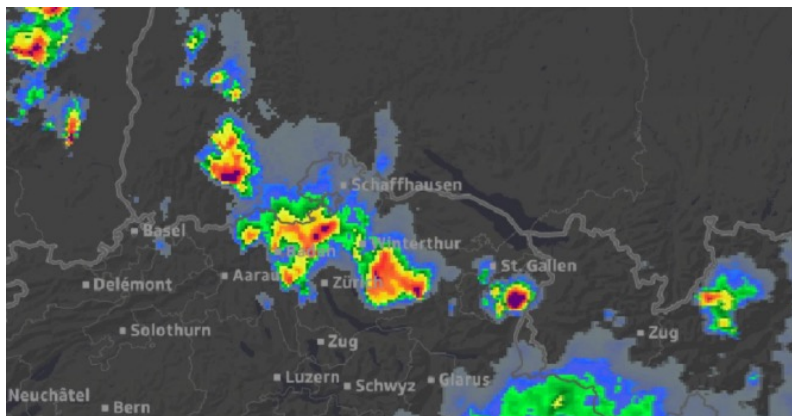
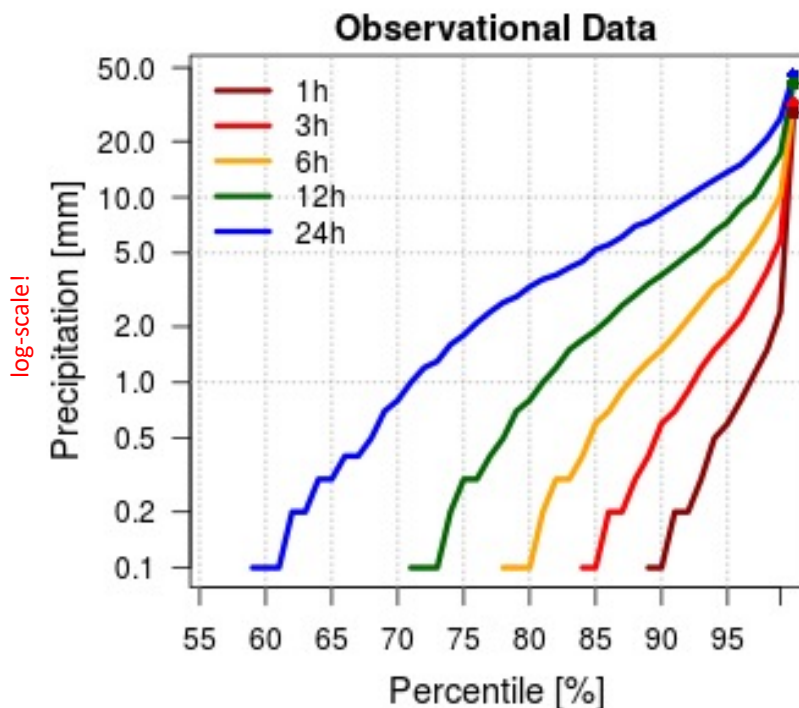
Temperature gEMOS closely follows topographical characteristics, but is able to show imprints of local- to regional-scale and weather situation-dependent patterns. Here: extended cold-pools due to fog in the Swiss low-lands and warm areas due to Föhn in die pre-Alps and Alpine valleys.

A map of Europe showing precipitation patterns. The background is a light blue and white color-coded map. Overlaid on this are several green and yellow patches, indicating areas of precipitation. The text "Precipitation gEMOS" is centered over the map.

Precipitation gEMOS

Precipitation

a major challenge



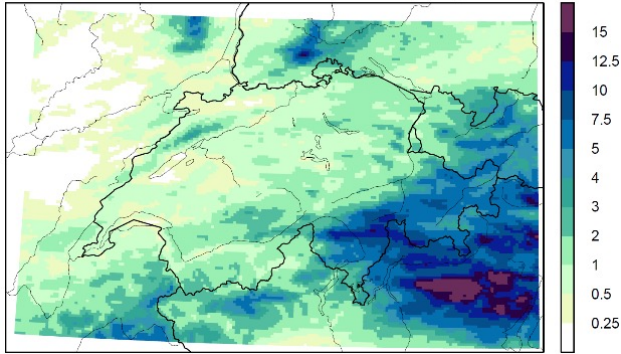
- A lot of 0s (dry samples), many moderate and some extreme.
 - Character accentuates for smaller aggregation periods.
 - CH: ~90% of samples are dry (0) for 1-hourly precipitation.
 - CH: ~60% of samples are dry (0) for daily precipitation.
- Spatial variability, especially during convective situations.
 - Precipitation often not sampled or seen by observations, double penalty issue.
- Systematic spatial mismatch (effective resolution of NWP model) and displacement of DMO vs. observations.

Postprocessing by (g)EMOS (?)

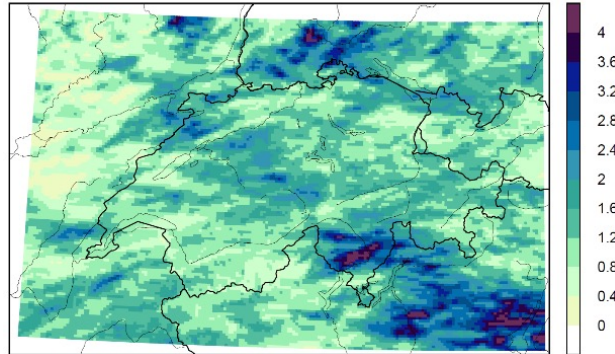
- Which distribution describes precipitation best?
 - Gamma, EV, mixture, ...
- Interpretation of forecasts for large lead-times and small aggregation periods (identifiable signal vs. climatology)
- Robustness of estimated coefficients for small aggregation periods.

Details of Precipitation gEMOS

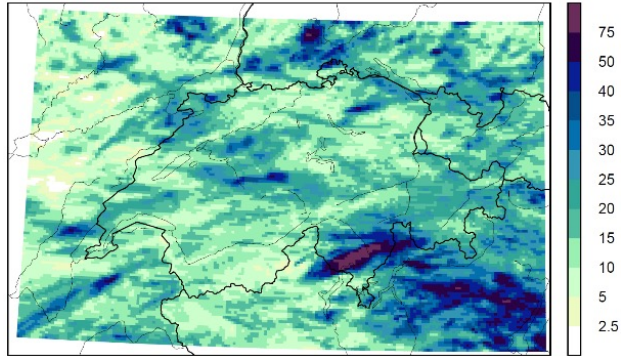
Ensemble mean (mm)



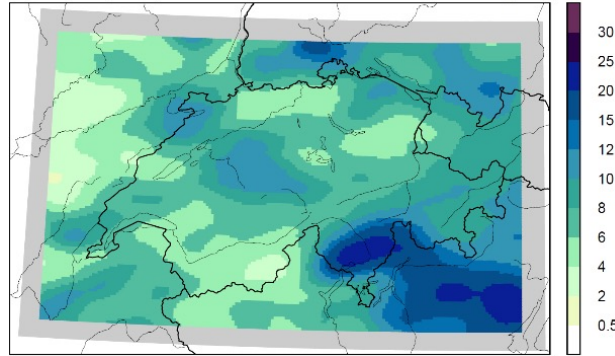
Ensemble st.dev. (mm)



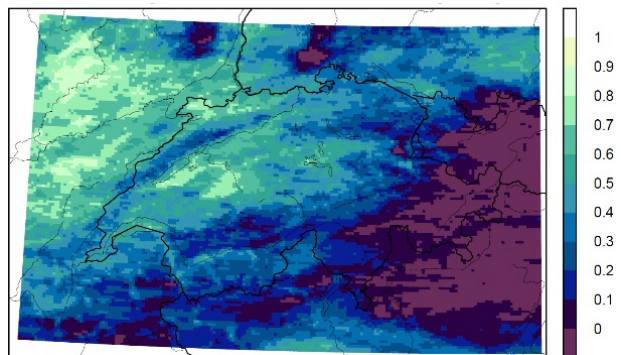
Ensemble maximum (mm)



30km N.borhood of ens. max.(mm)



fraction_dry (fraction)



... and quantiles
(q10, q25, q75, q90)

Dynamical Predictors

From 3 NWP model sources (COSMO-1, COSMO-E, ECMWF-IFS-ENS)

- Precipitation, ensemble statistics (see panel on the left)
- Temperature (T)
- Dew-point temperature (Tdew)
- Boundary layer height (BLH)

Static Predictors

At local- (~0.5km) and large-scale (~ 30km):

- Topographic position index (TPI)
- Elevation

At large-scale (~ 30km):

- South-North and East-West derivative (~orientation)

Local-scale only (0.5km in gridded product)

- Swiss coordinates (CHX,CHY)

Target Distribution

censored (at 0) logistic, applied to sqrt-transformed precip.

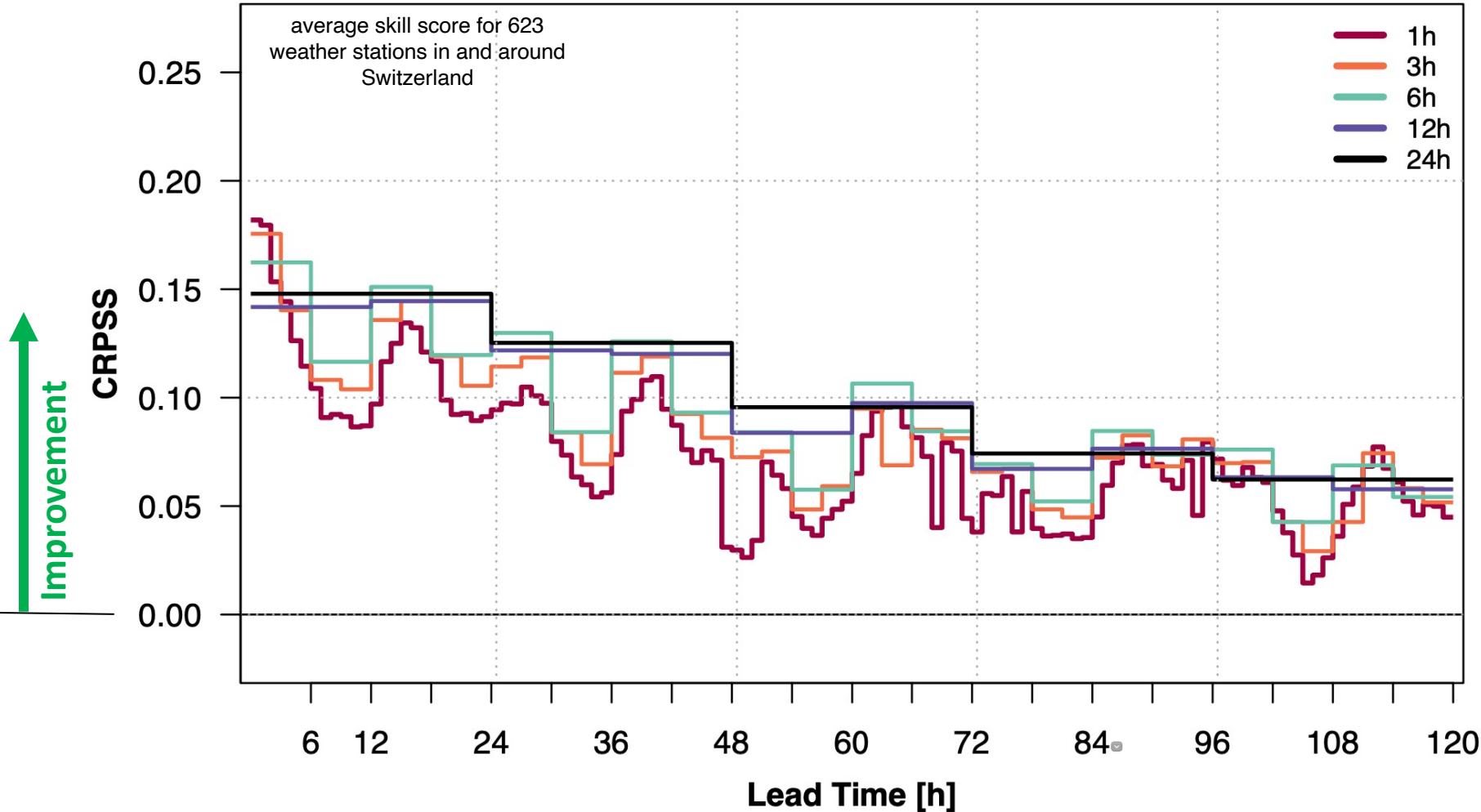
Figures shows set-up:

NWP Predictors (All models: precip.-stats + T + Tdew + BLH) + Static Predictors

Following figures temporally cross-validated, **but spatially in-sample!**

Skill Improvement by Precipitation gEMOS

gEMOS Skill w.r.t COSMO-E DMO – ANNUAL



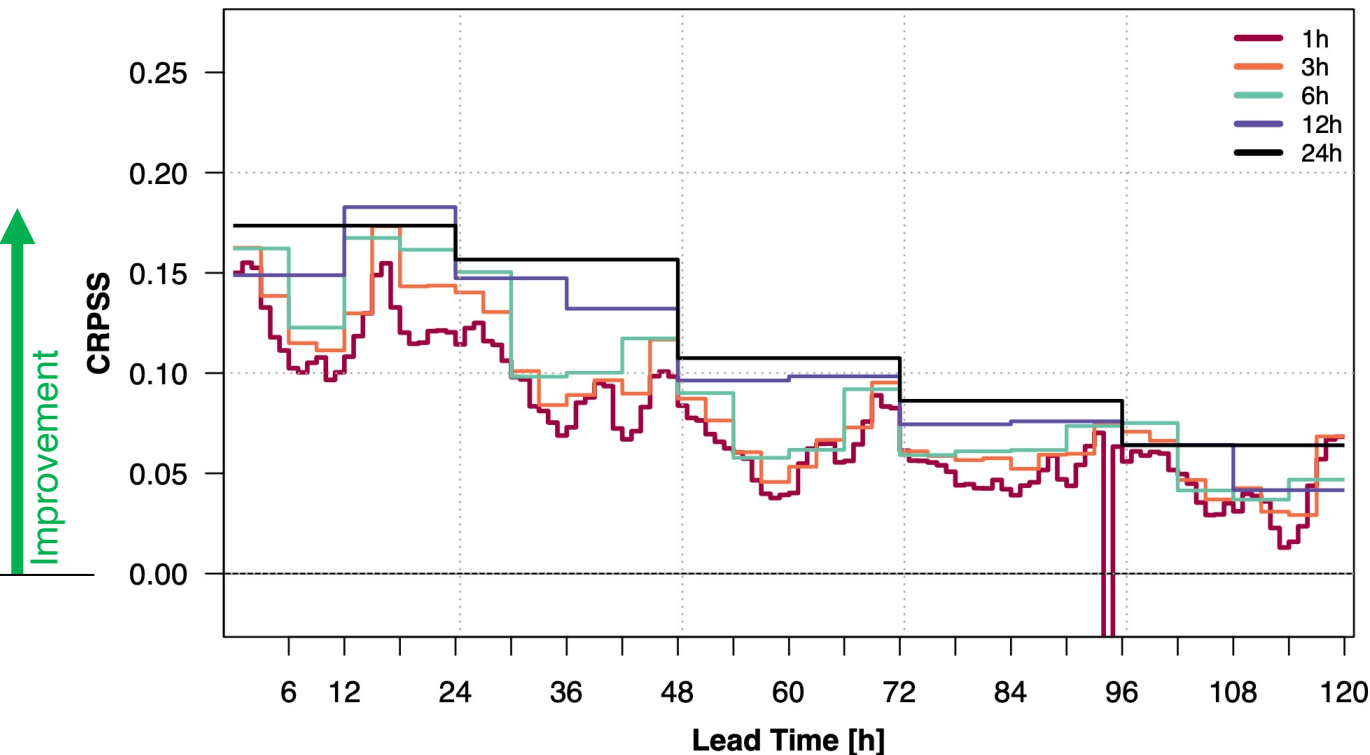
Improvement of gEMOS over COSMO-E DMO (mean over all 623 analyzed stations, all stations are in-sample)

Analysis of different aggregation periods shows similar skill for hourly aggregation periods as compared to daily aggregation periods.

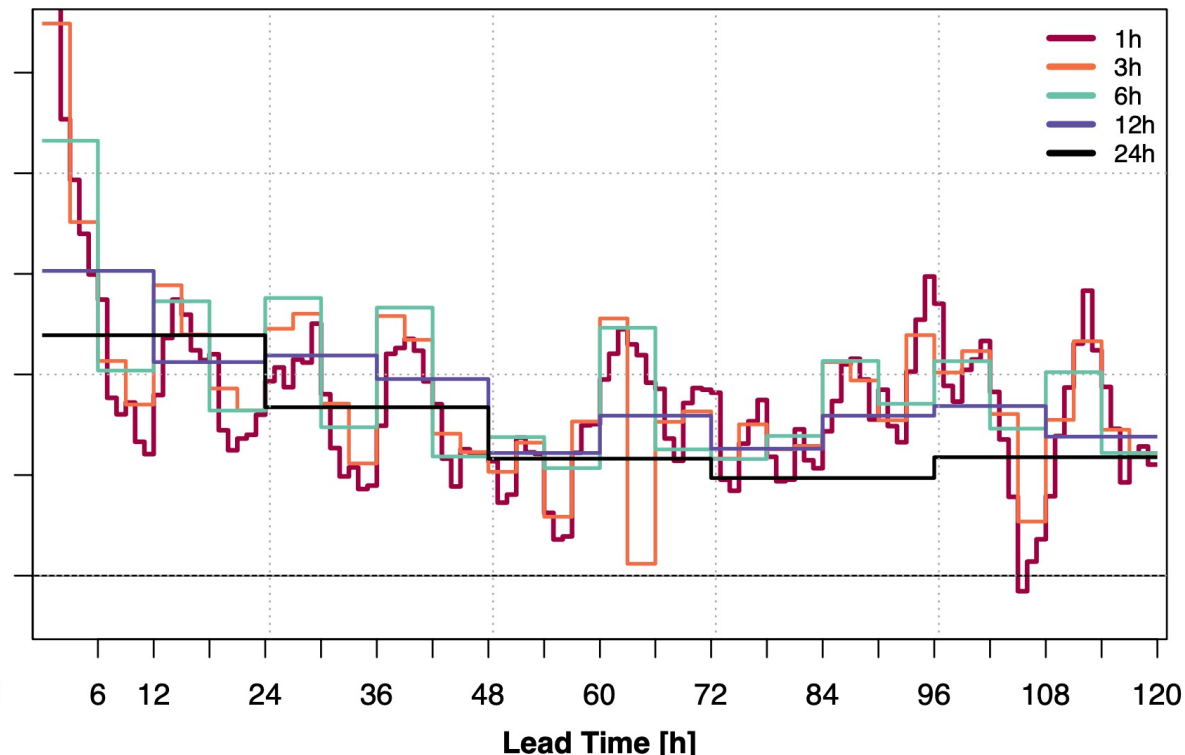
Improvement in the range of 0-20% depending on time-of-day, lead-time and aggregation period.

Skill Improvement by Precipitation gEMOS

Winter (DJF)



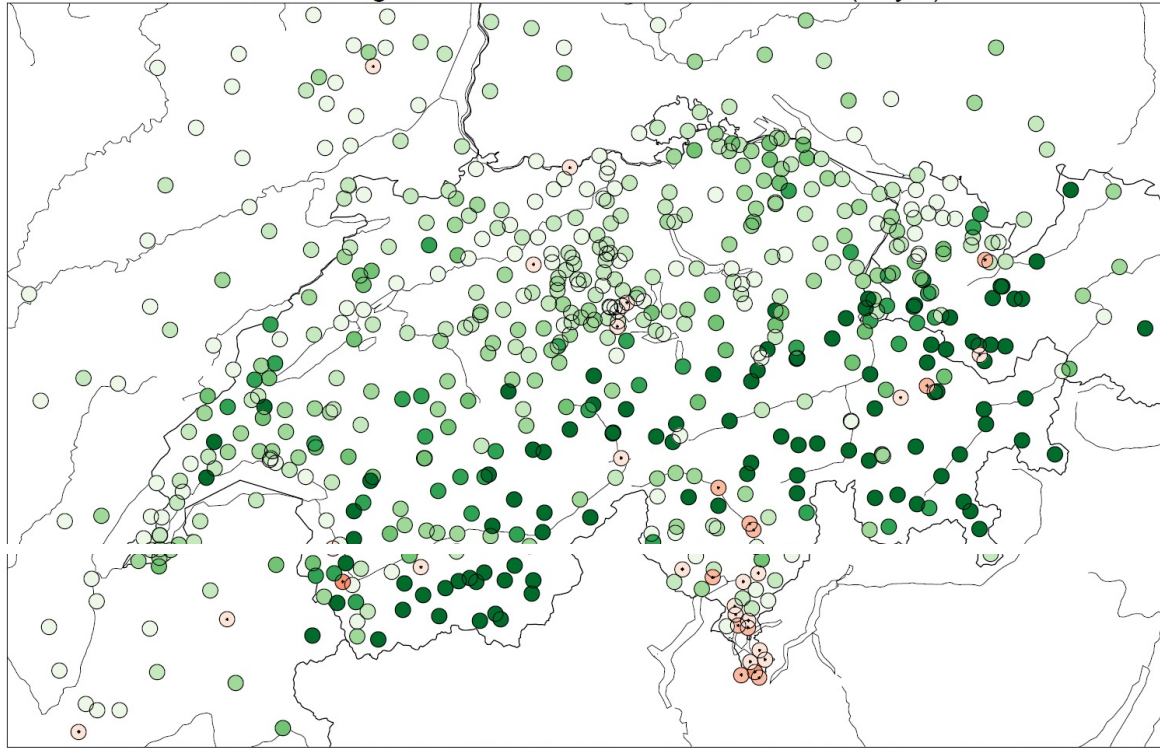
Summer (JJA)



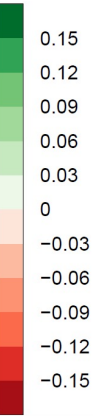
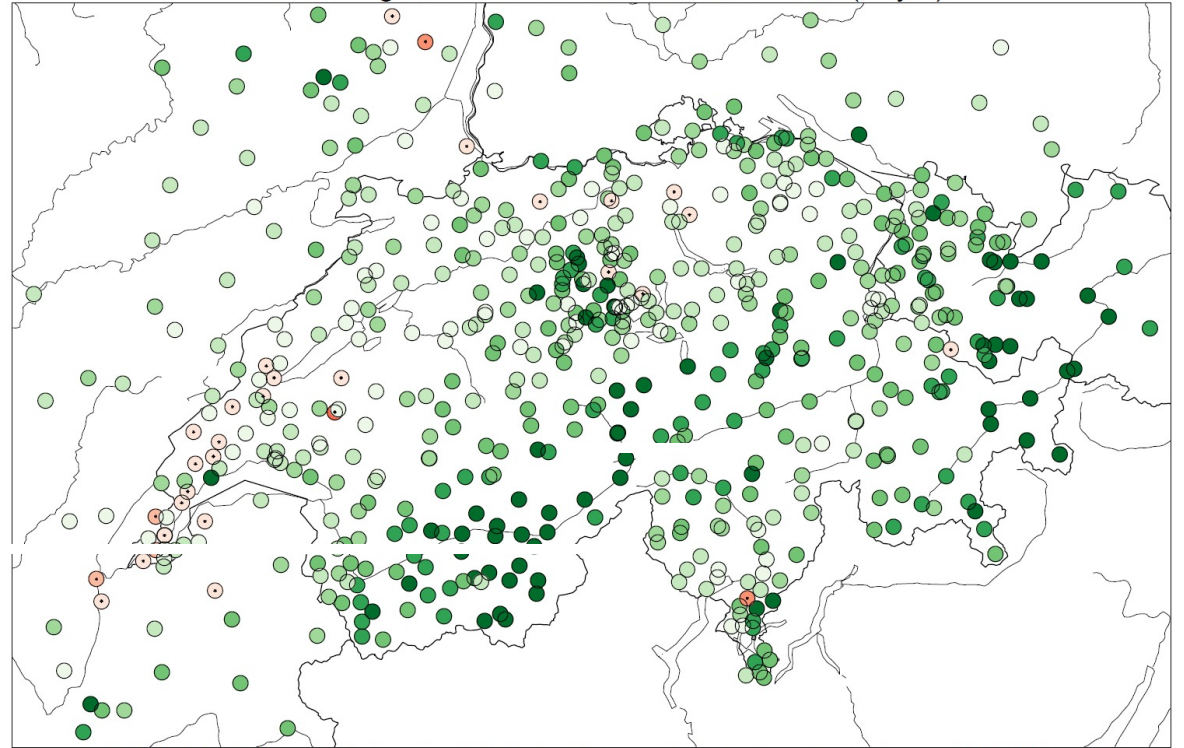
Seasonal differentiation shows similar improvements in winter (left) and summer (right), but larger intra-day variability in summer. Improvements in the range of 0 to +20% (+5 to +10% on average). Improvement is slightly dependent on aggregation period, with larger improvement for coarser aggregation (>12h) in winter.

Skill Improvement by Precipitation gEMOS

gEMOS_1h – DJF – CRPSS – DAY2



gEMOS_1h – JJA – CRPSS – DAY2

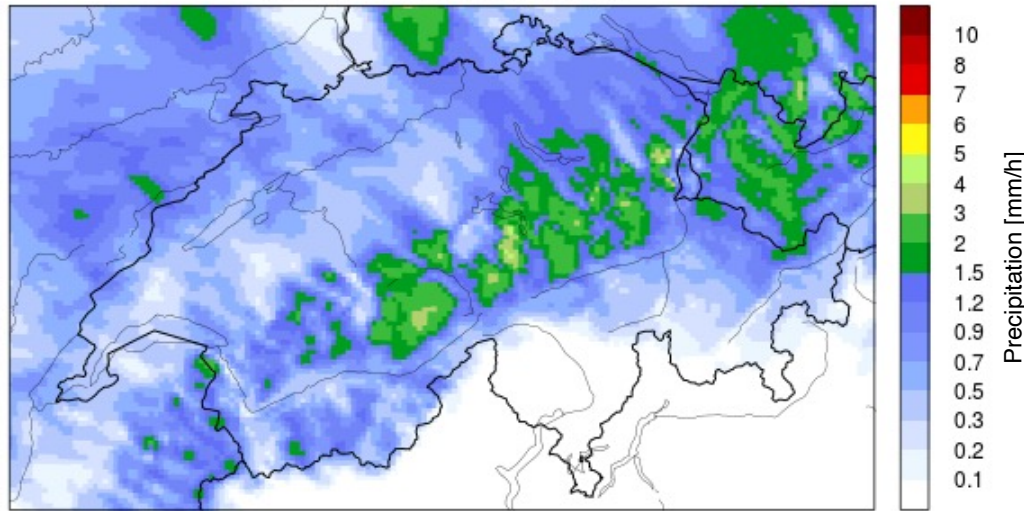


- Largest improvements in mountainous terrain
- Deterioration in southern Switzerland in winter and western Switzerland in summer (*lack of representativity of global approach in these regions?*)

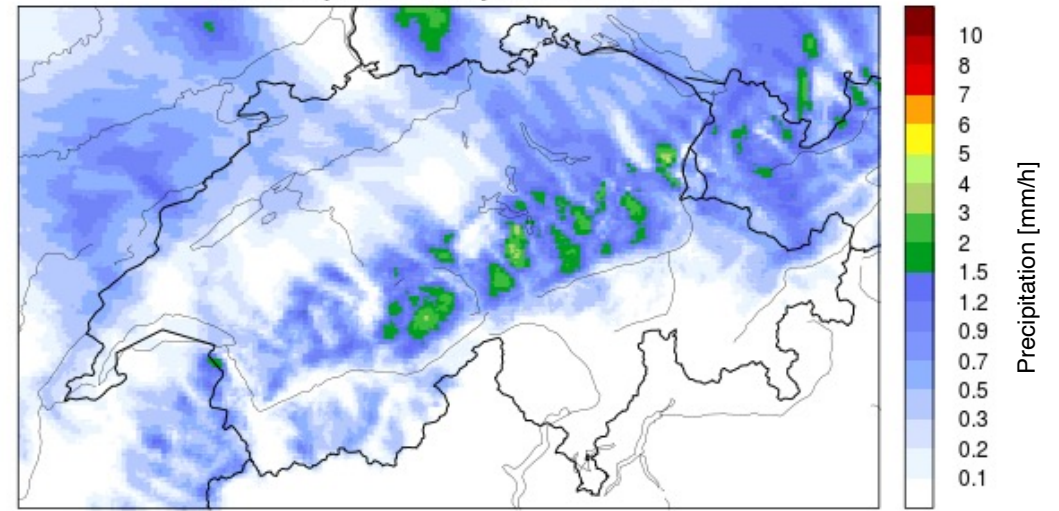
Shown locations are in-sample (out-of-sample evaluation might show less improvement and more locations with deterioration)

Exemplary Precipitation Prediction from gEMOS

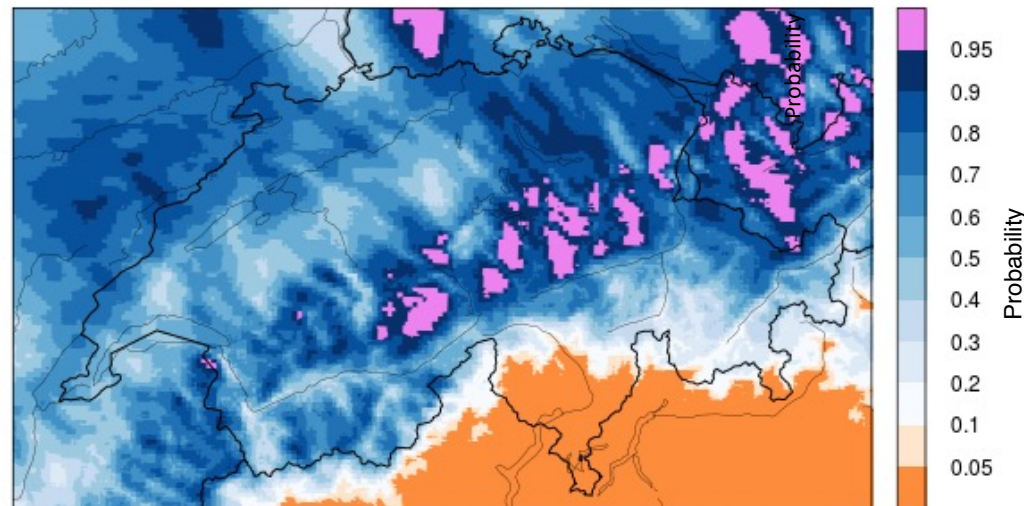
COSMO-E DMO (mean)



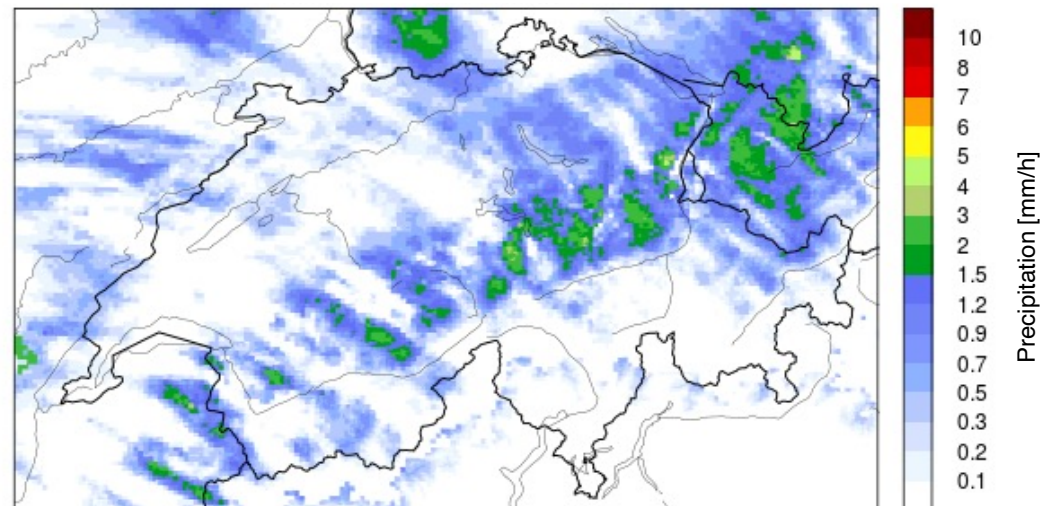
gEMOS (mean)



gEMOS – probability of wet hour



gEMOS – COSMO-E control run (via ECC)



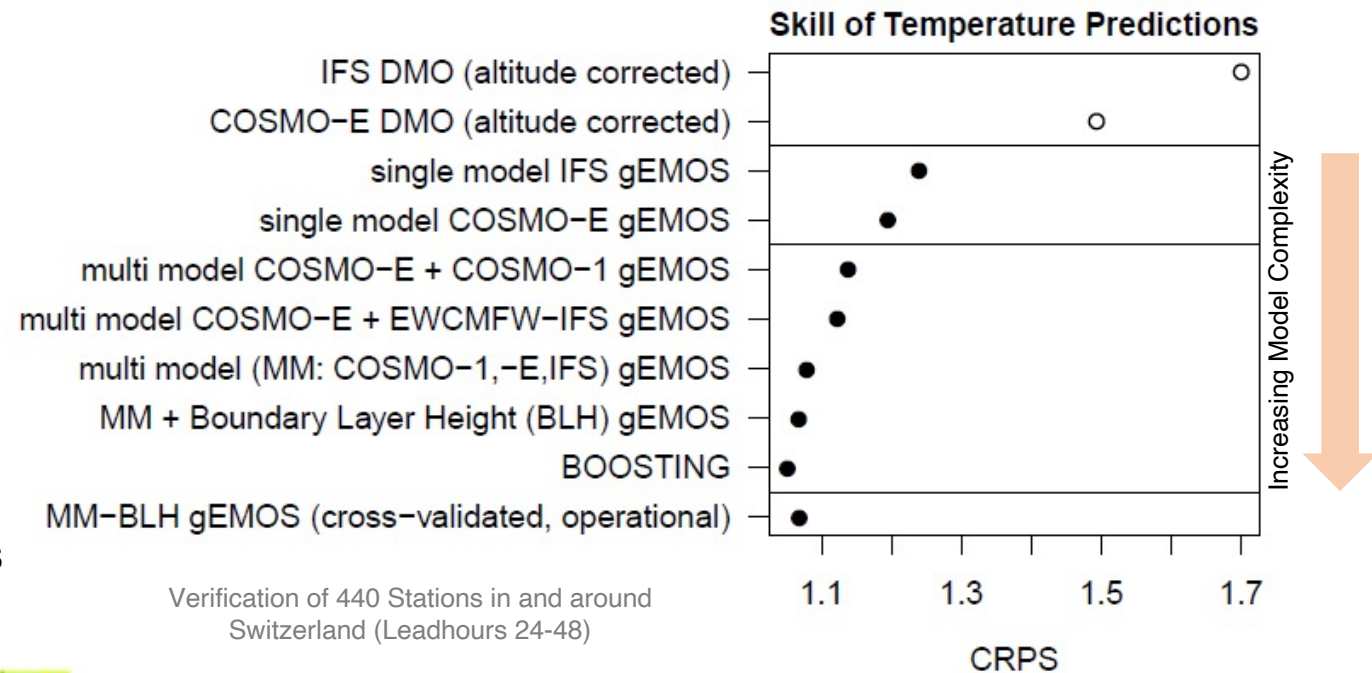
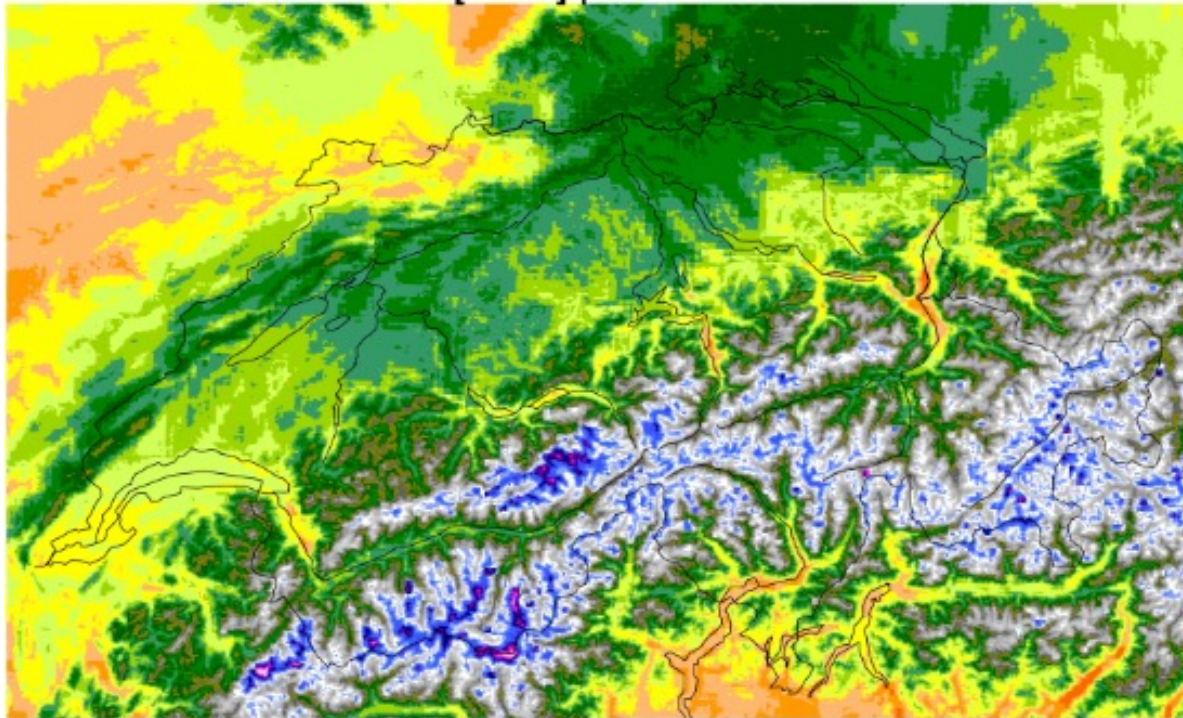
Conclusions

- gEMOS is able to improve NWP forecasts on average by ...
 - ... ~ +25% for temperature
 - ... ~ +10% for precipitationparticularly in regions of complex topography
- Combination of multiple models leads to further improvement of post-processed forecasts, even when adding the rather coarse resolution IFS-ENS NWP model.
- Inclusion of additional predictors and experiments with boosting indicate further potential to improve forecasts.
- In addition to calibration, multi-model gEMOS allows to seamlessly combine short-range and medium-range weather forecasting models (and thereby also reduces the risk of missing forecast information by increasing the number of independent model sources).
- gEMOS is computationally efficient and enables to generate forecasts at any point in space, making it a particularly attractive tool for operational applications in a weather service context.

A global EMOS postprocessing for temperature and precipitation forecasts for any location in Switzerland

Jan Rajczak et al. (MeteoSwiss)

Global EMOS allowing for calibrated forecasts
at any point in space



gEMOS concept

Traditional EMOS + **Static Predictor Variables**

mea = $a + bx + \dots + \text{static predictor variables}$

std = $\text{sqrt}(c + ds + \dots + \text{static predictor variables})$