Blending a probabilistic nowcasting method with a high resolution ensemble for convective precipitation forecasts

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Outline

1. Motivation
2. Data and Methods
3. Forecast Quality
4. Blending of the forecasts
5. Conclusions & Outlook
1. Motivation
Forecast skill for convective precipitation

Lin et al, 2005; Golding, 1998
Forecast skill for convective precipitation

- **Theory:**
  theoretical limit of predictability

- **Nowcasts:**
  rapid decrease of initially high skill

- **NWP:**
  superior after some time due to included dynamical effects

Lin et al, 2005; Golding, 1998
Forecast skill for convective precipitation

Intrinsic uncertainty in methods & phenomena requires:

1. Probabilistic view
2. Combination of forecasts

- Theory: theoretical limit of predictability
- Nowcasts: rapid decrease of initially high skill
- NWP: superior after some time due to included dynamical effects
2. Methods
2. Methods

Derivation of probabilities
Probabilistic Forecasts

forecast: Probability of exceedance (19dBZ)

\[ P(t_0 + \tau, x, L) = Prob\{\Psi(t_0 + \tau, x) \geq L\} \]

- \(\tau\): lead time
- \(Pr ob\): Probability operator
- \(x\): position
- \(\Psi\): precipitation field
- \(L\): threshold (here: always 19dBZ!)
2. Methods

Derivation of probabilities

NOWCASTING
Schematic overview Rad-TRAM

Radar Tracking and Monitoring

Rad-TRAM

Eu-Composite

Motion field -> Detection -> Tracking -> Nowcasting

Local Lagrangian

Fraction in search area, Displacement, Interpolation

deterministic nowcast
0-1h

probabilistic forecast
0-8h

Kober and Tafferner, 2009 & Kober et al., 2010
Schematic overview Rad-TRAM

Radar Tracking and Monitoring

Rad-TRAM

Motion field → Detection → Tracking → Nowcasting → deterministic nowcast 0-1h

Eu-Composite

Fraction in search area → Displacement → Interpolation → probabilistic forecast 0-8h

Local Lagrangian

Kober and Tafferner, 2009 & Kober et al., 2010
Rad-TRAM: Radar Tracking and Monitoring

European Radar Composite (DWD)

- 2 km horizontal resolution
- 15 min temporal resolution
- 6 reflectivity classes

Kober and Tafferner, 2009
Local Lagrangian:
temporal evolution of precipitation field is correlated to spatial variability
Probabilistic forecasts in Rad-TRAM

Local Lagrangian:
temporal evolution of precipitation field is correlated to spatial variability

Germann and Zawadzki, 2004
Probabilistic forecasts in Rad-TRAM

**Local Lagrangian:**
temporal evolution of precipitation field is correlated to spatial variability

- fraction of pixels > 19dbZ in search area

Germann and Zawadzki, 2004
Probabilistic forecasts in Rad-TRAM

**Local Lagrangian:**
temporal evolution of precipitation field is correlated to spatial variability

- fraction of pixels > 19dbZ in search area
- shifting with displacement vector
- interpolation with triangulation

Germann and Zawadzki, 2004
Probabilistic forecasts in Rad-TRAM

**Local Lagrangian:**
temporal evolution of precipitation field is correlated to spatial variability

- fraction of pixels > 19dbZ in search area
- shifting with displacement vector
- interpolation with triangulation
- size search area ~ lead time
- forecasts up to 8 hrs in 15min steps

Germann and Zawadzki, 2004
Rad-TRAM: 12.08.2007 23:15UTC

\[ \tau = 15 \text{min} \]
Rad-TRAM: 12.08.2007 23:15UTC

τ = 30min
Rad-TRAM: 12.08.2007 23:15UTC

\[ \tau = 45 \text{min} \]
Rad-TRAM: 12.08.2007 23:15UTC

\[ \tau = 60\text{min} \]
Rad-TRAM: 12.08.2007 23:15 UTC

\( \tau = 120 \text{min} \)
Rad-TRAM: for 12.08.2007 23:15UTC

15 min forecast
based on 23:00
observation
Rad-TRAM: for 12.08.2007 23:15UTC

15 min forecast based on 23:00 observation

60 min forecast based on 22:15 observation

[Map of weather patterns]
2. Methods

Derivation of probabilities

NWP: COSMO-DE-EPS
experimental ensemble of DWD based on COSMO-DE:

- 20 members
- 2.8 km horizontal resolution
- no parameterization of convection
- 24h forecast started at 0 UTC
- instantaneous synthetic radar reflectivity
Schematic overview

SREPS

- ECMWF
- DWD
- NCEP
- UKMO

COSMO-DE + 5 phys perturbations

COSMO-DE-EPS
Entrainment rate

cloud cover at saturation

laminar layer depth

laminar layer depth

maximal turbulent length scale

12.08.2007
23:15 UTC

experimental COSMO-DE-EPS

Gebhardt, 2010
Perturbation of parameters that influence the formation of precipitation:

boundary layer-, turbulence- & shallow convection parameterization

Goal: Maximize the variability in the precipitation forecast
COSMO-DE-EPS – synthetic radar reflectivity 850 hPa
Schematic overview

SREPS
- ECMWF
- DWD
- NCEP
- UKMO

COSMO-DE
+ 5 phys perturbations

COSMO-DE-EPS

3 Probability operator
1. fraction
2. Neighbourhood
3. mean
1. Traditional method: fraction
COSMO-DE-EPS – Fraction
COSMO-DE-EPS – Fraction
COSMO-DE-EPS – Fraction

frac

0 10 30 50 70 90 %
1. Traditional method: fraction

2. Treating every members as deterministic solution:

   ➡️  neighbourhood - method (Theis et al., 2005)
Spatial neighbourhood:
Uncertainty in time and space is considered through spatial variability.

Theis, 2005
COSMO-DE-EPS – neighbourhood method

Spatial neighbourhood:
Uncertainty in time and space is considered through spatial variability

mem01
Spatial neighbourhood:  
Uncertainty in time and space is considered through spatial variability

- Fraction of pixel > 19 dBZ in search area
COSMO-DE-EPS – neighbourhood method

**Spatial neighbourhood:**
Uncertainty in time and space is considered through spatial variability.

- Fraction of pixel > 19 dBZ in search area
- no displacement
- constant search area size

Theis, 2005
COSMO-DE-EPS – neighbourhood method

mem01

12.08.2007
23:15 UTC
COSMO-DE-EPS – neighbourhood method

12.08.2007
23:15 UTC
COSMO-DE-EPS – neighbourhood method
Probabilistic forecasts with COSMO-DE-EPS

1. Traditional method: fraction

2. Treating every members as deterministic solution:
   - neighbourhood - method (Theis et al., 2005)

3. Mean of neighbourhood members: mean
COSMO-DE-EPS – mean of neighbourhood members
Probabilistic forecasts with COSMO-DE-EPS

1. Traditional method: fraction

2. Treating every members as deterministic solution:
   - neighbourhood - method (Theis et al., 2005)

3. Mean of neighbourhood members: mean

→ 22 probabilistic forecasts based on COSMO-DE-EPS
2. Data and Methods

Calibration of model forecasts
Effect of Calibration (Reliability diagram statistics method)

before

after
3. Forecast Quality
Quality measures

- Brier Score and its decomposition
- Reliability diagrams
- ROC-curves
- CSRR (Conditional Square root of Ranked Probability Score)
Overview

time frame: 08.08.2007 – 16.08.2007

1. Development of skill with time (time series)

2. Development of skill with lead time

in the following: calibrated model forecasts
Overview

time frame: 08.08.2007 – 16.08.2007

1. Development of skill with time (time series)

2. Development of skill with lead time

in the following: calibrated model forecasts
lines denote different lead times
08. - 16.08.2007 – time series – Brier score

lines denote different lead times

Brier Score 08.- 16.08.2007 (Rad-TRAM)

Brier Score 08.- 16.08.2007 (COSMO-DE-EPS)

lines denote different methods
08. - 16.08.2007 – time series – Brier score

lines denote different lead times

lines denote different methods
lines denote different lead times

lines denote different methods
Overview

time frame: 08.08.2007 – 16.08.2007

1. Development of skill with time (time series)

2. Development of skill with lead time

in the following: calibrated model forecasts
Forecast skill with lead time

COSMO-DE-EPS

Rad-TRAM
Forecast skill with lead time

COSMO-DE-EPS

1h 5h

Rad-TRAM

1h 5h
Forecast skill with lead time

Brier Score

- mem01
- mem02
- mem03
- mem04
- mem05
- mem06
- mem07
- mem08
- mem09
- mem10
- mem11
- mem12
- mem13
- mem14
- mem15
- mem16
- mem17
- mem18
- mem19
- mem20
- frac
- mean

Rad-TRAM mean
Rad-TRAM stddev

nowcast lead time [h] vs. brier score
Forecast skill with lead time
Forecast skill with lead time
4. Blending of the forecasts
Combination – methodology

Derivation of weighting functions for additive combination
Derivation of weighting functions for additive combination
Weighting function for Rad-TRAM:

\[ w_r(\tau) = 2.11 - \frac{1}{1 - CSRR(\tau)^{2.8}} \]
Combination – methodology

Weighting function for Rad-TRAM:

\[
    w_r(\tau) = 2.11 - \frac{1}{1 - CSRR(\tau)^{2.8}}
\]

Weighting function for COSMO-DE-EPS:

\[
    w_c(\tau) = 1 - w_r(\tau)
\]
Weighting function for Rad-TRAM:

$$w_r(\tau) = 2.11 - \frac{1}{1 - CSRR(\tau)^{2.8}}$$

Weighting function for COSMO-DE-EPS:

$$w_c(\tau) = 1 - w_r(\tau)$$
Combination – methodology

Weighting function for Rad-TRAM:

$$w_r(\tau) = 2.11 - \frac{1}{1 - CSRR(\tau)^{2.8}}$$

Weighting function for COSMO-DE-EPS:

$$w_c(\tau) = 1 - w_r(\tau)$$

$$P_{blend,i} = w_r(\tau) \cdot P_{LL}(\tau) + w_c(\tau) \cdot P_{EPS,i}$$
Combination – example 12.08.2007

\[ \tau = 1.25 \text{h} \]

\[ \tau = 7.25 \text{h} \]
Combination – forecast quality
Combination – forecast quality

Brier Score 08.- 16.08.2007

blended brier score

nowcast lead time [h]

mem01
mem02
mem03
mem04
mem05
mem06
mem07
mem08
mem09
mem10
mem11
mem12
mem13
mem14
mem15
mem16
mem17
mem18
mem19
mem20
frac
mean
Combination – forecast quality of components
Combination – forecast quality

Brier Score 08.-16.08.2007

CSRR 08.-16.08.2007

ROC area 08.-16.08.2007
Combination – forecast quality

ROC area 08.-16.08.2007

nowcast lead time [h]

ROC area

mem01
mem02
mem03
mem04
mem05
mem06
mem07
mem08
mem09
mem10
mem11
mem12
mem13
mem14
mem15
mem16
mem17
mem18
mem19
mem20
frac
mean
Rad-TRAM mean
Combination – forecast quality

ROC area 08.-16.08.2007

COSMO-DE-EPS
Rad-TRAM
blended

ROC area vs. nowcast lead time [h]

100% 73% 68%
5. Conclusions & Outlook
1. **Methodology:**

   - calculation of probabilistic forecasts with nowcasting and NWP methods
   - evaluation of forecast quality
   - blending of forecasts
Conclusions

1. **Methodology:**
   - calculation of probabilistic forecasts with nowcasting and NWP methods
   - evaluation of forecast quality
   - blending of forecasts

2. **Results:**
   - cross-over period between 5.5 and 7 hours
   - blended forecast reproduces skill for short and long lead times
   - improved skill through blending for the cross-over lead times
- Most potential for improvement: model forecasts
  lead time dependent evaluation
  (time-lagged Ensemble)
- Most potential for improvement: model forecasts
  lead time dependent evaluation
  (time-lagged Ensemble)

- Rerun the study with larger amount of data:
  analysis (calibration, derivation of weighting functions)
  within different meteorological regimes:

  **Identification with convective time scale** (Done et al., 2006)
End

- Thank you for your attention!
6. Further slides
lines denote different lead times

lines denote different methods
lines denote different lead times

lines denote different methods
lines denote different lead times

lines denote different methods