## Statistical postprocessing of heavy precipitation

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Spatial extremes in the hydro－and atmosphere：understanding and modelling EGU2020：Sharing Geoscience Online at a glance

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## extreme precipitation events are rare

$\Rightarrow$ example: RR/1h $>15 \mathrm{~mm}$
$\rightarrow$ all observed events from 08.12.2010 until 31.12.2017 (> 7 years) in Frankfurt (similar in Berlin, etc.)
$\rightarrow$ COSMO-DE-EPS starting at 12 UTC, value of the next grid point

| date | hours after 12 UTC | EPS-mean | EPS-Stddev | observation |
| :---: | :---: | :---: | :---: | :---: |
| 22.06.2011, 13 UTC | +01 | 1,4 | 0,4 | 15,2 |
| $\mathbf{0 6 . 0 8 . 2 0 1 2 , ~} 00$ UTC | +12 | 0,6 | 0,6 | 15,0 |
| $16.08 .2012,02$ UTC | +14 | 1,2 | 1,3 | 37,3 |
| $\mathbf{0 8 . 0 6 . 2 0 1 3 , 1 8 ~ U T C ~}$ | +06 | 0,0 | 0,0 | 34,8 |
| $29.11 .2015,22$ UTC | +10 | 2.0 | 1,8 | 15,6 |
| $29.05 .2016,23$ UTC | +11 | 1,8 | 2,1 | 15,2 |
| $30.05 .2016,00$ UTC | +12 | 1,2 | 2,2 | 17,3 |
| $14.06 .2016,16$ UTC | +04 | 8,8 | 9,8 | 19,1 |

$\rightarrow$ verification of precipitation amount RR/1h
$\rightarrow$ forecast period May-June 2016
$\rightarrow$ forecast period: 1 h for MOS (3h for COSMO-DE-EPS)


COSMO-DE-EPS mean


Ensemble-MOS
$\rightarrow$ small correllation between forecast (next grid point) and observation
$\rightarrow$ small improvement by statistical optimisation with EnsembleMOS
$\rightarrow$ climate mean might be the best statistical forecast

## optimisation of precipitation

$\rightarrow$ verification of precipitation amounts $R R / 1 \mathrm{~h}$ (nearest point, linear regression)
$\rightarrow$ forecast period May-June 2016
$\rightarrow$ forecasting time: 1h for MOS (3h for COSMO-DE-EPS)


COSMO-DE-EPS Mean


Ensemble-MOS
$\rightarrow$ overestimation of precipitation amounts for COSMO-DE-EPS (above about 1.5 mm )
$\rightarrow$ significant improvement by statistical optimisation with Ensemble-MOS

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$\rightarrow$ point probability: precipitation occurs exactly at given location (grid centre)
$\Rightarrow$ area probability: precipitation occurs anywhere in an area (grid cell)

point probabilities on 20 km grid

area probabilities for 20 km grid


## area precipitation probabilities


point probabilities on 20 km grid

area probabilities for 0.625 km grid
(c) (i)
$\triangle$ UT®

point probabilities on 20 km grid

area probabilities for 1.25 km grid
(c) (9)
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## area precipitation probabilities


point probabilities on 20 km grid

area probabilities for 2.5 km grid
(c) (9)

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## area precipitation probabilities


point probabilities on 20 km grid

area probabilities for 5 km grid
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## area precipitation probabilities


point probabilities on 20 km grid

area probabilities for 10 km grid

## area precipitation probabilities


point probabilities on 20 km grid

area probabilities for 20 km grid

point probabilities on 20 km grid

area probabilities for 40 km grid

## area precipitation probabilities


point probabilities on 20 km grid

area probabilities for 80 km grid

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$\rightarrow$ derive area probabilities from calibrated point probabilities
$\rightarrow$ basic idea of approach:
$\rightarrow$ model precipitation as circular precipitation cells
$\rightarrow$ cells are randomly distributed by stochastic process
$\rightarrow$ match the relative number of coverages to point probabilites
$\rightarrow$ for an arbitrary area: count coverages (also partial coverages)
$\rightarrow$ radii of precipitation cells are estimated from variability of point probabilities (semivariogram)
$\rightarrow$ adjust for convective events or large scale precipitation


3 of about 1000 Monte Carlo-simulations
(c) (i)


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$\rightarrow$ enhancement for high precipitation thresholds ( $5 \mathrm{~mm} / \mathrm{h}, 10 \mathrm{~mm} / \mathrm{h} . .$. )
$\rightarrow$ model area precipitation amounts
$\rightarrow$ assigne a symmetric response function to each cell
$\rightarrow$ multiply response function with random scaling variable
$\rightarrow$ sum up scaled response functions
$\rightarrow$ fit scaled response functions to point probabilities
$\rightarrow$ sum up for arbitrary areas
$\rightarrow$ derive probabilities for high thresholds

typical realisation

estimated amounts based on 5000 realisations
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$\rightarrow$ gauge adjusted radar products as predictands
$\rightarrow$ for point probabilities instead of synoptical observations
$\rightarrow$ for area probabilities of predefined areas


1-hourly estimation of precipitation (gauge adjusted at stations)
$\rightarrow$ radar probabilities of precipitation
$\rightarrow$ radar precipitation in $1 \times 1 \mathrm{~km}$ resolution (RW-product of DWD)
$\rightarrow$ surrounding of synoptical stations ( $\mathrm{r}=8 \mathrm{~km}$ and 40 km )
$\rightarrow$ relative frequencies in surrounding is used as predictand of point probability
$\rightarrow$ improved statistical sample higher representativity more extreme cases
$\rightarrow$ area related predictands

## Thank you for attention

## $\rightarrow$ question:

what is the best compromise between spatial resolution and predictability?

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