

Calibration with MOS at DWD

ECMWF Calibration Meeting 12 February 2015

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Calibration with MOS at DWD

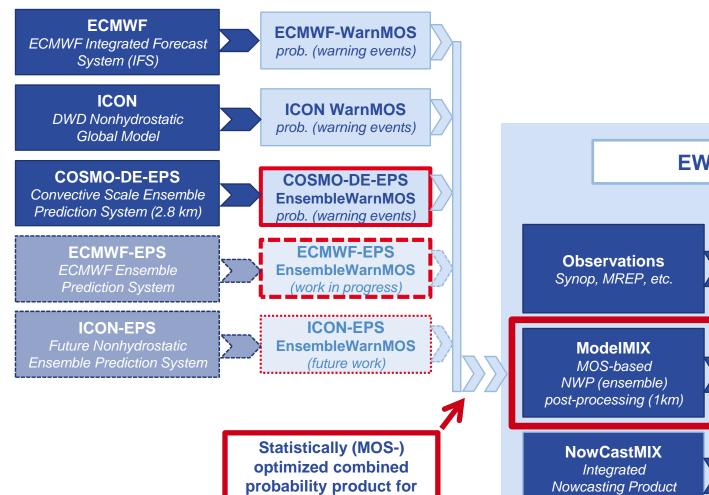
- Outline
 - Overview of MOS Systems at DWD
 - Ensemble MOS
 - ModelMIX: MOS of MOS
 - Ensemble MOS for ECMWF-EPS (TIGGE/THORPEX data)
 - Verification
 - Bonus



EWA: ModelMIX

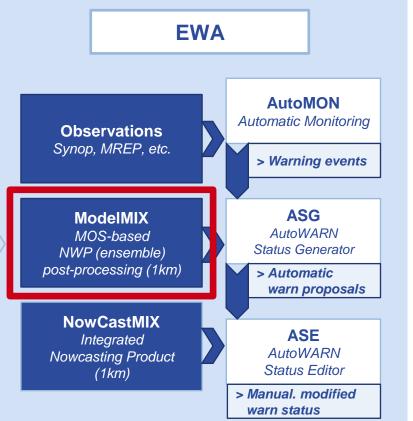
decision support for weather warnings





warning events

on 1km grid





MOS Systems at DWD

- Operational Systems at DWD
 - ICON-MOS, ECMWF-MOS, MOS-MIX
 global, medium scale, at synoptic stations, based on ICON and IFS/ECMWF
 - ICON-WarnMOS, ECMWF-WarnMOS, WarnMOS-MIX provides 27 warning criteria on 1x1 km grid for Germany
 - AUTO-TAF spezialised forecasts for airports
 - **CellMOS** nowcasting thunderstorms on advecting cells (Lagrange)
 - Ensemble-MOS, ModelMIX (in development, based on WarnMOS)
 calibration of ensemble forecasts (COSMO-DE-EPS, ECMWF-EPS, ICON-EPS)



Ensemble-MOS

- Enhancement of MOS Systems for Ensembles
 - apply for COSMO-DE-EPS and EZMW-EPS (later ICON-EPS)
 - optimization, calibration and interpretation using synoptical observations
 - ensemble products as model predictors
 - ensemble mean and stddev (quantiles, etc.)
 - surrounding of stations (mean and stddev of surrounding)
 - linear regression for continuous forecast elements (e.g. 2m temperature)
 - logistic regression for probabilistic forecast elements (e.g. prob(RR>15mm))
 - use of long time series, e.g. 3 years for COSMO-DE-EPS
 - multistation approach (9 climatological cluster in Germany, currently redesigned)
 - multi time equations for extreme and rare events (wind gusts, precipitation with high thresholds)
 - gauge adjusted radar data alternatively to precipitation observations
 - forecast of forecast errors, forecast uncertainty



MOS: stepwise linear and logistic regression

- provide set of predictors, e.g. model forecasts, observations, derived predictors (e.g. sqrt RR, Rel_Div_10m, CAPE index, etc.)
- select predictor with highest statistical correlation to predictand
- select further predictors correlated to residuum, as long as statistically significant
- example: 2m temperature
 - based on 3 UTC issue of COSMO-DE-EPS

_MS: medium scale: 28 km

_LS: large scale: 54 km

Co: coefficient of regression

■ Wgt: normalised weigth of predictor in equation

forecast time: 1h

1 equation for each predictand (about 160), cluster (9), forecast time (21), season (4), issue of EPS(8)



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- Wgt: normalised weigth of predictor in equation

99903 Issue=02:00z TTT Season: spr	+019:00
Name Lin Reg 1	Co Wgt
T_2M_MS TD_2M_MS TTT(-24)Obs TTT(-1)StF Cos_Dag	0.12 11 0.05 4 0.05 4 0.77 65 0.02 2
Const. = -11.3	RMSE = 13.47

forecast time: 19h

1 equation for each predictand (about 160), cluster (9), forecast time (21), season (4), issue of EPS(8)





Forecast of Forecast Errors (of MOS forecast)

- compute regression of any forecast element
- use MAE of residuum as predictand
- compute regression of this predictand
- example: MAE of 2m temperature
 - → based on 12 UTC issue of ECMWF-EPS (TIGGE/THORPEX data, 4 variables)

99906 Issue=12:00z +024 TTT Season: win	:00		
Name Lin Reg 1	Со	Wgt	
temp Cos Dag	1.04	88 3	
temp_dev	0.04		
Sin_3*Dag wind -	0.16	3	
Const. = -2.5 RMSE	=	10.90	T2m

_						
Name	Lin	Reg	1		Со	Wgt
temp_d	ev			0	.05	37
wind				-0	.19	29
temp				-0	.02	18
Sin_3*	Dag			-0	.01	16
Const	=	9.3	RN	1SE	=	7.10

99906 Issue=12:00z +024:00

E TTT Season: win

MAE of T2m

temp: ensemble mean of temperature

temp_dev: standard deviation of ensemble

stddev is increased and calibrated (stddev = MAE/0.8 for Gaussian distribution)

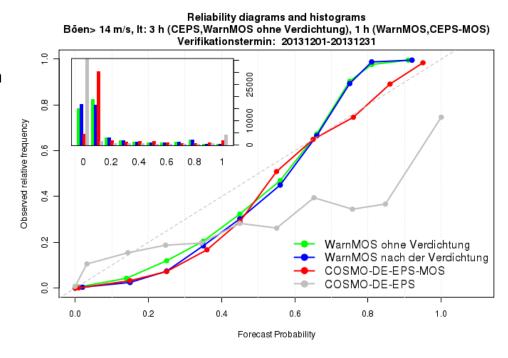




Calibration of wind gusts > 14m/s

Impact of logistic regression

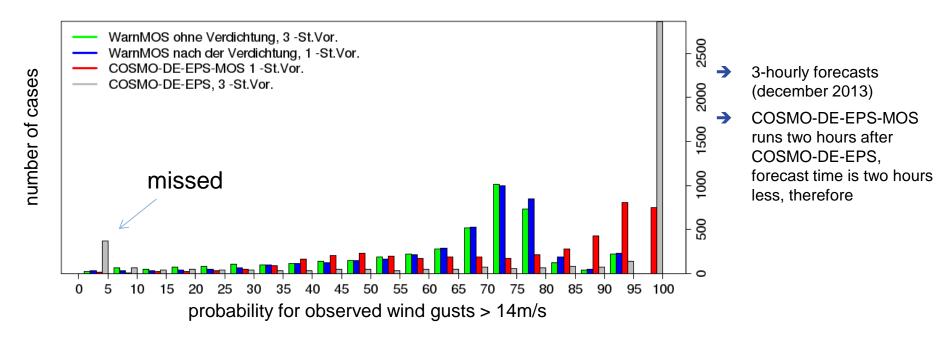
- reliability diagram for 3-hourly forecasts
 - → COSMO-DE-EPS (not calibrated, grey) shows significant overforecsting for high probabilities.
 - → MOS with linear regression (blue, green) shows underforecasting for high probabilites.
 - → Ensemble MOS with logistic regression (red) is correcting, however not yet perfectly. Still overforecasting for small probabilities (problem found).







threshold probabilites for observed wind gusts > 14m/s



- → COSMO-DE-EPS (grey) has many cases with probability 0, despite observed wind gusts >14m/s
- COSMO-DE-EPS-MOS corrects "U-shape" of COSMO-DE-EPS



ModelMix – MOS of MOS

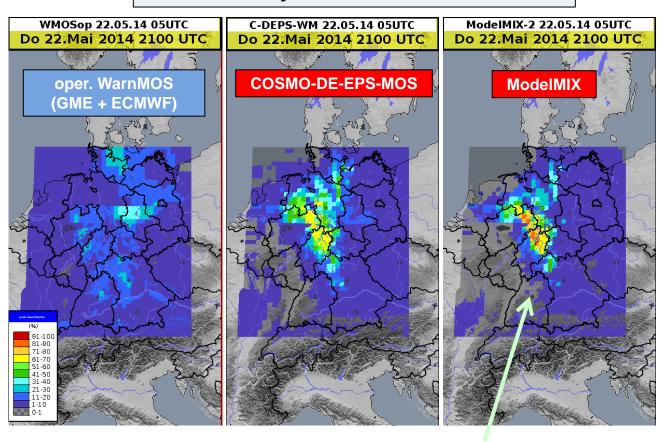
- combination of MOS systems
 - ICON-WarnMOS
 - ECMWF-WarnMOS
 - COSMO-DE-EPS-WarnMOS
 - ECMWF-EPS-WarnMOS
 - **...**
 - statistically optimal combinations
 - consistent probabilitatic products for warning criteria
 - at locations of stations and on 1km-grid

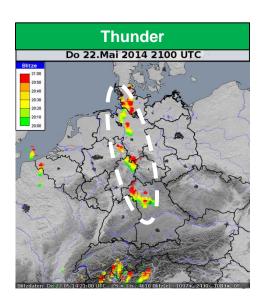


ModelMIX: Thunderstorm



Probability for thunderstorm +16h





Combination of MOS forecasts



signal for thunderstorm is enhanced



ModelMIX: weights of the individual MOS Systems

- → mix of 2 x COSMO-DE-EPS-MOS, GME-MOS und ECMWF-MOS (latest issues)
- relative weights according to linear regression
- → example: T2m all seasons, alle forecast times up to 21h, all stations

Aus- gabezeit	C-EPS 00h	C-EPS 03h	C-EPS 06h	C-EPS 09h	C-EPS 12h	C-EPS 15h	C-EPS 18h	C-EPS 21h	GME 00h	GME 12h	EZMW 00h	EZMW 12h
02h	74%							3%		2%		21%
05h	24%	54%							6%			16%
08h		21%	62%						3%			14%
11h			35%	44%					2%		19%	
14h				29%	53%				1%		17%	
17h					30%	49%				8%	13%	
20h						18%	62%			6%	14%	
23h							4%	62%		2%		32%



ModelMIX: weights of the individual MOS Systems

- → mix of 2 x COSMO-DE-EPS-MOS, GME-MOS und ECMWF-MOS (latest issues)
- relative weights according to linear regression
- → example: FX/1h>25kn all seasons, alle forecast times up to 21h, all stations

Aus- gabezeit	C-EPS 00h	C-EPS 03h	C-EPS 06h	C-EPS 09h	C-EPS 12h	C-EPS 15h	C-EPS 18h	C-EPS 21h	GME 00h	GME 12h	EZMW 00h	EZMW 12h
02h	39%							28%		7%		25%
05h	8%	44%							24%			24%
08h		6%	53%						16%			25%
11h			13%	45%					13%		30%	
14h				10%	52%				10%		38%	
17h					10%	49%				22%	18%	
20h						11%	59%			14%	16%	
23h							13%	54%		4%		29%



ModelMIX: weights of the individual MOS Systems

- → mix of 2 x COSMO-DE-EPS-MOS, GME-MOS und ECMWF-MOS (latest issues)
- relative weights according to linear regression
- → example: RR/1h>15mm all seasons, alle forecast times up to 21h, all stations

Aus- gabezeit	C-EPS 00h	C-EPS 03h	C-EPS 06h	C-EPS 09h	C-EPS 12h	C-EPS 15h	C-EPS 18h	C-EPS 21h	GME 00h	GME 12h	EZMW 00h	EZMW 12h
02h	54%							22%		14%		11%
05h	31%	45%							17%			7%
08h		43%	44%						6%			7%
11h			30%	43%					9%		17%	
14h				22%	57%				8%		13%	
17h					34%	35%				20%	11%	
20h						26%	56%			8%	9%	
23h							25%	43%		10%		22%



■ TIGGE/THORPEX data

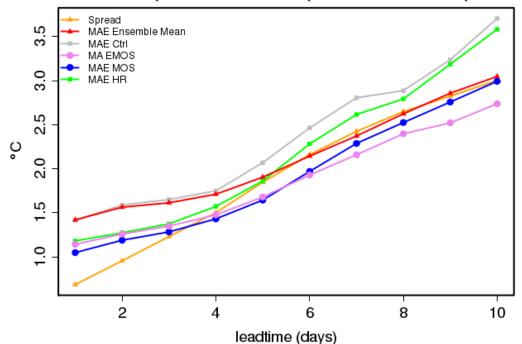
- 36 TIGGE stations
 - 50 ensembles, 1 high resolution run
 - 2m temperatur, mean wind, cloud coverage, 24h precipitation
 - observations as predictands
 - ensemble products, mean, stddev as predictors
 - training sample 2002-2012 (10 years)
 - free forecasts for 2013
 - variables and errors (smoke plumes, "Rauchfahnen")
 - verification





■ Verification of 2013 – 2m temperature errors

Comparison of Ensemble, MOS, High Res. and Control of Temperature in Frankfurt (20130102 - 20140110)



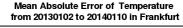
Frankfurt

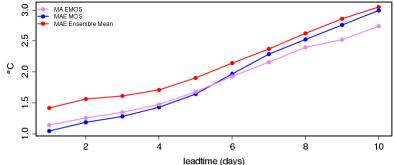
MAE MOS: MOS Errors (blue)

MA EMOS: Estimated Errors (pink)

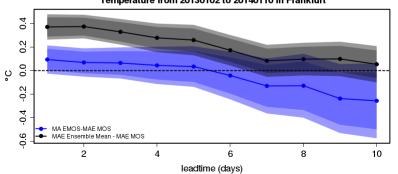


■ Verification of 2013 – 2m temperature errors





Difference of MAE and 95% and 99% Confidence Interval Temperature from 20130102 to 20140110 in Frankfurt



Frankfurt

MAE MOS: MOS Errors (blue)

MA EMOS: Estimated Errors (pink)

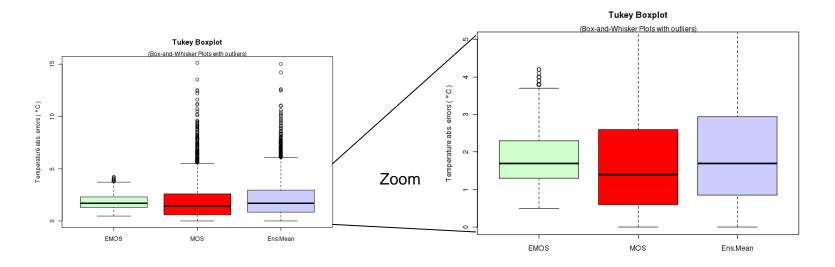
Ensemble-MOS (black): significantly better until day 6

Estimated-True Errors (blue): no significant difference



■ Verification of 2013 – 2m temperature errors

Frankfurt



Ens. Mean: Errors of Ensemble Mean

MOS: Errors of MOS

EMOS: Estimated Errors of MOS

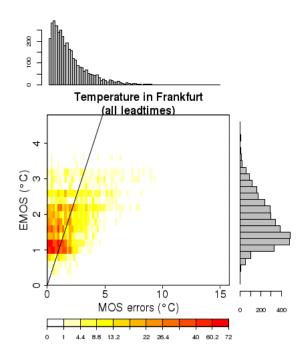
Estimated Errors are usually too small, but show weaker outliers





■ Verification of 2013 – 2m temperature errors

Frankfurt

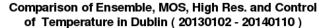


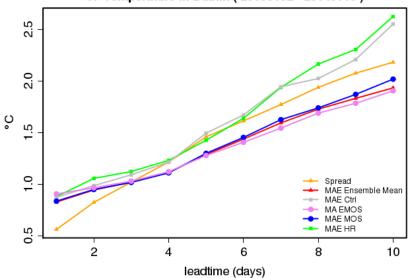
MOS: Errors of MOS

EMOS: Estimated Errors of MOS

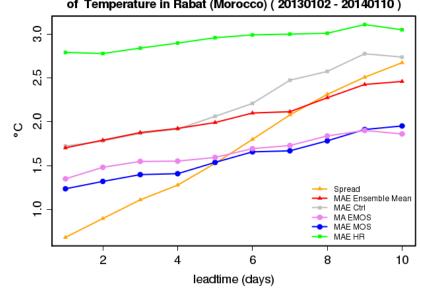


■ Verification of 2013 – 2m temperature errors





Comparison of Ensemble, MOS, High Res. and Control of Temperature in Rabat (Morocco) (20130102 - 20140110)

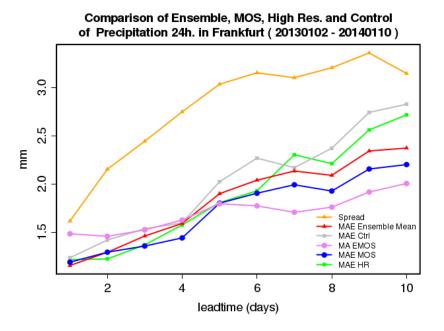


Dublin

Rabat



■ Verification of 2013 – 24h precipitation errors



Comparison of Ensemble, MOS, High Res. and Control of Precipitation 24h. in Dublin (20130102 - 20140110)

Spread

MAE Ensemble Mean

MAE Ctrl

MAE MOS

MAE MOS

MAE HR

Leadtime (days)

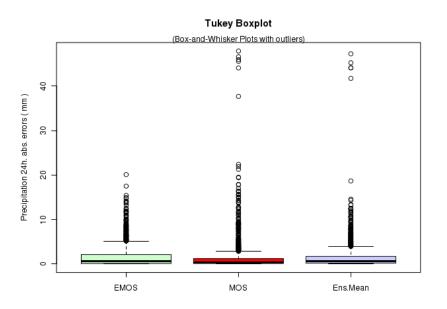
Frankfurt

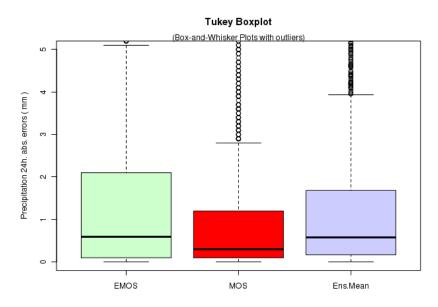
Dublin



Frankfurt

■ Verification of 2013 – 24h precipitation errors

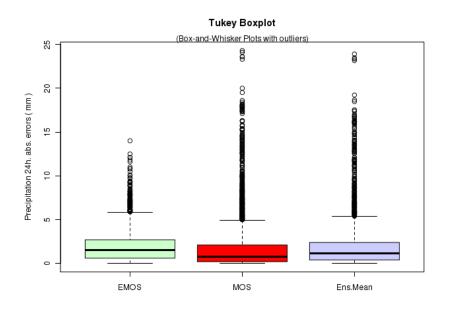


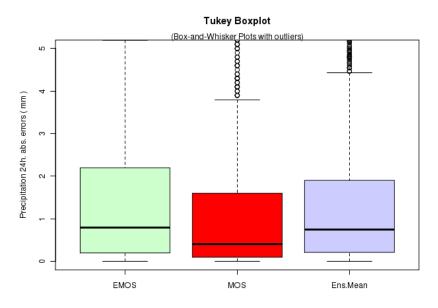




Dublin

■ Verification of 2013 – 24h precipitation errors



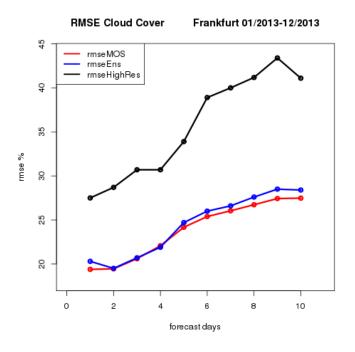


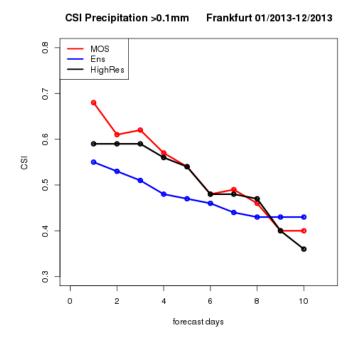




Frankfurt

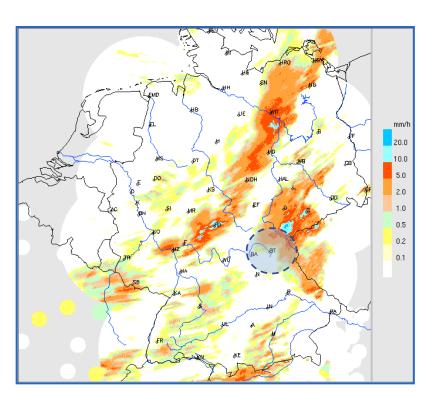
Verification of 2013 – cloud coverage and 24h precipitation (CSI, TS)







Gauge adjusted radar products as predictands (T. Hirsch)



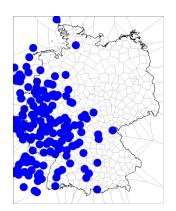
- Probabilities of Precipitation
 - P(RR>15 mm/ 1h)
 - P(RR>40 mm/12h)
- standard: synoptic observations
- idea: use radar-data (RW, 1x1 km)
 - surrounding of stations (r=8 km und 40 km)
 - relative frequencies of threshold exceedances in surrounding
- improved statistical sample
 - higher representativity
 - more extreme cases

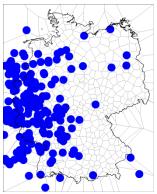
1-hourly estimation of precipitation (gauge adjusted at stations)

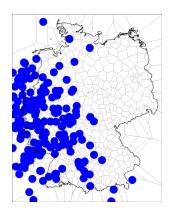


Area based probabilites

- Probability that an event occurs at least one time in any point of an area (for precipitation events currently)
- correct comparison between point observation (synop) and area mean (numerical model)
- derive area probabilites from point probabilites for arbitrary areas







3 of about 1000 Monte Carlo Simulations

Radar for validation



- Idea: place randomly circular precipitation cells so that the relative number of coverages match forecasted point probabilities at stations and count coverages for an arbitrary area.
- → Reference: B. Krische, R. Hess, B. K. Reichert, V. Schmidt: "A probabilistic approach to the prediction of area weather events, applied to precipitation", Spatial Statistics, Elsevier, accepted 2015



Thank you for attention

