A spatial verification scheme `SLX´ based on observed and forecasted local extremes

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OUTLINE

- Why develop a spatial verification scheme verifying extremes ?
- Computational procedure
- Examples verifying precipitation fields
- Simulation of SLX based on 5 years of operational results for June and December
- Conclusions and outlook

Why develop a spatial verification scheme targeted for extremes e.g. of precipitation?

- **Precipitation events are expected to become more extreme in an expected warmer future climate**
- **Users of NWP forecasts including the society in general expect to be warned against expected extreme events**
- **In order to improve NWP predictions of extreme events it is desirable to monitor via suitable NWP scores whether the models get better skill in predicting extremes**

References:

Bao, Jiawei , Steven C. Sherwood, Lisa V. Alexander and Jason P. Evans , 2017: Future increases in extreme precipitation exceed observed scaling rates, Nature Climate Change , 7 (10.1038/nclimate3201)

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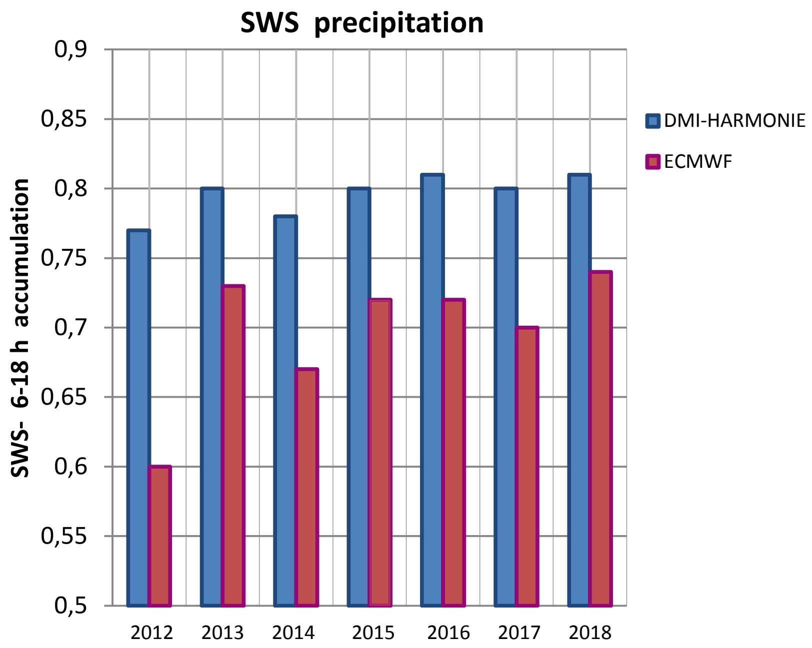
Witze, A. 2018: Why extreme rains are getting worse : *Nature, Vol. 563 , Nov 2018*

`SLX´ verification scheme
(**S**tructure of **L**ocal e**X**tremes)
Characteristics

- SLX is a generalization of the scheme SWS by Sass and Yang (2012) verifying extreme point observations in a forecast neighborhood.



Multi-year timeseries of SWS (`Significant Weather Score ´) computed on the basis of 3 highest and 3 lowest observations compared with a corresponding model grid point extreme in a neighborhood around observation

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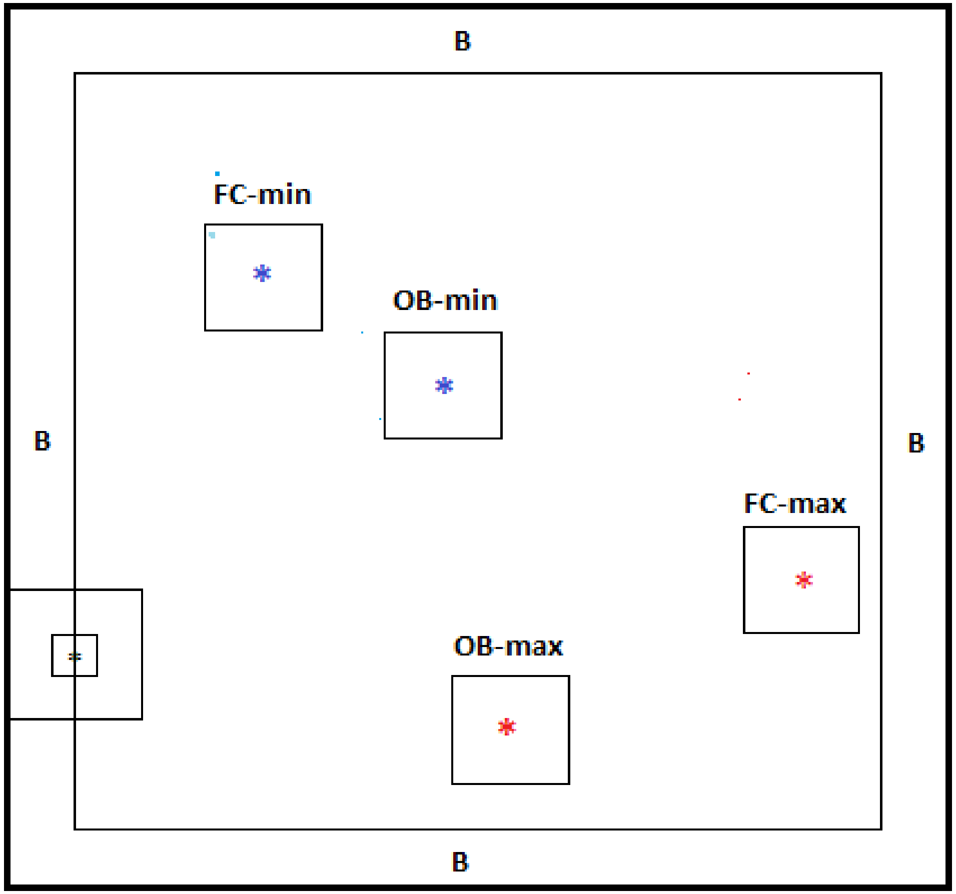
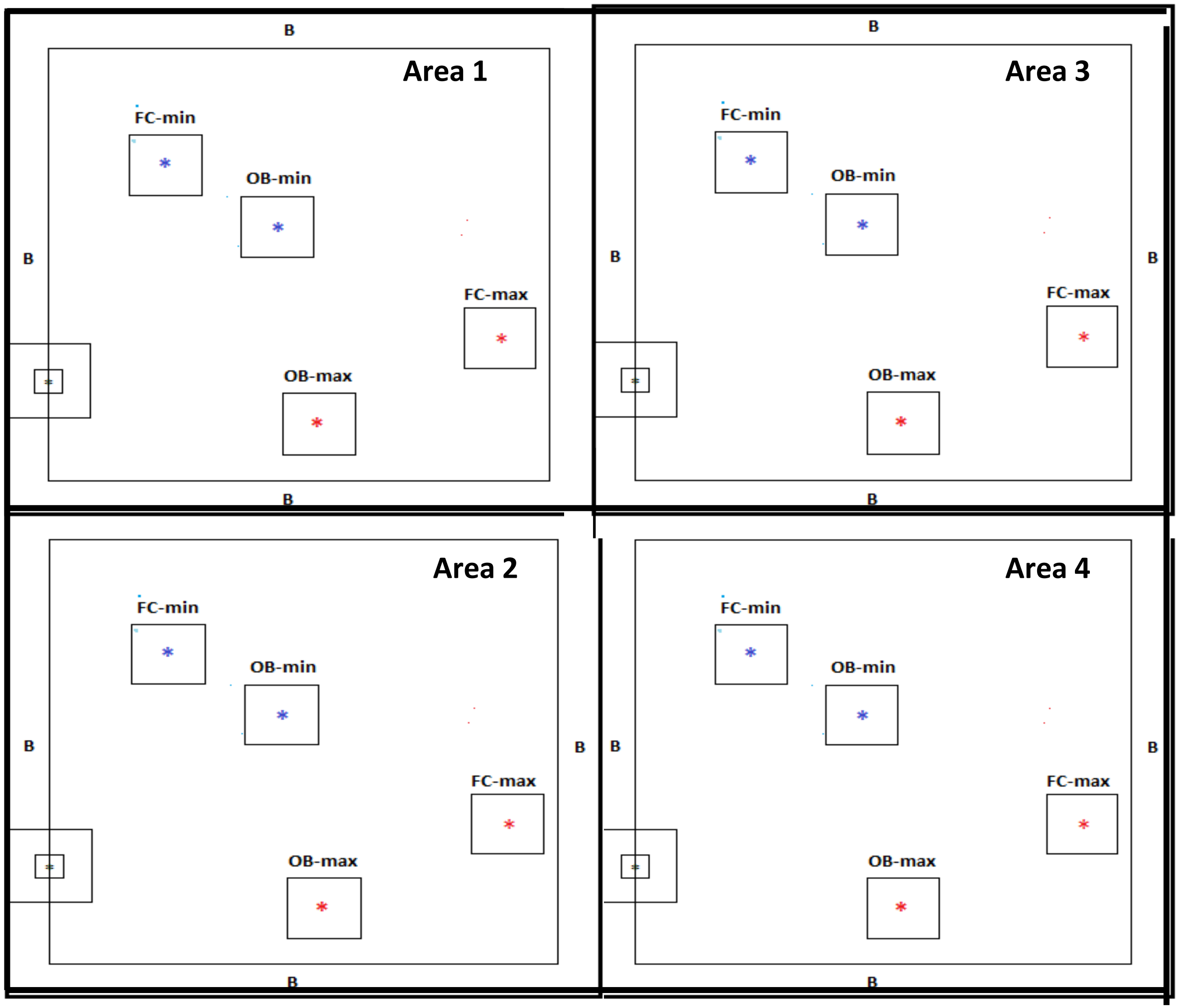
`SLX´ verification scheme
(**S**tructure of **L**ocal e**X**tremes)
Characteristics

- SLX scheme is flexible - e.g. a score fuction can be defined in collaboration with users, e.g. depending on the parameter verified and its applications

- Flexibility also exists with regard to the partitioning of model area into subareas verified separately , and all combined.



The computations of SLX in the case of only one area equal to the entire model area: Neighborhoods around observed (analyzed) minimum and maximum respectively are considered with regard to correspondingly forecasted minimum and maximum respectively. Similarly observed (analyzed) neighborhoods around forecasted minima and maxima respectively are considered. An outer region of size B makes it possible to include a neighborhood being symmetric in the whole internal domain.



The computations of SLX may be divided into several subareas. The combined SLX-result is the average of results from all sub-areas

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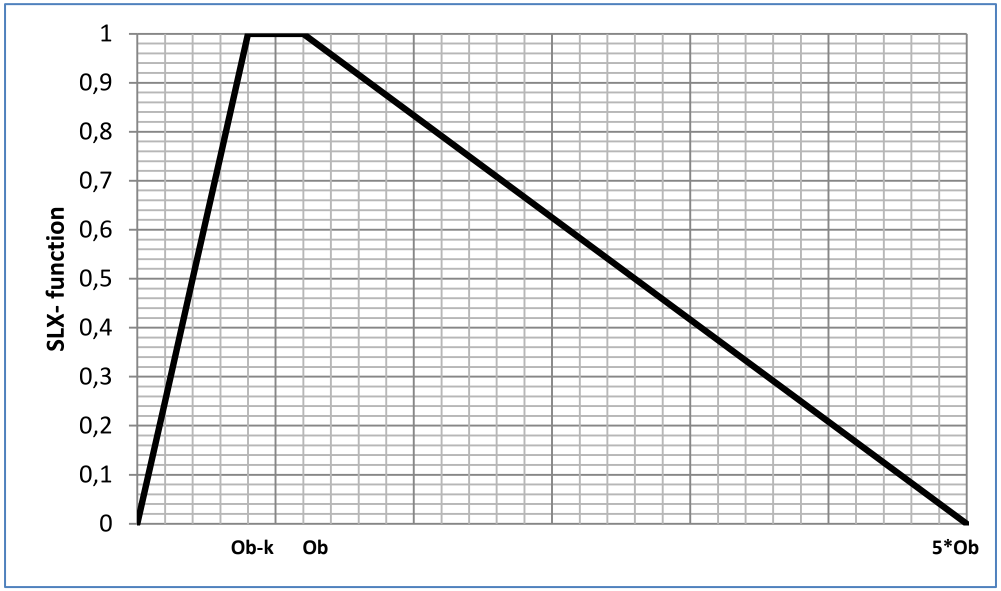

SLX score function used in the present study. The value 0 is assigned to no skill and 1 to perfect skill. The function is essentially a function of the fraction between forecast and analysis involved in the comparison.

`SLX´ verification scheme
(**S**tructure of **L**ocal e**X**tremes)

Total score SLX is a weighted sum of the above mentioned local scores computed in a neighborhood comparison

$$SLX = \frac{1}{4} \left(SLX_{ob\text{-}max} + SLX_{ob\text{-}min} + SLX_{fc\text{-}max} + SLX_{fc\text{-}min} \right)$$

$$SLX_{ob\text{-}max} = S\left(P_{ob\text{-}max},\ P_{fe\text{-}max} / P_{ob\text{-}max} \right), \quad P_{fe\text{-}max} = Max\{ P_{fe}(i, j, \tau) \}, \ (ob\text{-}max)$$
$$0 < \tau \leq \tau_m, \quad i \in [1, \ldots, N], \ j \in [1, \ldots, N] \qquad (1)$$

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$$0 < \tau \leq \tau_m, \quad i \in [1, \ldots, N], \ j \in [1, \ldots, N] \qquad (2)$$

$$SLX_{fc\text{-}max} = S\left(P_{fc\text{-}max},\ P_{oe\text{-}max} / P_{fc\text{-}max} \right), \quad P_{oe\text{-}max} = Max\{ P_{oe}(i, j, \tau) \}, \ (fc\text{-}max)$$
$$0 < \tau \leq \tau_m, \quad i \in [1, \ldots, N], \ j \in [1, \ldots, N] \qquad (3)$$

$$SLX_{fc\text{-}min} = S\left(P_{fc\text{-}min},\ P_{oe\text{-}min} / P_{fc\text{-}min} \right), \quad P_{oe\text{-}max} = Min\{ P_{oe}(i, j, \tau) \}, \ (fc\text{-}min)$$
$$0 < \tau \leq \tau_m, \quad i \in [1, \ldots, N], \ j \in [1, \ldots, N] \qquad (4)$$

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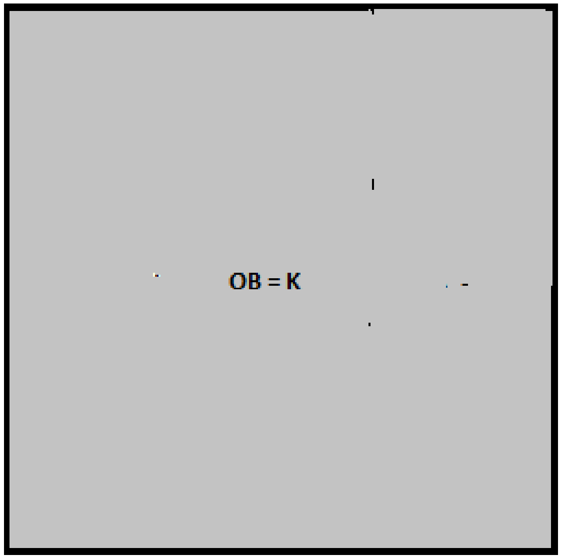
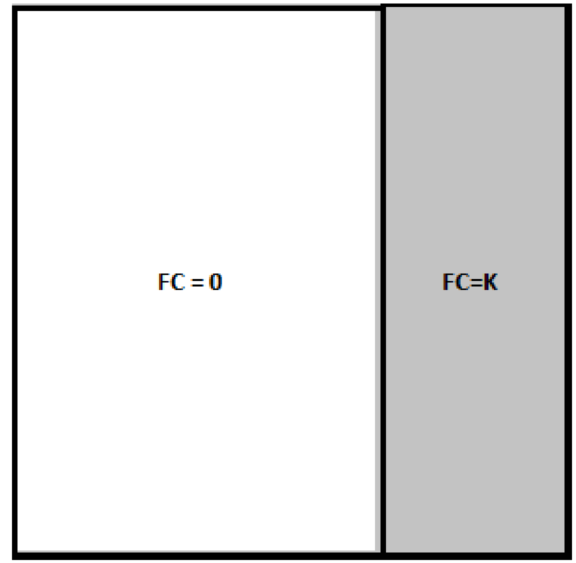
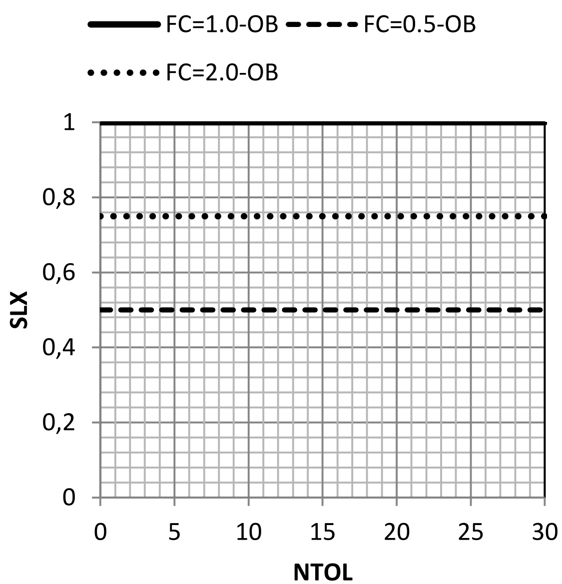
Example 1 : Constant or partially constant fields



Constant fields

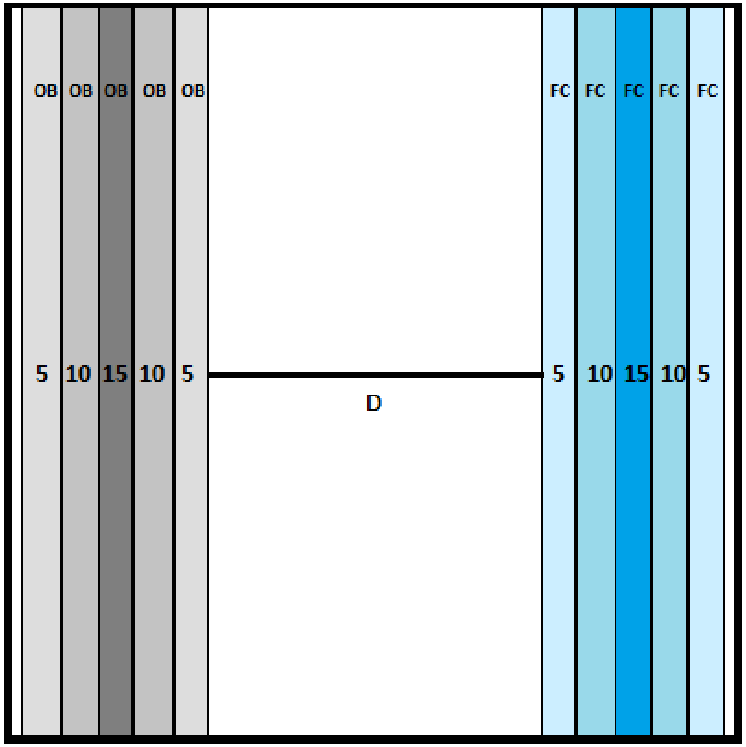


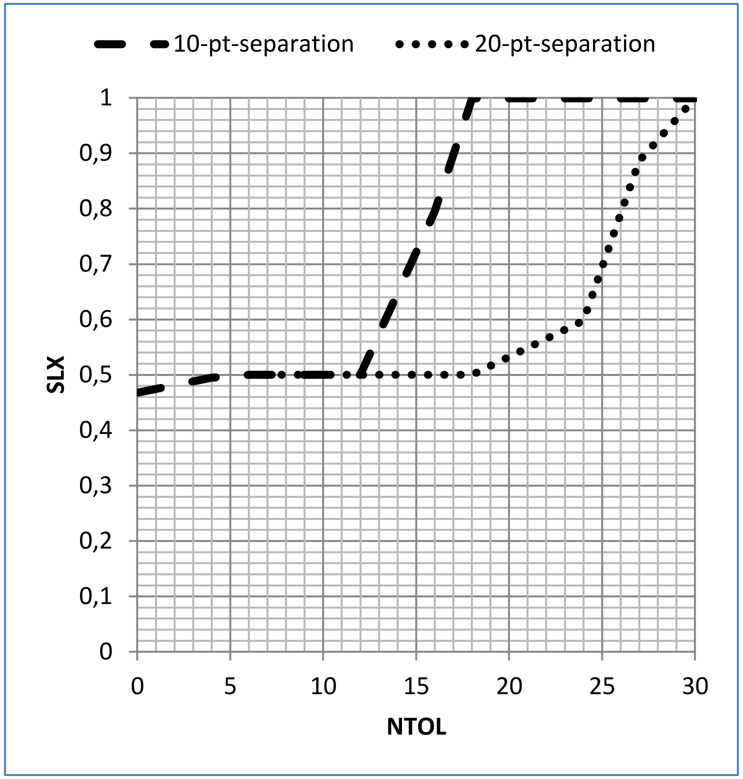
Constant fields over parts of the grid



If the forecast and analysis fields are constant or constant over part of the domain all points qualify equally, i.e. a weighted average should take place. This is not changing result if the entire fields are constant, but has impact if one field is only constant over a fraction of the area verified ! The computational scheme takes care of this !

Example 2 : Precipitation bands displaced





Schematic representation of parallel precipitation band displaced

Combined SLX as a function of displacement (grid points) between end of observed precipitation band and start of forecasted precipitation band. NTOL is size of the neighborhood. NTOL is the size of the neighborhood

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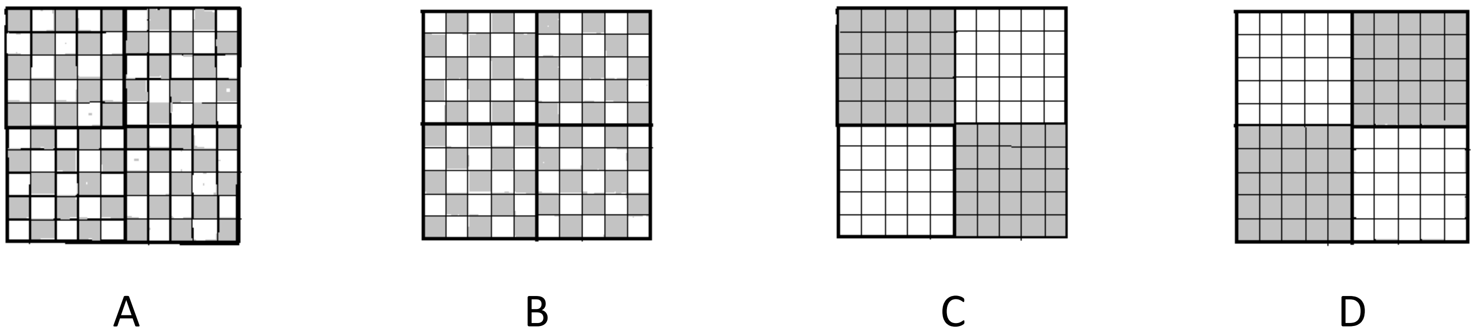
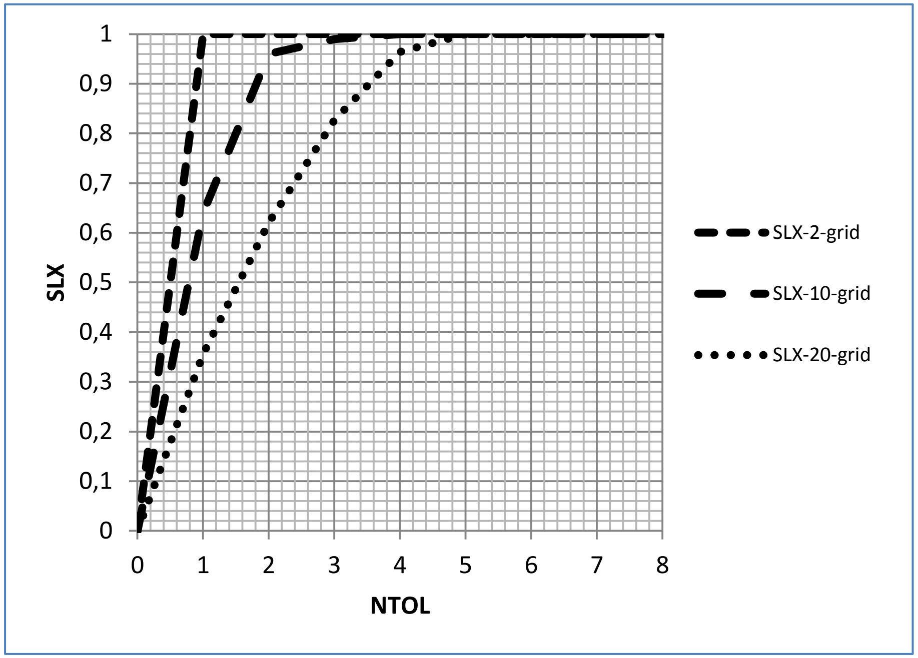
Example 3 : Noisy fields with different size





SLX as a function of neighborhood size for different dimension (symmetric) noisy pattern, e.g. with values 0 and 1 .

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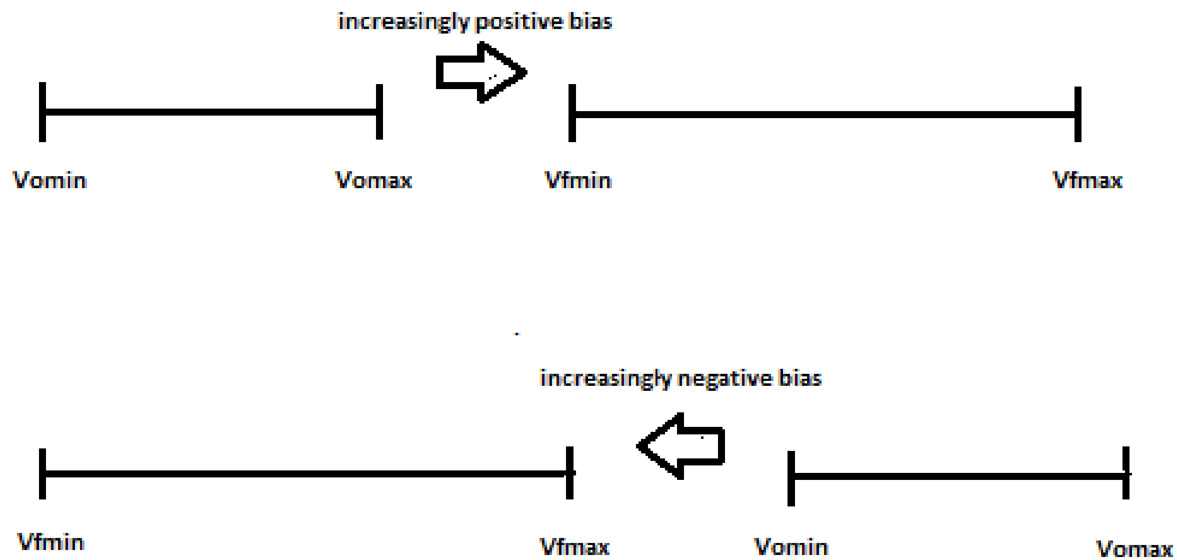
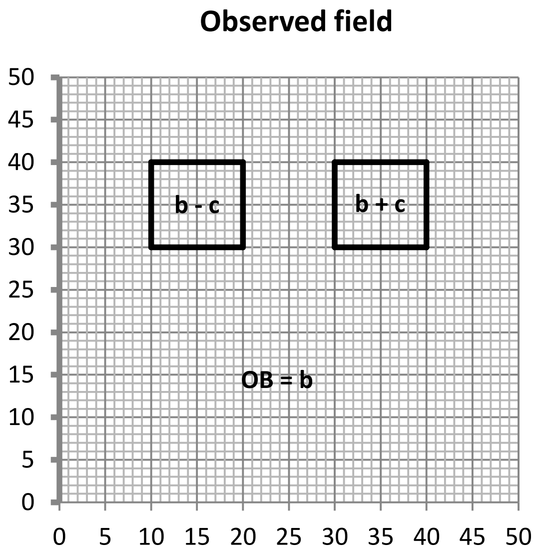
Examples illustrating robustness to `hedging´ (effects of bias)

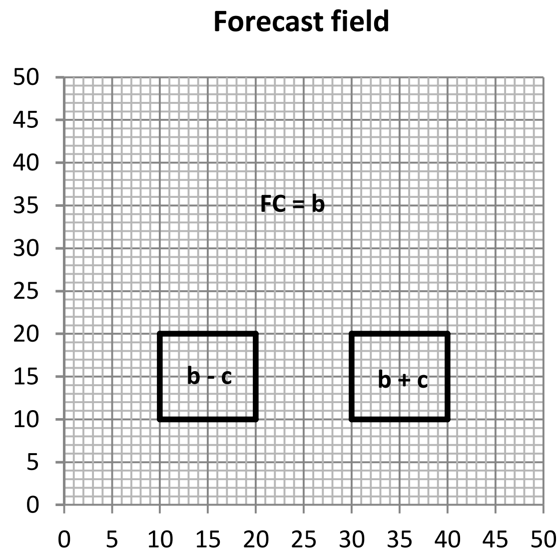


Increasing separation between forecast field range and observed field range implies that SLX decreases → no `hedging´ possible by increasing the bias

Example 4 a-d

Observed and forecast `background field ´ b = 5,10,20,40 (mm)
Minima (b-c) and Maxima (b+c) , c = 5mm are displaced as shown in the figures.





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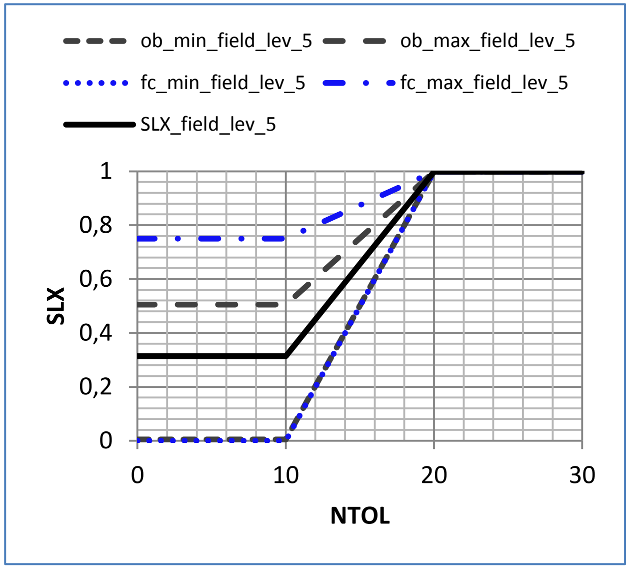
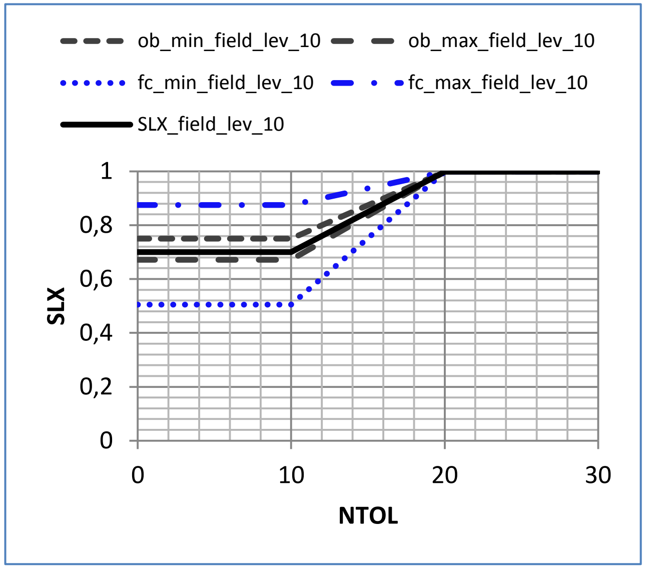
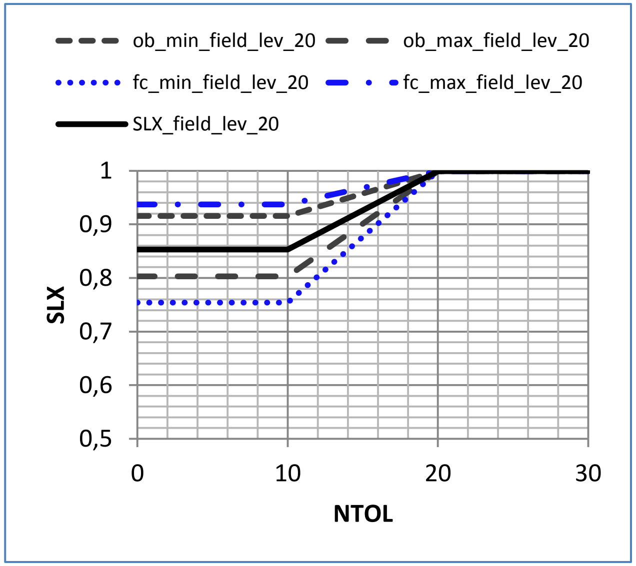
SLX –components increase as the field level increases



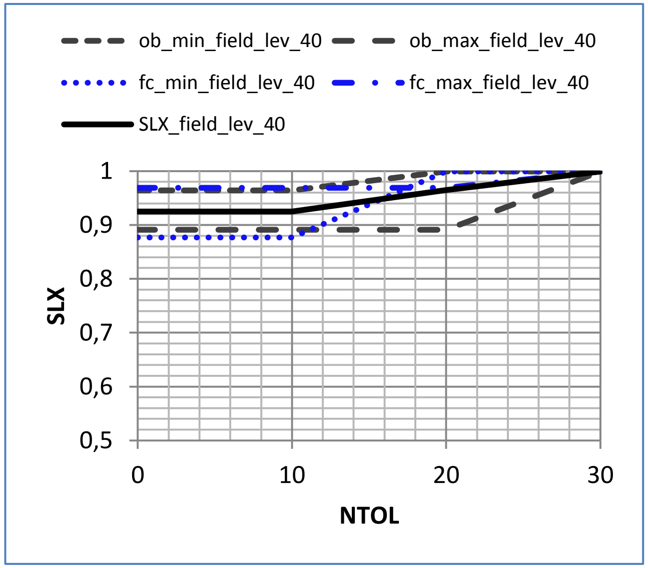
4a



4c



4b



4d

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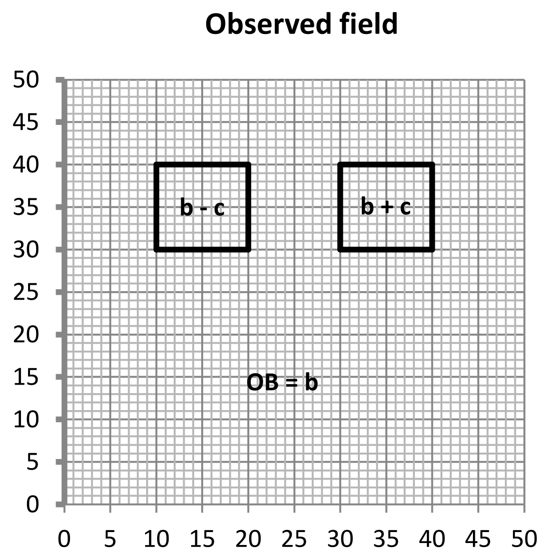
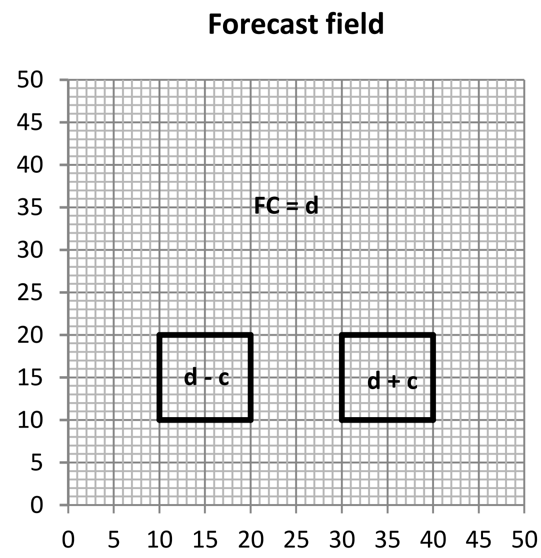
Example 5 a-d

Observed `backgound field ´ b = 5 mm in all experiments 5a-d
Forecast `background field´ d = 5, 10 ,20, 40 (mm)
Minima and Maxima are displaced as in examples 4a-d ,
c = 5mm as in experioare displaced as shown in the figures.
Experiment 4a equals 5a





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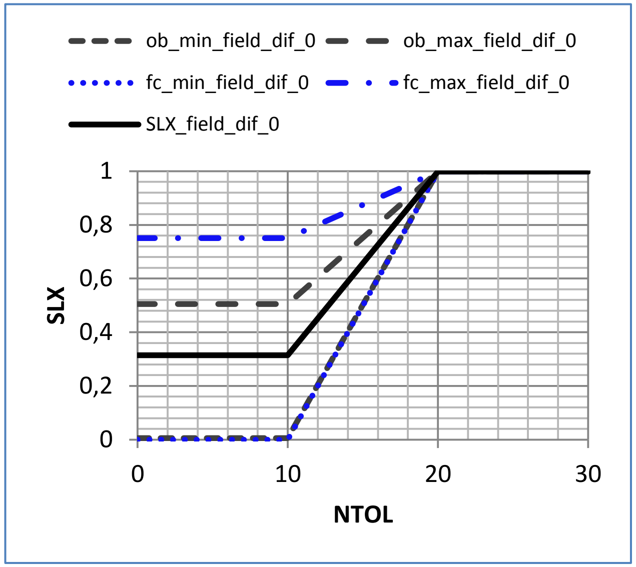
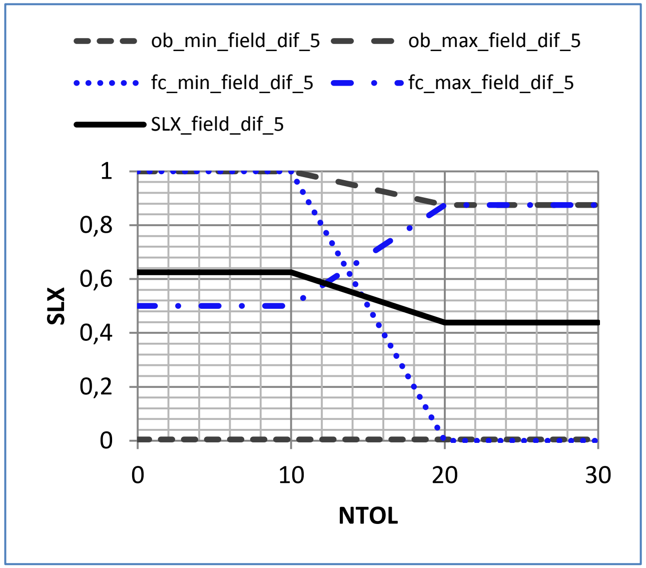
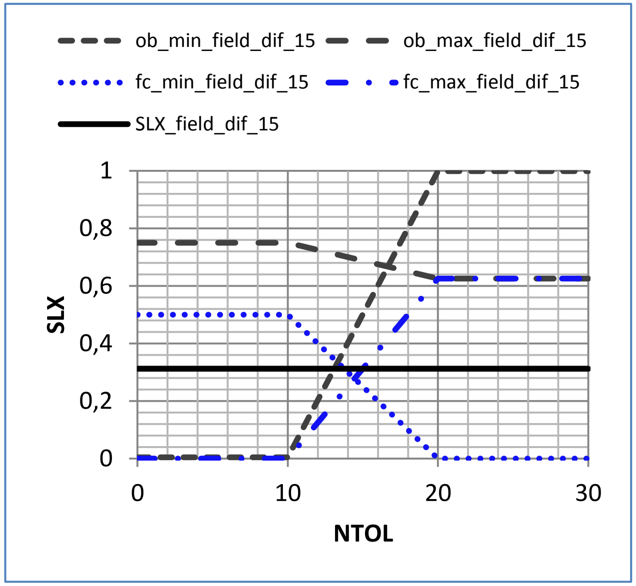
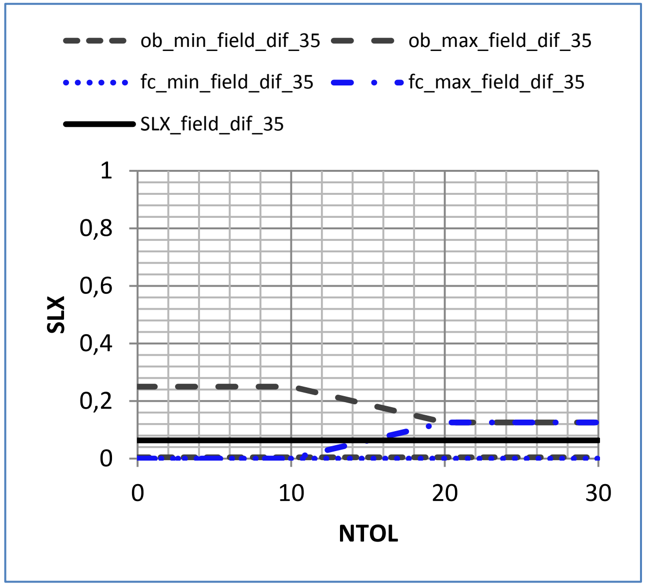
SLX –components decrease as the field level difference increases









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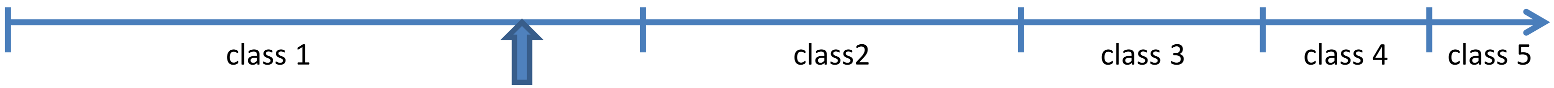
Simulation of SLX for 5 year operational results of June and December

(12h accumulated precipitation data for Danish station list of ~30 stations are used and compared with 12 h forecast accumulations (6h -18h forecasts) over the 5 years.
Limitation: The forecast model is not constant over the period.

Approach: Assume that we can transfer statistics from the 5 year period to synthetic observed (analyzed) and forecasted fields by the following steps:

STEP 1: Organize all data points , observations and forecasts separately, according to size in 5 classes : Choose an arbitrary number which will determine the selected class which may often be different between forecast and observation.

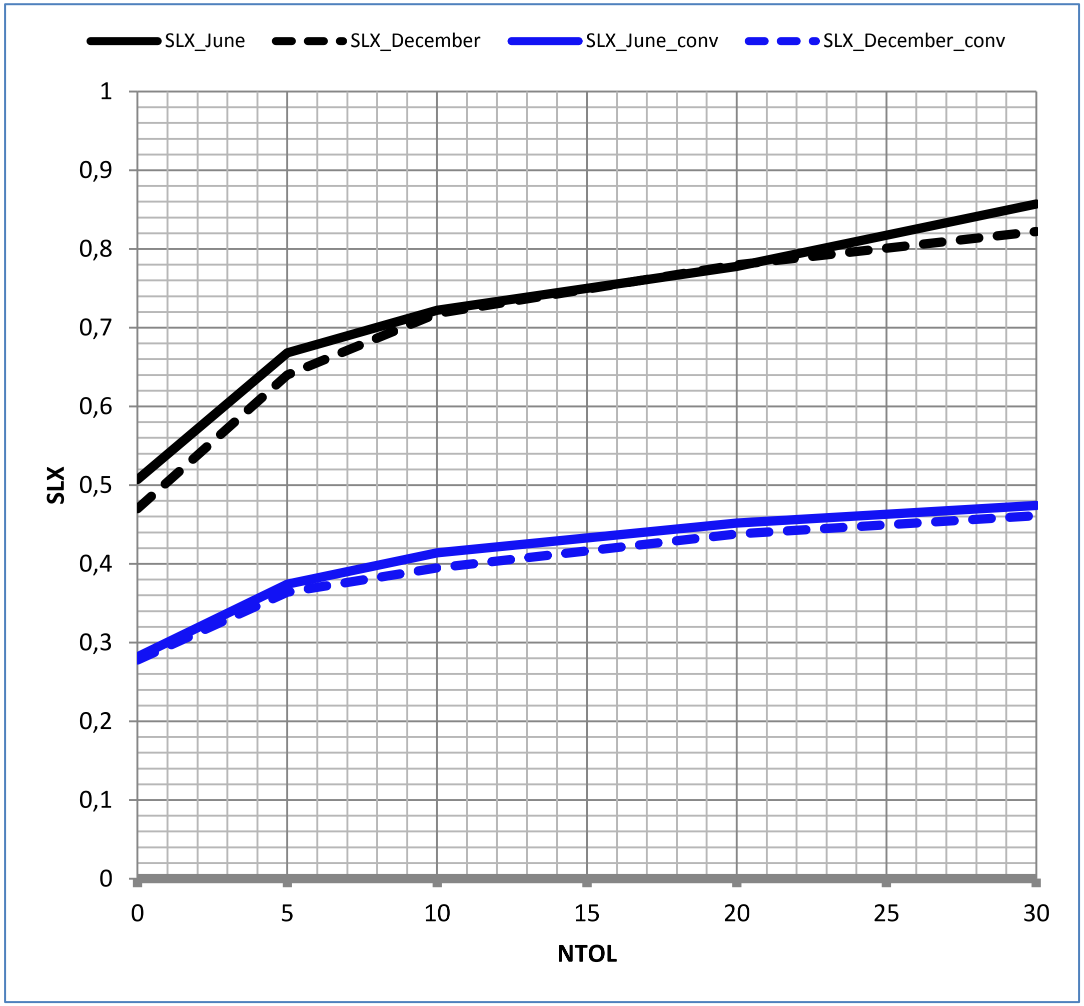


STEP 2: Convert number chosen (separate for analysis and forecast) to a value (mm accumulation) depending on position in interval

STEP 3: Conversion to entire fields by choosing a characterisic dimension N of (quadratic) grid area , e.g. N*N = 10*10 grid points , representative of 12 hour accumulations not changing much on average. (e.g. correlation between forecasted neigboring grid point in 12h accumulations is normally high). The statistical choice of each N*N points are repeated for enough N*N entities to cover the whole verification area.

STEP 4: Any number of different consecutive synthetic fields may be verified to investigate a typical score of SLX. In the present study the average score of 500 synthetic fields is studied

Examples: 500 synthetic fields verified



500 runs, statistics valid for June (black solid line) and Dec. (black dashed line). Similarly blue lines apply to 500 runs with imposed limitation that all cases had observed fields of precipitation > 1mm (harder to predict)

Conclusions and Outlook

- The SLX scheme fulfils some desirable properties for operational use of precipitation forecasts.

- It is a generalization of a scheme already used operationally in DMI and is a natural step when trying to verify precipitation spatially. This is now possible from 2019 at DMI using quality controlled precipitation analyses combining radar data with ground based in situ observations.

- The scheme is currently written in R and may therefore be implemeted in HARP verification package.

- Generalization to ensembles is an interesting extension. An obvious choice is to verify the median of an ensemble.

END

Thanks for your attention
много благодаря

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