18 May 2016

Workshop on Stochastic Weather Generators

Generating precipitation ensembles from satellite observations: reproducing intermittency

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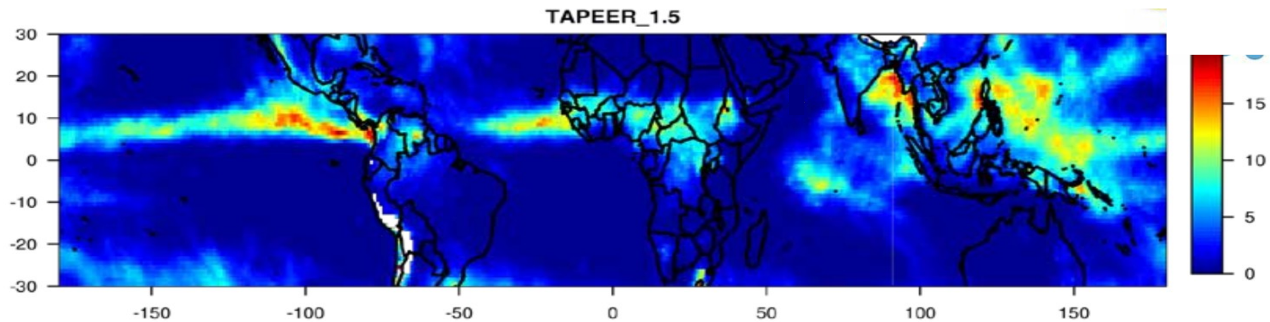
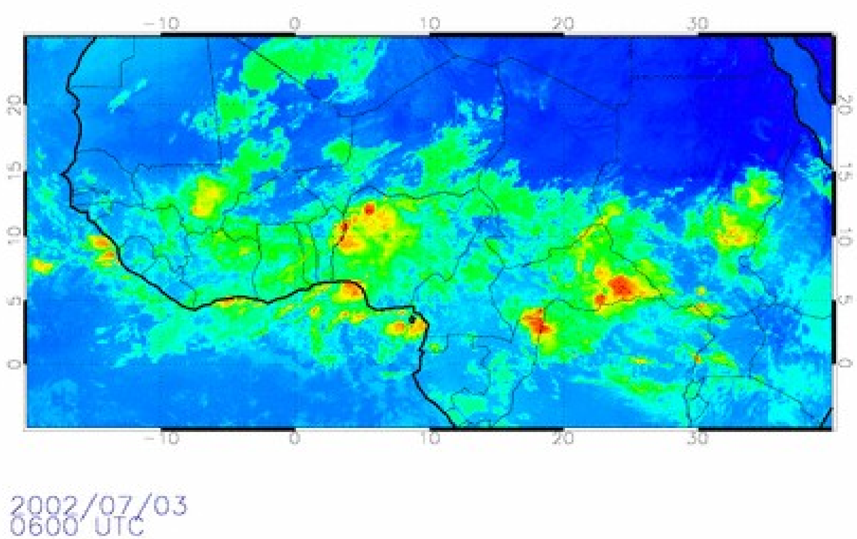
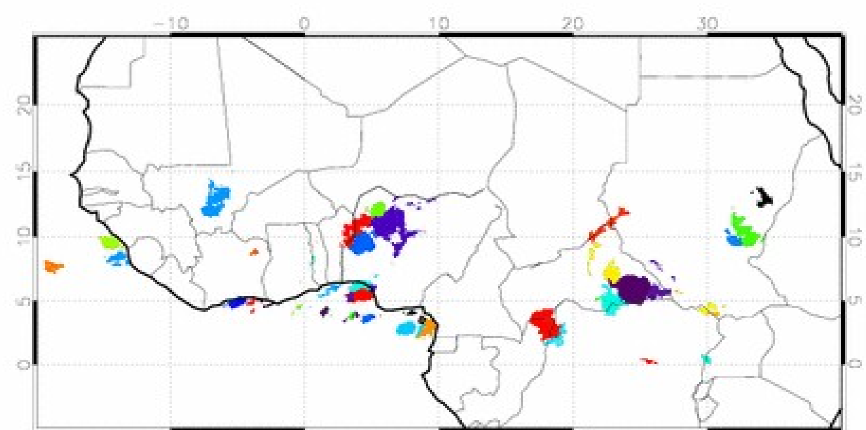
Rain in the continental Tropics



mm/day Jully-September 2012

- Monsoon regime
- Predominance of convection
- In the Sahel: Mesoscale Convective Systems

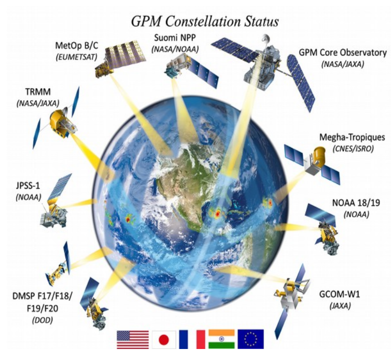




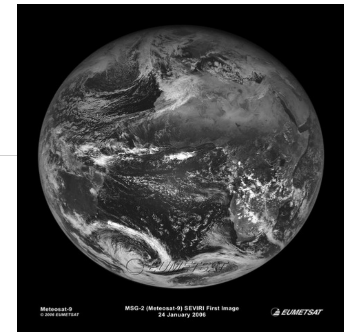
Courtesy of T. Fiolleau and R. Roca

Tropical Amount of Precipitation with Estimate of ERror

MW radiances measured by GPM constellation's radiometers



colocation

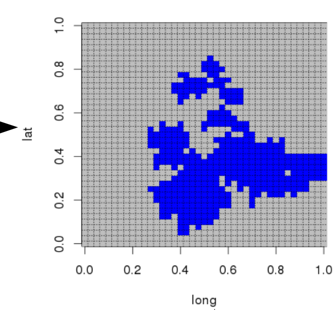


SEVIRI IR 10.8 µm imagery at 2.8 km every 15 minutes

local (3°, daily) training

Mean rain intensity in precipitating areas $\overline{R}_{cond}$

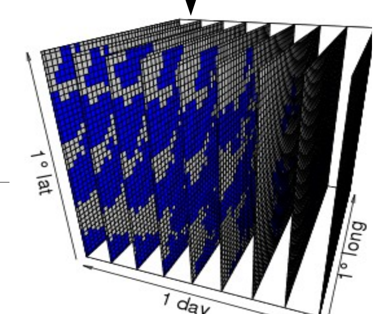
optimal BT threshold for rain detection



Rain mask M_{TAP} at SEVIRI's resolution

Estimated 1°, daily mean rain rate

$\overline{R}_{1dd} = \overline{PF}_{1dd} \times \overline{R}_{cond}$



96 images a day

aggregation

daily 1° precipitation fraction $\overline{PF}_{1dd}$

How much information does a rain / no rain mask contain ?

radar coverage area

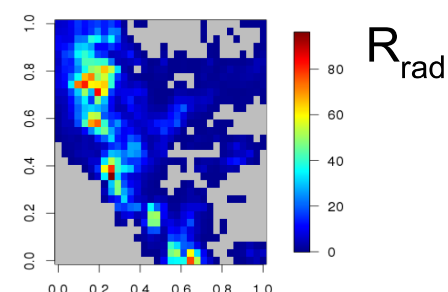
- $R_{Rad}(x, y, t)$:series of instantaneous radar rain fields measured by Xport radar in Burkina Faso in 2012, aggregated to a spatial resolution of 2.8 km, 7.5 min sampling period.

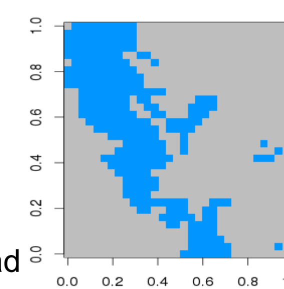
- R_{Rad} are binarized by thresholding to generate a mask M_{Rad}:

$$M_{Rad} = \begin{Bmatrix} 0 \ if \ R_{Rad} < 6.2\, mm/h \\ 25\, mm/h \ if \ R_{Rad} > 6.2\, mm/h \end{Bmatrix}$$

M_{Rad} and R_{rad} have same mean and variance by construction.

=> Multiscale comparison of M_{Rad} and R_{rad} through wavelet transform.

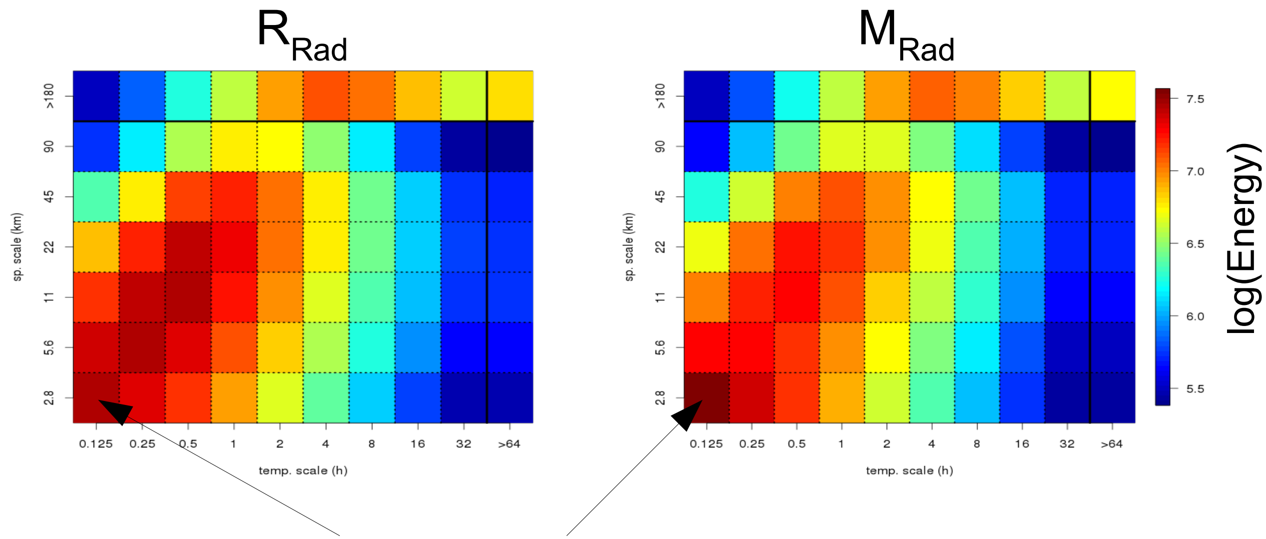




Spectral comparison of M_{Rad} and R_{Rad}

- Spectral energy:

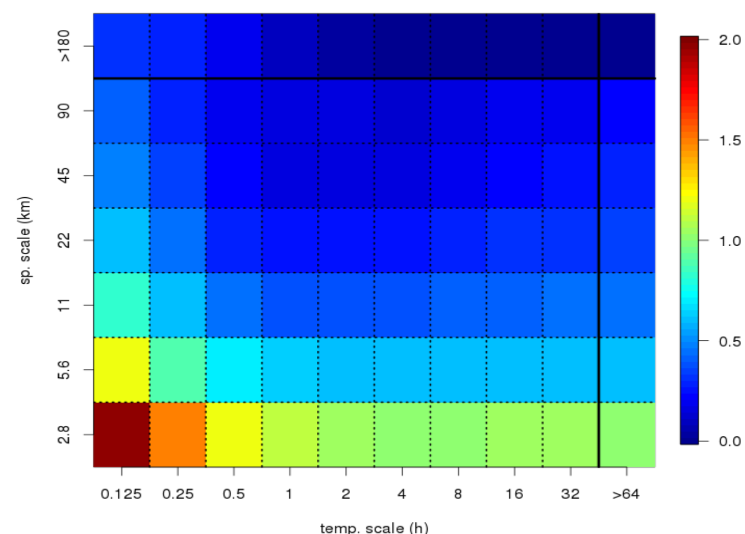
  Quasi-indentical



'smooth transitions':low rain rates at the edges of cells

- Spectral energy of the difference:

  The two fields are significantly different only for scales finer than 22 km and 30 min.



normalized by R_{Rad}'s energy

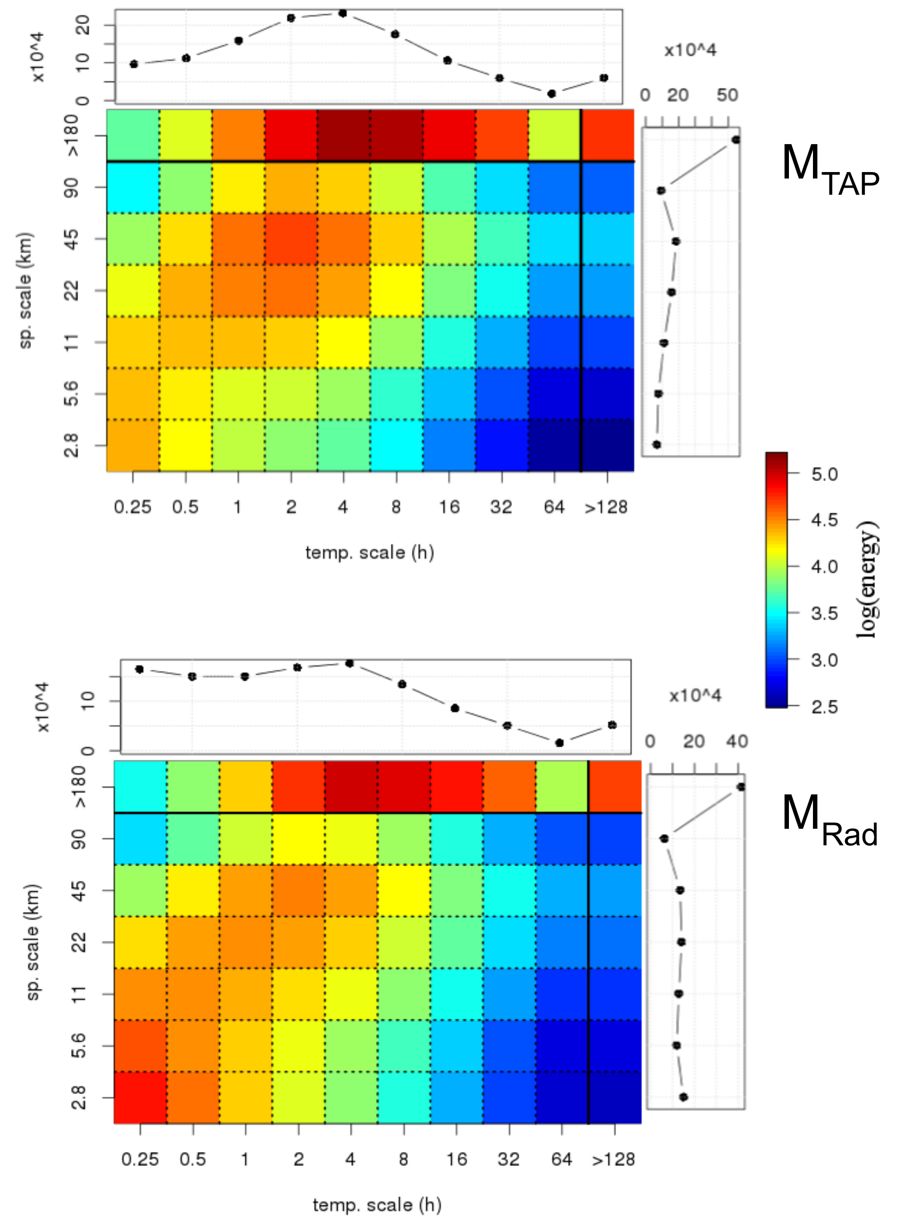
=> At 1°, 1day, the correlation between PF and R is 0.96

Spectral comparison of M_{Rad} and M_{TAP}

- Spectral energy:

  - Similar spectra

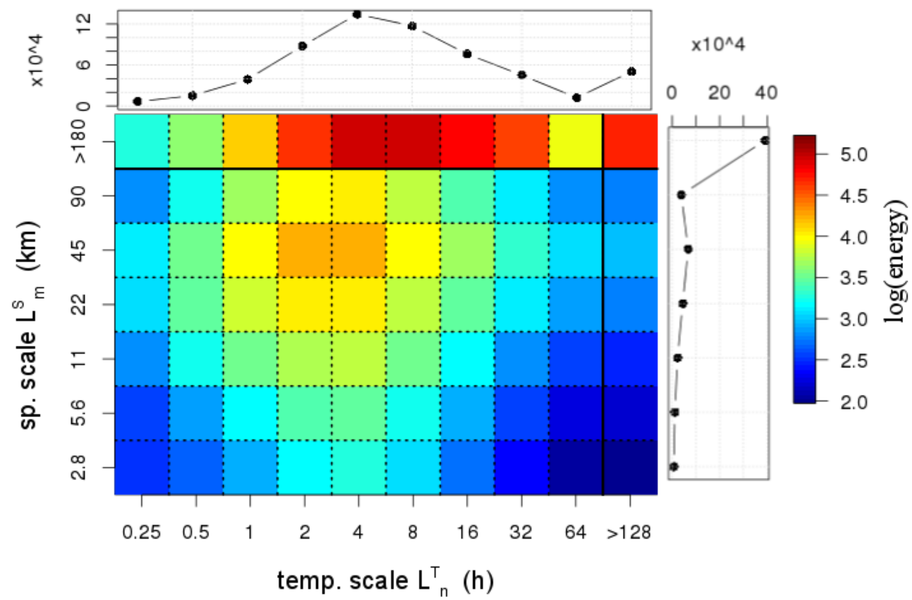
  - Small deficit of variance for TAPEER's mask in fine scales (<5.6 km and <30min): radar rain mask is more scattered.



Spectral comparison of M_{Rad} and M_{TAP}

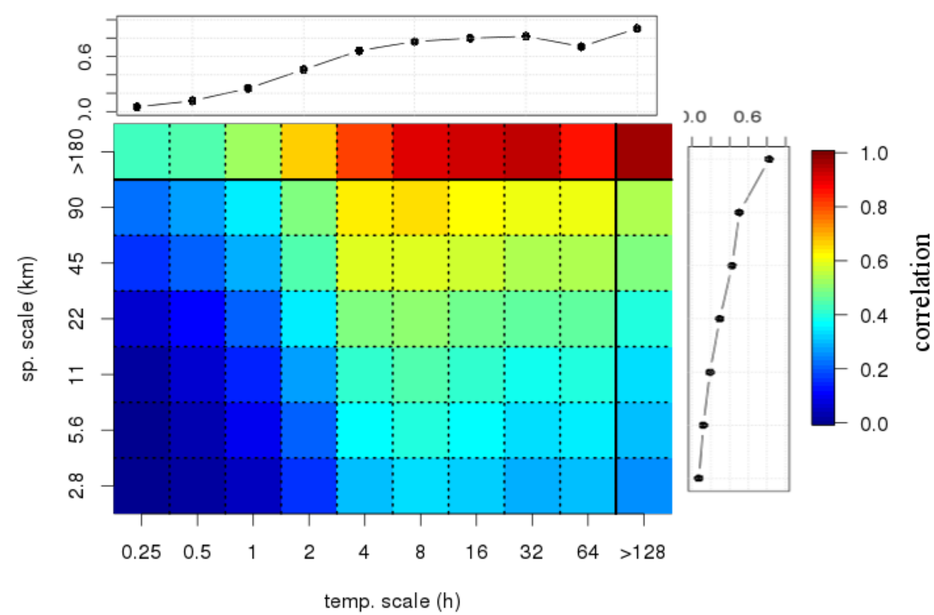
- Cospectral energy:

  concentrated around
  45 km, 2~4 h



- Wavelet coefficients' correlation:
  (wavelet coherence)

  consistency of large scales variations, fine scales nearly uncorrelated

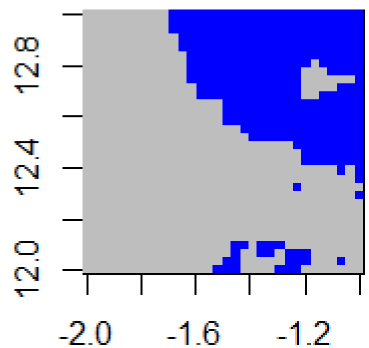


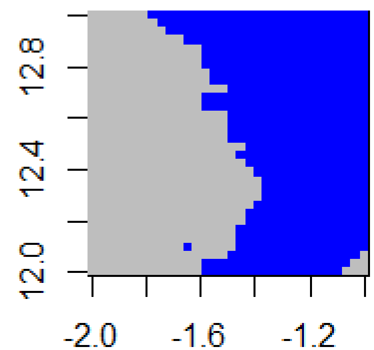
Guilloteau C, Roca R, Gosset M, 2016: A multiscale evaluation of the detection capabilities of high-resolution satellite precipitation products in West Africa, J. Hydrometeorology

Toward a probabilistic approach of rain detection

- At high resolution the relation between clouds IR brightness temperature and the occurrence of precipitation is not deterministic: FAR>0.45 at 3km resolution.

Radar detection





Satellite detection

- This advocates for a probabilistic approach of rain detection from satellite.

- Fine scale variations in satellite rain masks are not representing actual rain / no rain variability. These random variations can be considered as a "noise". Let's suppress it !

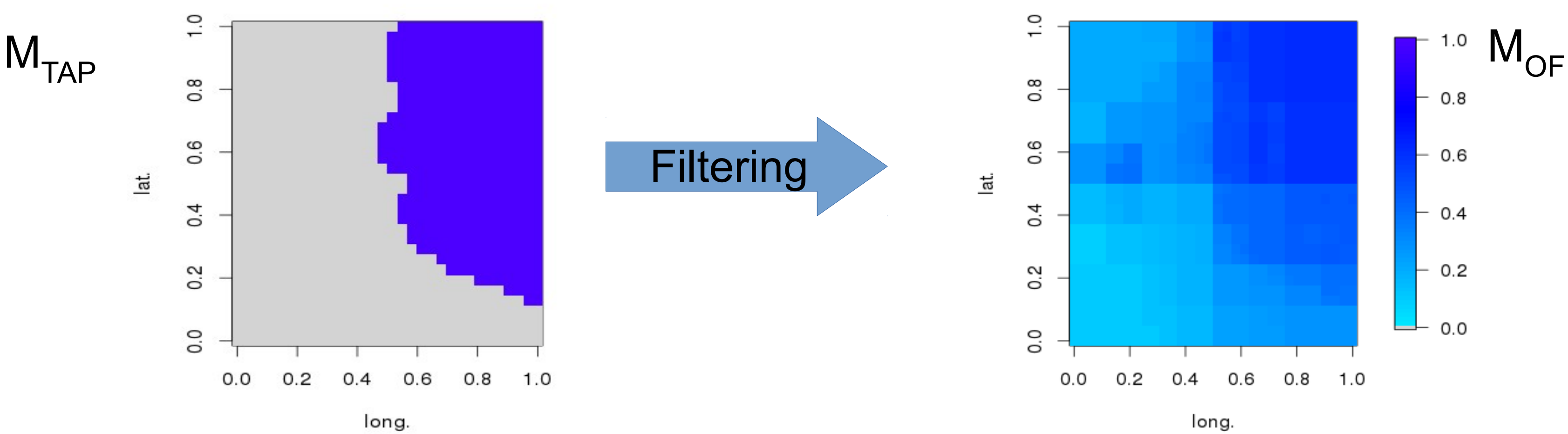
=> Wavelet based optimal filtering (Turner et al. 2004): wavelet coefficients are weighted to minimize the mean square difference with the radar mask. Large scale coefficients are retained, small scale ones are filtered out.

Turner, B. J., I. Zawadzki, and U. Germann, 2004: Predictability of Precipitation from Continental Radar Images. Part III: Operational Nowcasting Implementation (MAPLE). *J. Applied Meteorology*, 43(2), 231-248.

Wavelet-based optimal filtering

- Wavelet transform : $M(X) \Rightarrow W_M(X, L_S, L_T)$
- Weights determination for filtering:

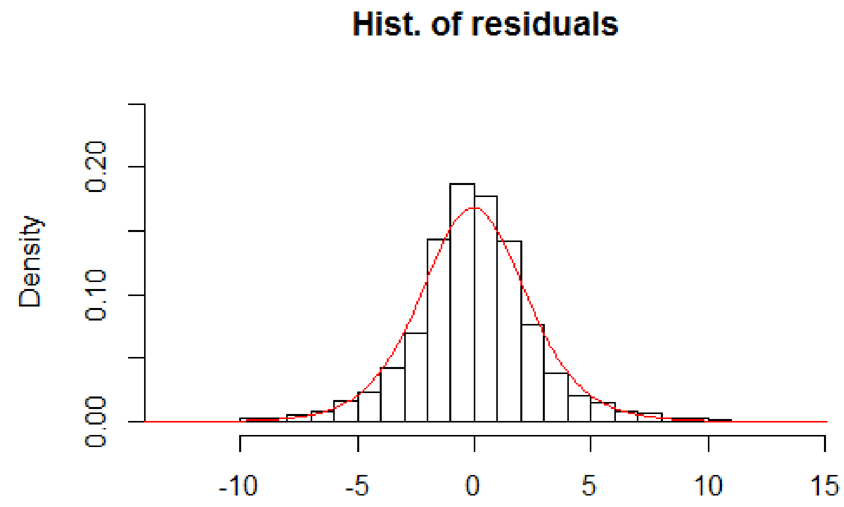
  $\alpha(L_S, L_T) = \mathrm{cov}(W_{sat}(L_S, L_T), W_{radar}(L_S, L_T)) / \mathrm{var}(W_{sat}(L_S, L_T))$
- Inverse WT : $\alpha(L_S, L_T)\, W_I(X, L_S, L_T) \Rightarrow I_{OF}(X)$



- M_{OF} is no more a mask. It is the mean value of M over a fuzzy neighborhood around (x,y,t). It can be interpreted as a probability of rain, or a precipitating fraction.

Residuals analysis after filtering

- Residuals M_{OF}-M_{rad} analyzed through wavelet transform

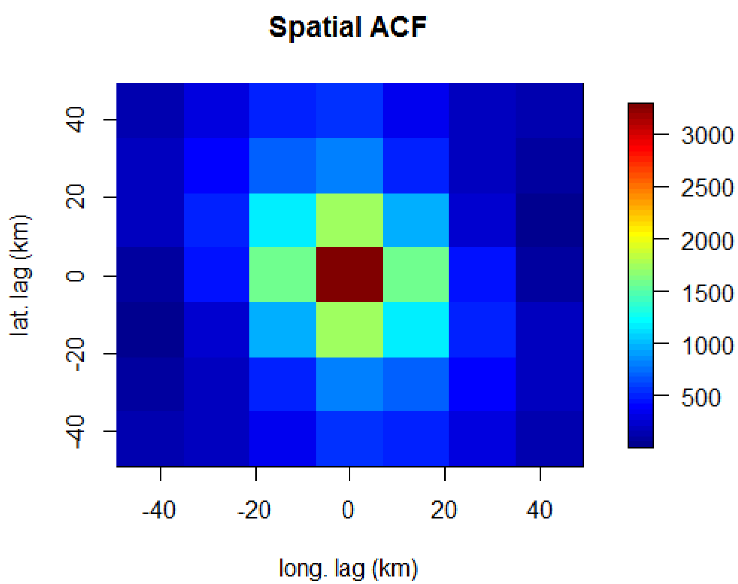


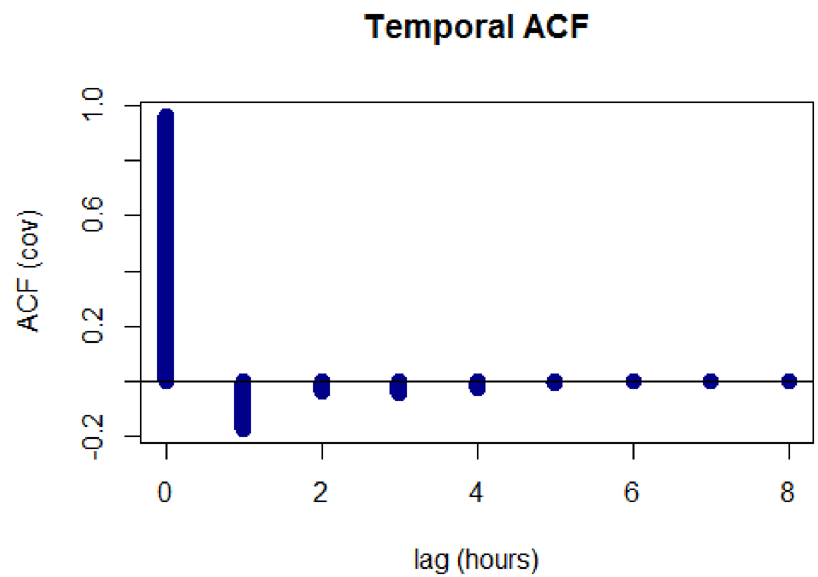
LLH, L_T=1h, L_S=12km

- Distribution of wavelet coefficients:

  A Pearson-type model at each scale

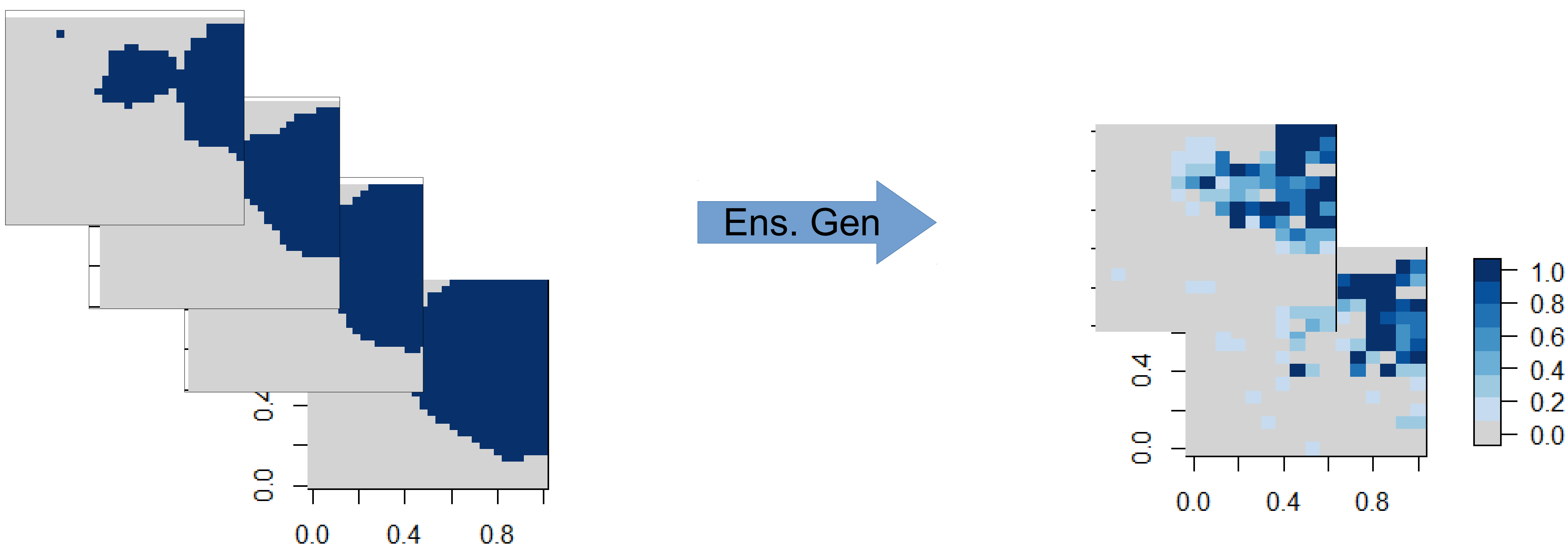
- Autocorrelation: rapidly decreasing





Wavelet-based optimal filtering + random signal

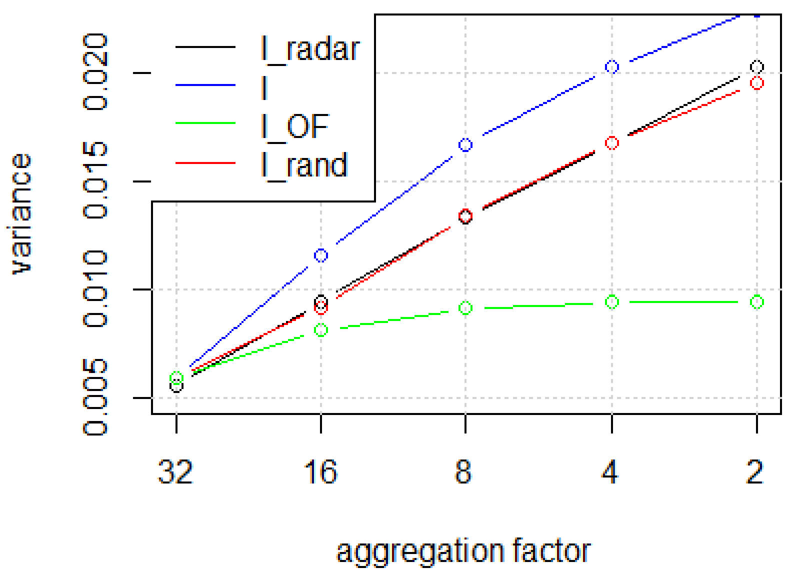
- Stochastic re-generation of the filtered-out fine scale variability.
- Inverse WT : $\alpha(L_S, L_T)\ W_M(X, L_S, L_T) + \beta_{rand}(X, L_S, L_T) \Rightarrow M_{rand}(X)$
- Because the result M_{rand} must be bounded between 0 and 1 some control is necessary: generated random variations are normalized (by the local value of the PF).
- The IWT is not performed down to the finest scale to avoid discretization issues.



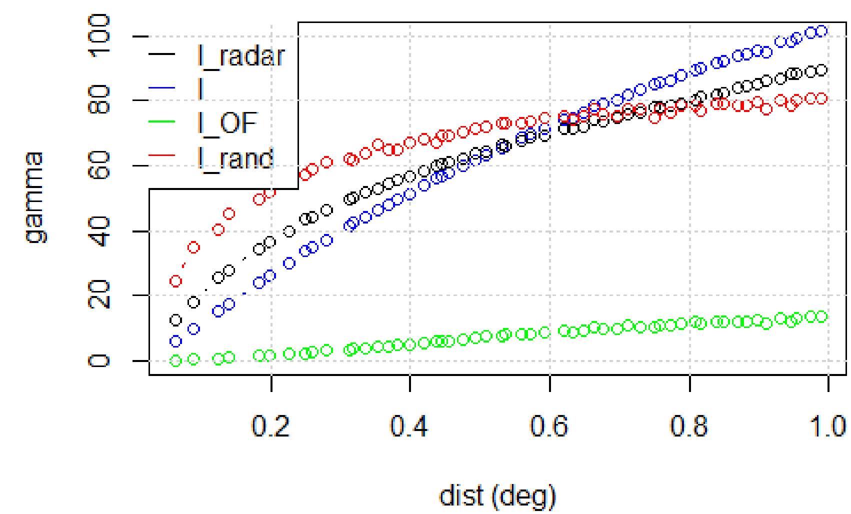
Generated PF fields properties

2012 season radar data for the learning
2013 season for validation

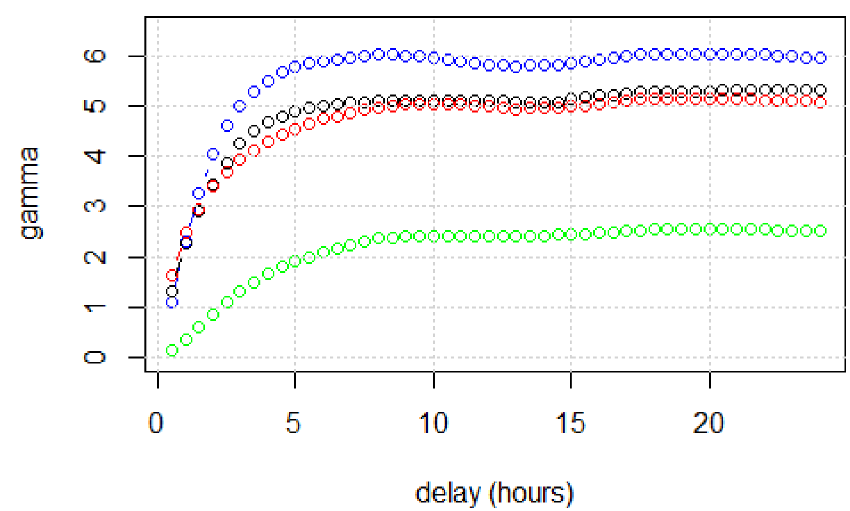
Variances at scales (8h,1°) (4h,0.5°) (2h,25km) (1h,12km) (30min,6km)



Spatial variograms

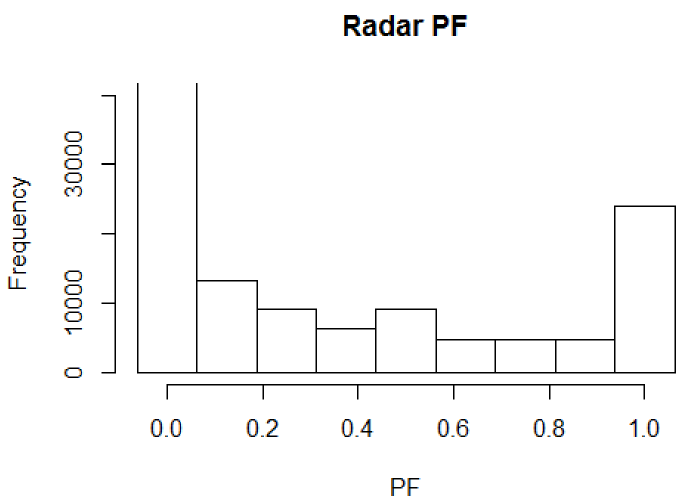


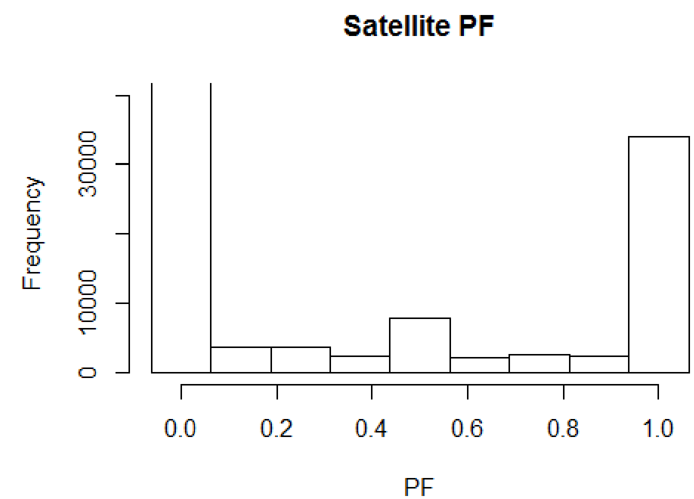
Temporal variograms

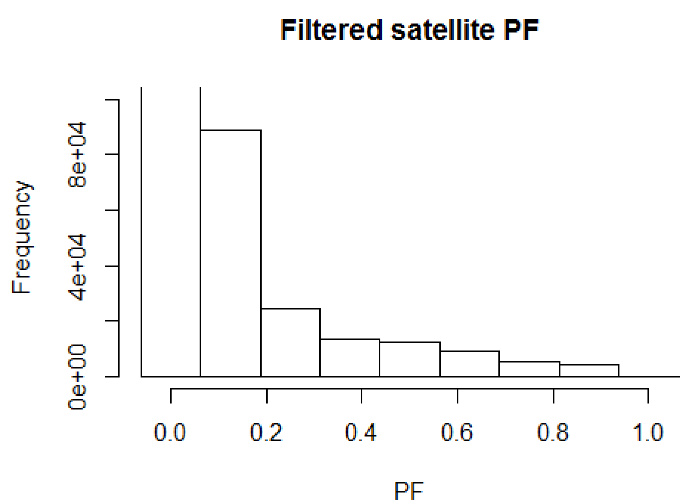


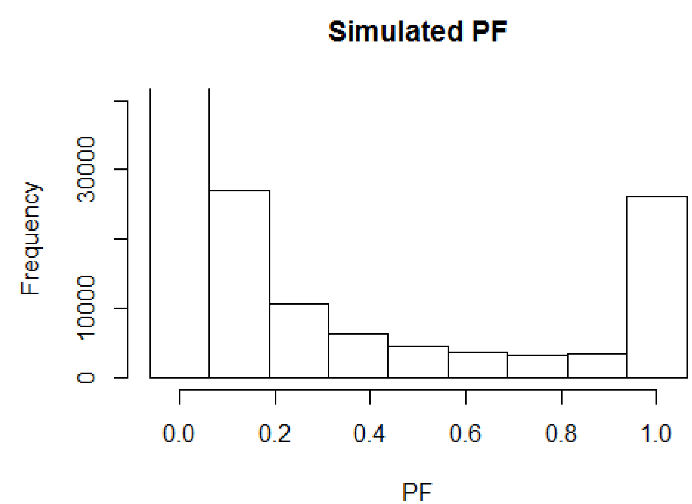
Generated PF fields properties

Precipitating fractions at 6km, 30min resolution









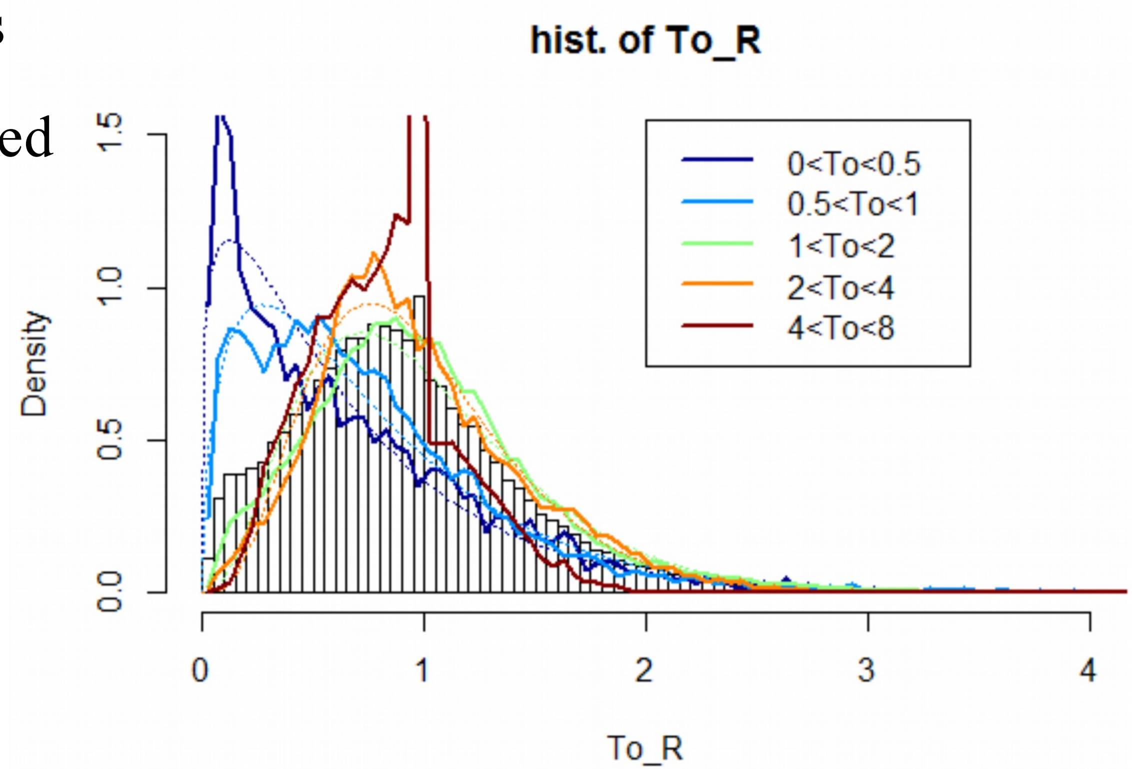
Simulating R_{cond} variability

- Estimated value of $\overline{R}_{cond}$ at the resoltion 1° × 1° × 8h
- Fine scale R_{cond} variability generated through a mutiplicative cascade:

  - A "volume" $2\Delta x*2\Delta y*2\Delta t$ is devided into 8 sub-volumes $\Delta x*\Delta y*\Delta t$

  - $R_{cond,1/8} = \tau_R * \overline{R}_{cond}$ with τ_R randomly drawn from a pre-defined distribution

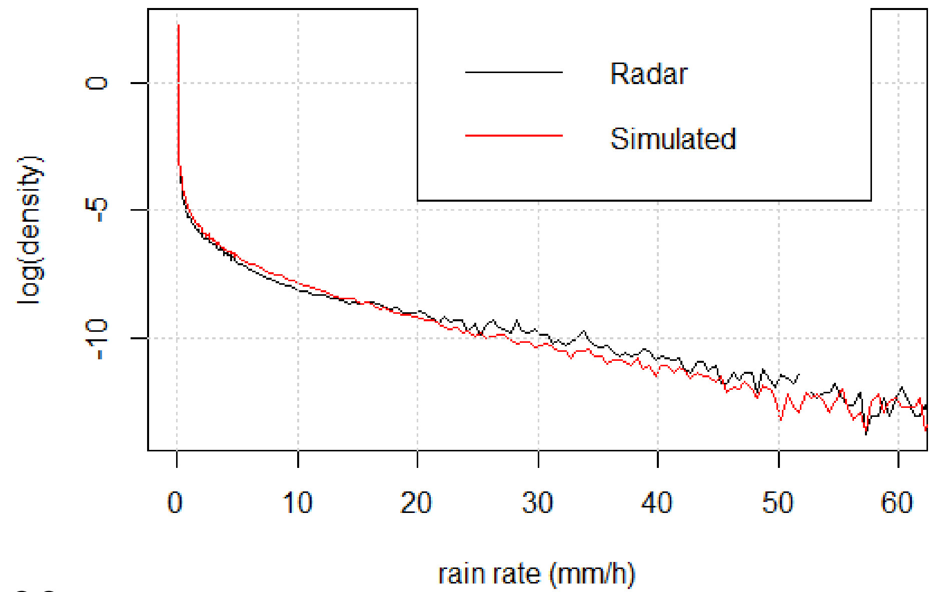
  - The distribution for τ_R depends on $\tau = FP_{1/8} / \overline{FP}$. It is parmetrized as a gamma.



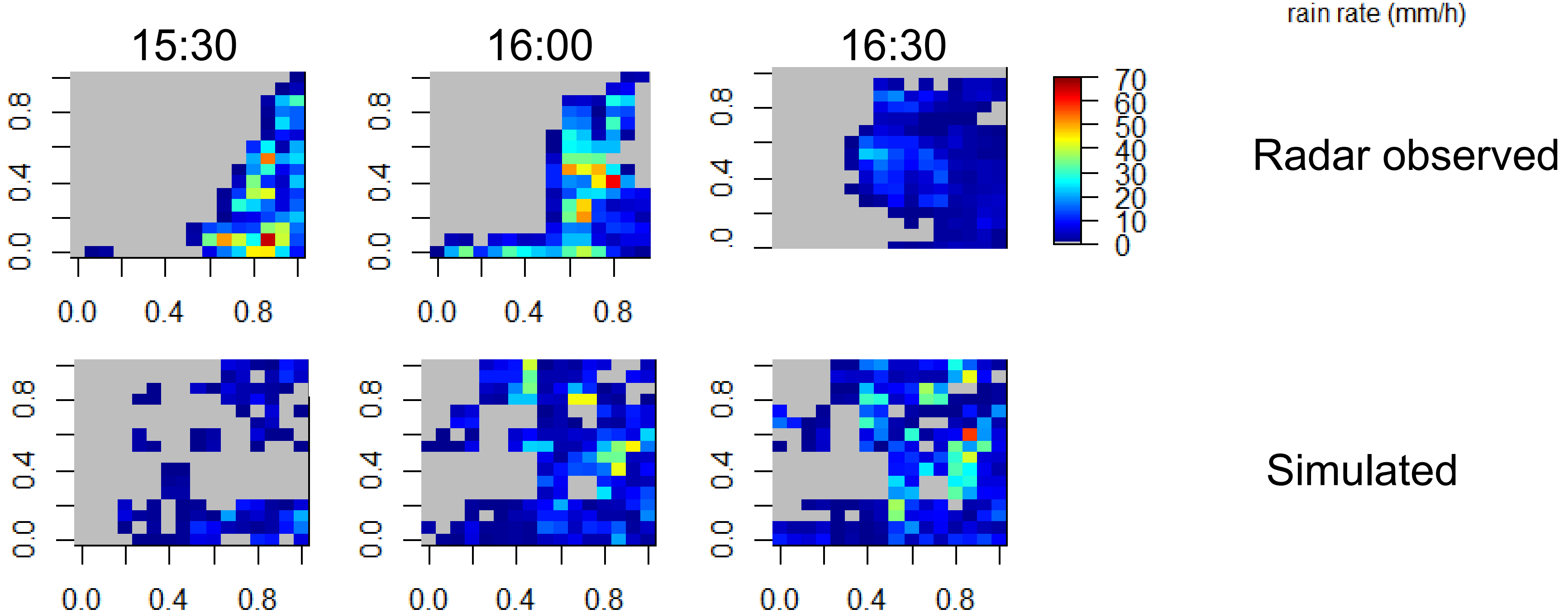
Generated R fields properties

Distribution of 6km, 30min rain rates:

2013 rainy season (May-October)

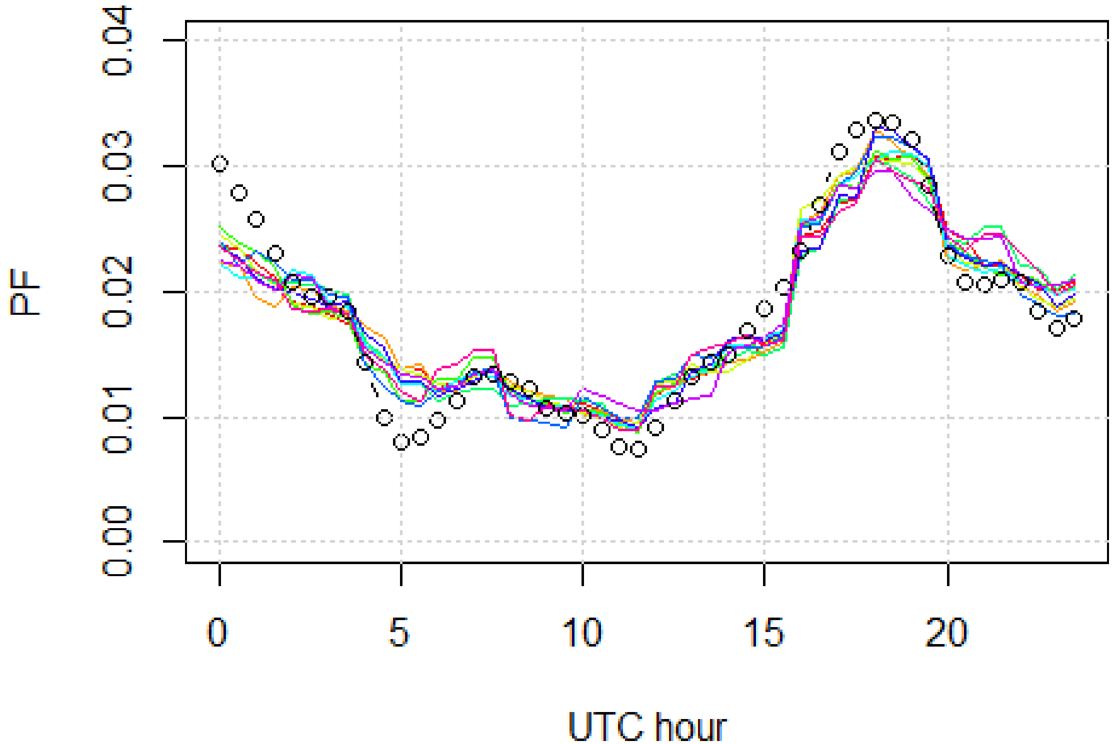


Simulated sequence (2013-05-27)



Diurnal Cycle of rain occurrence

Mean diurnal cycle, 2012-2013



Black dots: raw satellite detection fields

Colored lines: simulated ensembles

The filtering and adding of random variations preserved the diurnal cycle.

Conclusions

- A convenient framework to use time-area averages as constrain.
- At each scale the variations are partially deterministic and partially stochastic.
- The autocorrelation is constrained through the wavelet energy spectrum.
- Temporal and spatial variability handled by one process.
- The method can be seen as a stochastic downscaling or constrained simulation.
- Enables to quantify uncertainty on estimated precipitating fraction / cumulated depth at any resolution.

Perspectives

- A more global perspective: how variable are the estimated parameters in space and time?

  => Verify it using radar data from other climatic areas. For spatial-only variability spaceborne radars (TRMM-PR, GPM-DPR).

- A better way to handle R_{cond} variability. Under sahelian weather this variability is essentially driven by the convective or stratiform type of precipitation

- Use the generated fields to force an hydrological model.