

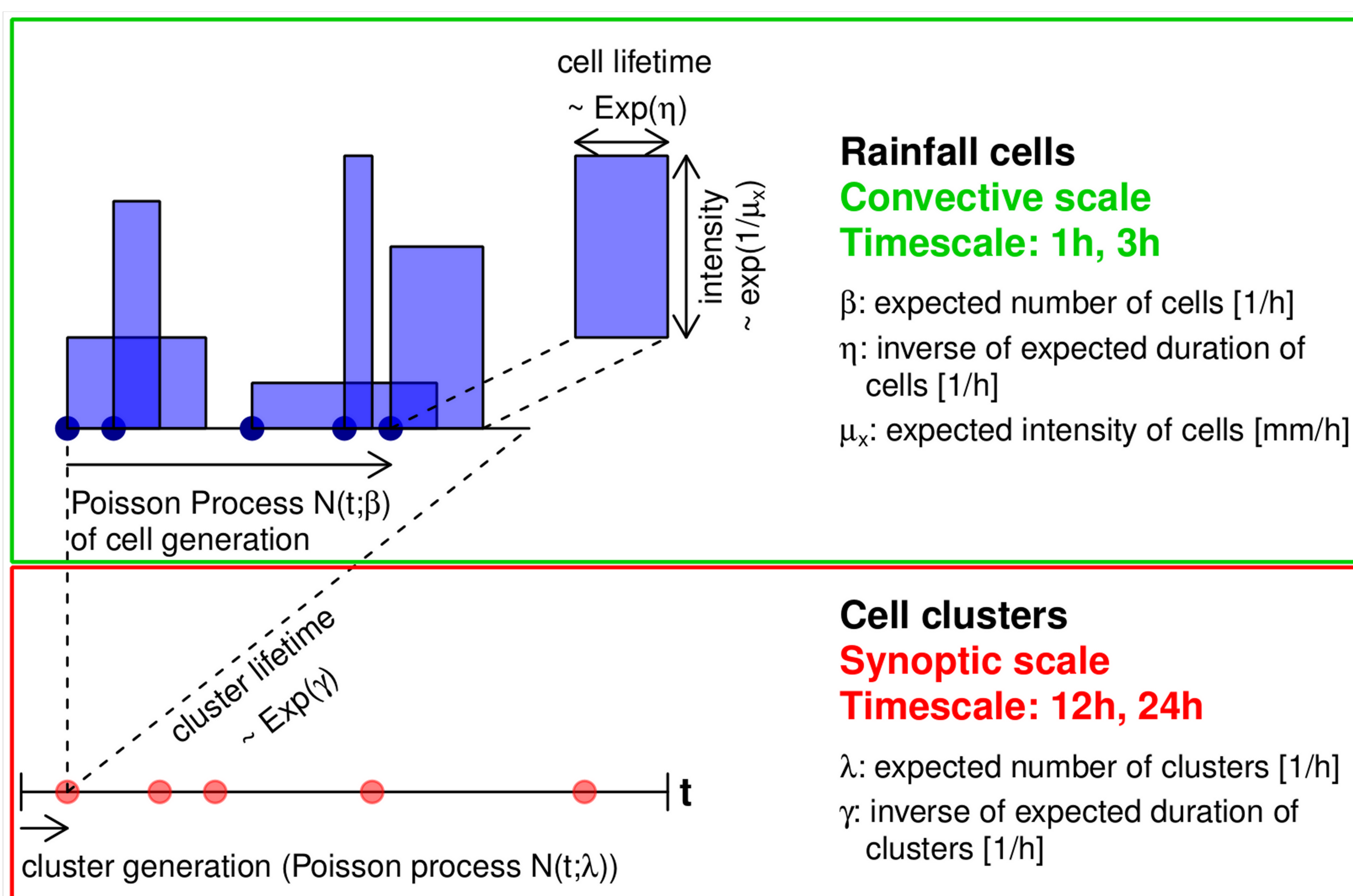
Precipitation extremes on multiple time scales - Original Bartlett-Lewis model and IDF curves

Christoph Ritschel, Annette Müller, Henning Rust, Peter Nèvir, Uwe Ulbrich
Institut für Meteorologie, Freie Universität Berlin, Germany

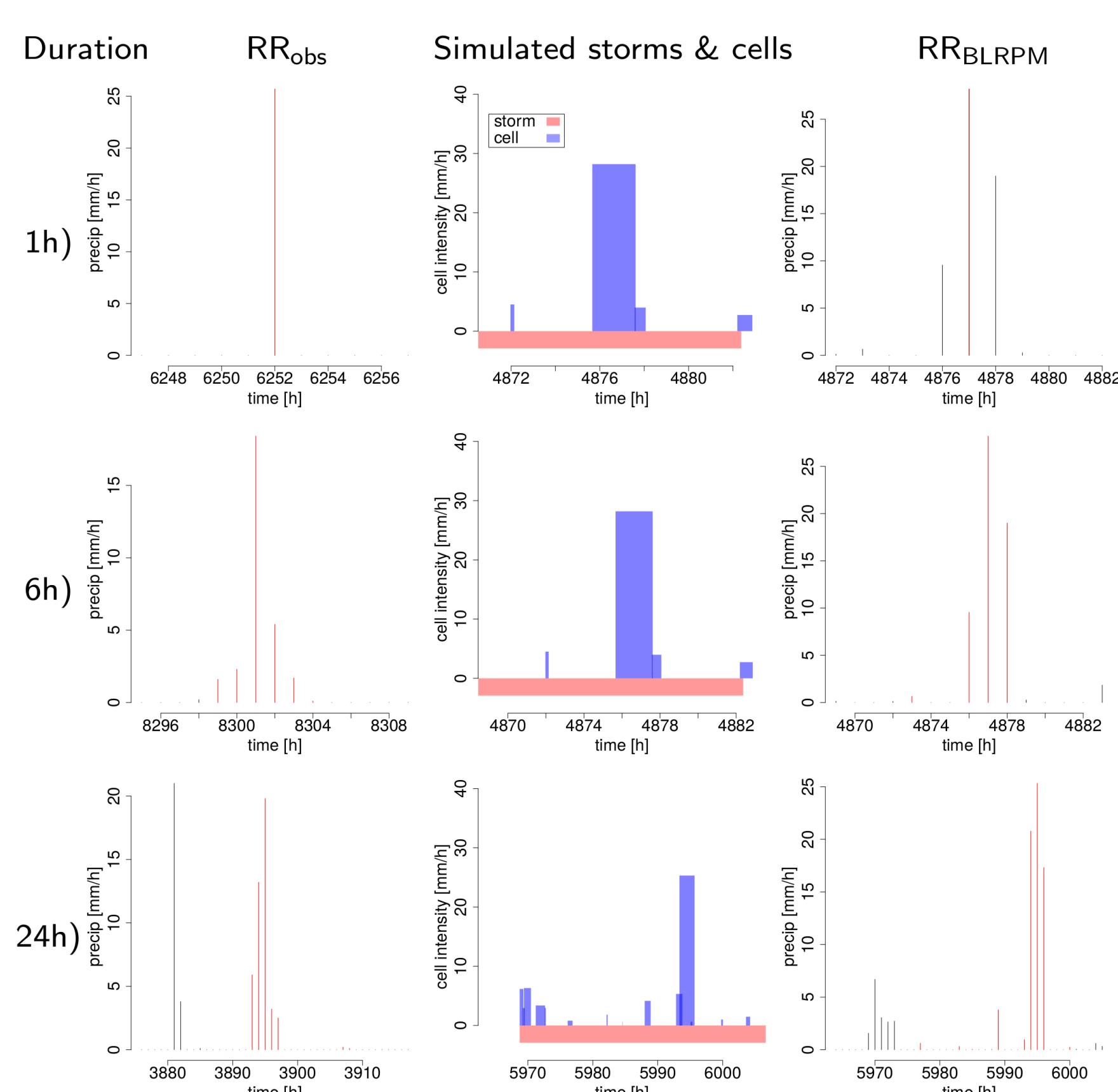
Multi-level stochastic precipitation modeling

Precipitation processes show a high variability on spatial (localized thunderstorms up to mesoscale hurricanes) and temporal (minutes to weeks) scales. Processes relevant on scales of extreme precipitation are not resolved in regional (RCMs) and global climate models (GCMs) and are thus not well represented. Improving their representation in these models is necessary for impact assessment and confidence in R/GCMs. Typically, parameterization of these processes is based on idealized and highly simplified models of sub-grid scale processes. Here, we explore the class of Poisson-cluster processes [Onof et al., 2000] for their suitability in subgrid-scale parametrizations. They are based on a hierarchy of Poisson processes living on different scales and are a natural approach for small scale (km, h) precipitation modelling, e.g. [Rodriguez-Iturbe et al, 1987, Cowpertwait, 1994].

Precipitation Model: Bartlett-Lewis rectangular pulse model



Characteristics of extremes in the BLRPM



Visualization of July extremes as observed (RR obs, left column) and simulated by the OBL model (RR OBL, right column). Shown are short segments including the maximum observed/simulated rainfall (red vertical bars) at durations 1h (top row), 6h (middle row) and 24h (bottom row). Additionally, the middle column shows the simulated storms (red rectangles) and cellsm (blue rectangles) corresponding to the extreme event of the simulated time series

Intensity-Duration-Frequency Analysis

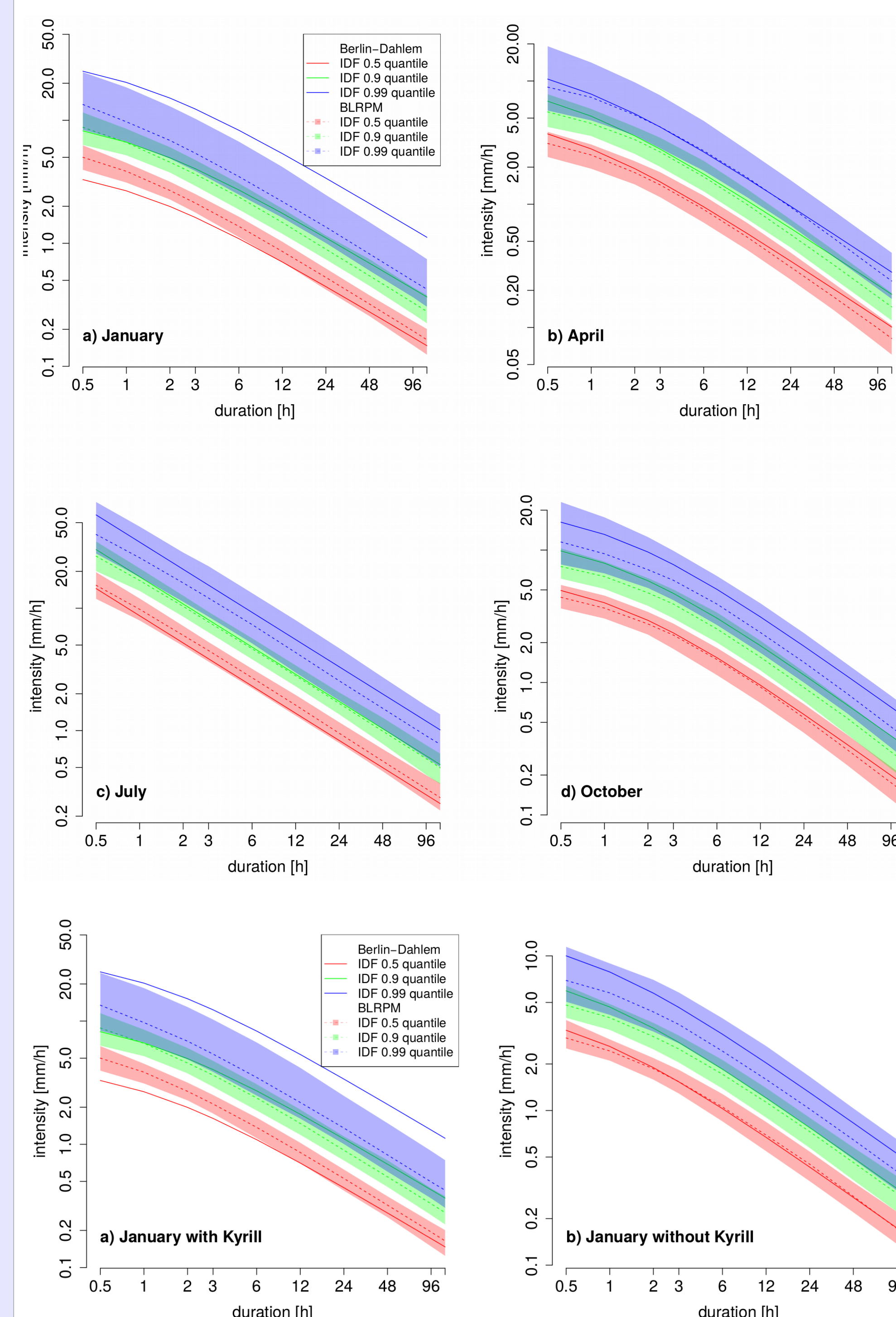
Intensity-duration-frequency (IDF) curves show return levels as a function of rainfall duration, typically for a range of return periods. We estimate IDF curves from monthly maxima of precipitation with different aggregation times (1h to 72h) using the generalised extreme value (GEV) distribution (Coles et al., 2001) and the following relation for different durations d Koutsoyiannis et al. (1998), leading to a duration dependent formulation of the GEV:

$$\sigma_d = \frac{\sigma}{(d + \theta)^\eta} \quad F(x; \mu, \sigma_d, \xi) = \exp \left\{ - \left[1 + \xi \left(\frac{x}{\sigma_d} - \mu \right) \right]^{-\frac{1}{\xi}} \right\}$$

with θ , η and σ being independent of d .

This allows simultaneous modelling of rainfall maxima across different durations using a single GEV distribution at the cost of only two additional parameters which can be estimated by maximum-likelihood (Solyk et al., 2014).

IDF curves for Berlin-Dahlem



▪ **Data:** Berlin-Dahlem 5min-precipitation time series recorded by a tipping bucket from 2001 until 2013 and calculated block-maxima for every month at 1h, 3h, 6h, 12h, 24h, 48h, 72h and 96h for IDF analysis.

▪ IDF curves for Berlin-Dahlem can be well reproduced with BLRPM simulated rainfall across the year

▪ Discrepancies for January are due to Kyrill (18/19.01.2007) with extreme precipitation which lead to a large shape parameter; the outstanding value does not propagate to the BLRPM parameters and lead thus to smaller spacings between the quantiles in the IDF plot

▪ If Kyrill is excluded in fitting the January extremes, the model is able to capture the remaining observed extremes.

Conclusions

- Extremes in OBL model mainly due to one long lasting cell with high intensity
- IDF relationship generally well reproduced with the OBL model, tendency to underestimate extremes with long return period
- Problems with very rare extremes in short time-series, e.g. Kyrill in 2007
- Including third moment in fitting the OBL parameters does not significantly improve the extremes in the OBL model (not shown)

Outlook: Link between stochastic simulated precipitation and DSI on multiple scales

Radar image

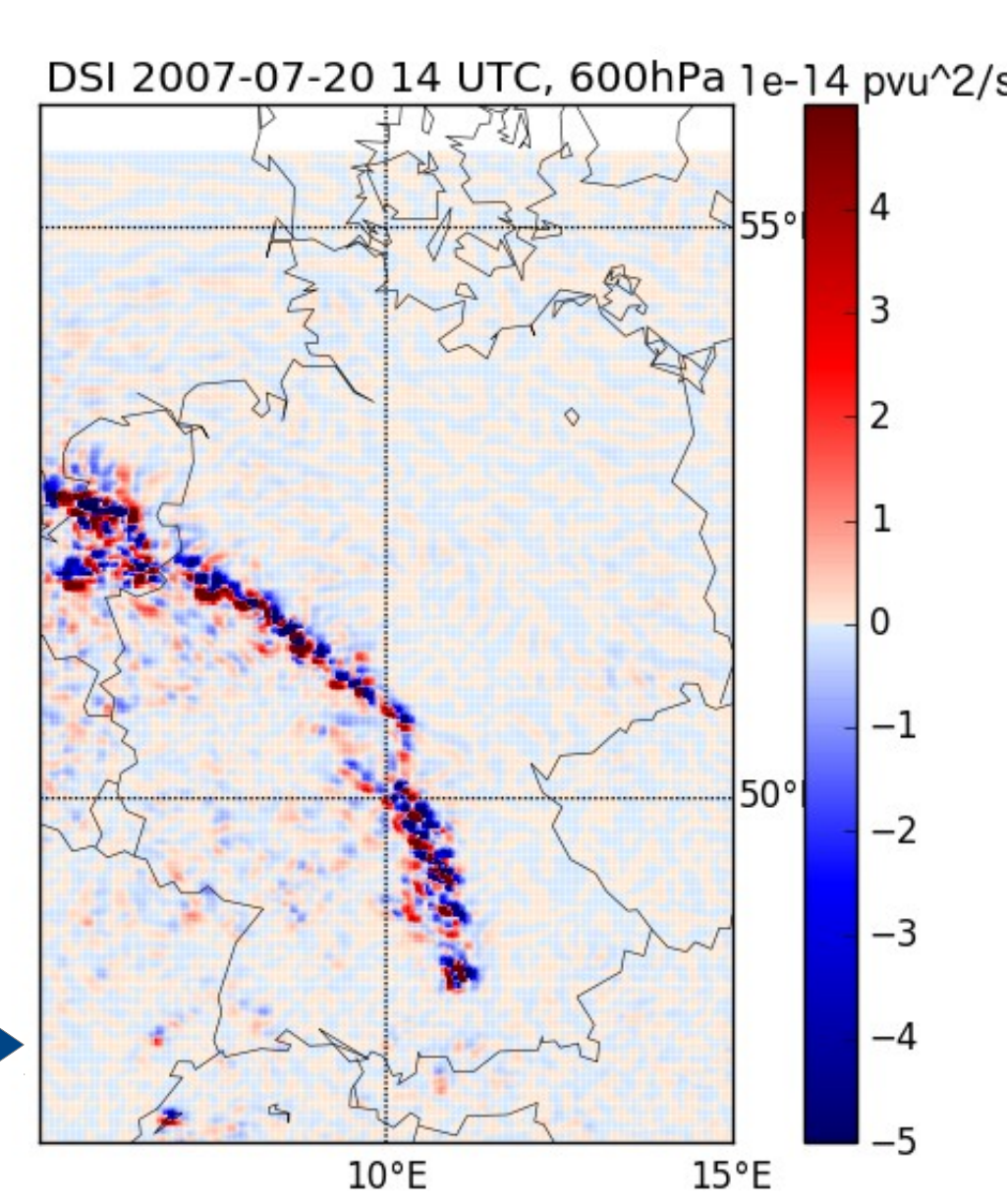


$$\Theta = \Theta(\text{DSI}, \text{CAPE}, \dots)$$

Coupling the stochastic precipitation model and a GCM requires (a) downward-coupling from the grid-scale (or larger) to the stochastic precipitation model, conceiving how the large scale flow shapes a convection permitting environment, and (b) upward-coupling, specifying the effects convection and the associated condensation with latent heat release has on the grid scale flow.

Stochastic precipitation model
Precip(Θ)

Stochastic Parametrization
DSI, CAPE(Precip)



Acknowledgments and References

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