Recent research work on stochastic parameterization using cellular automata

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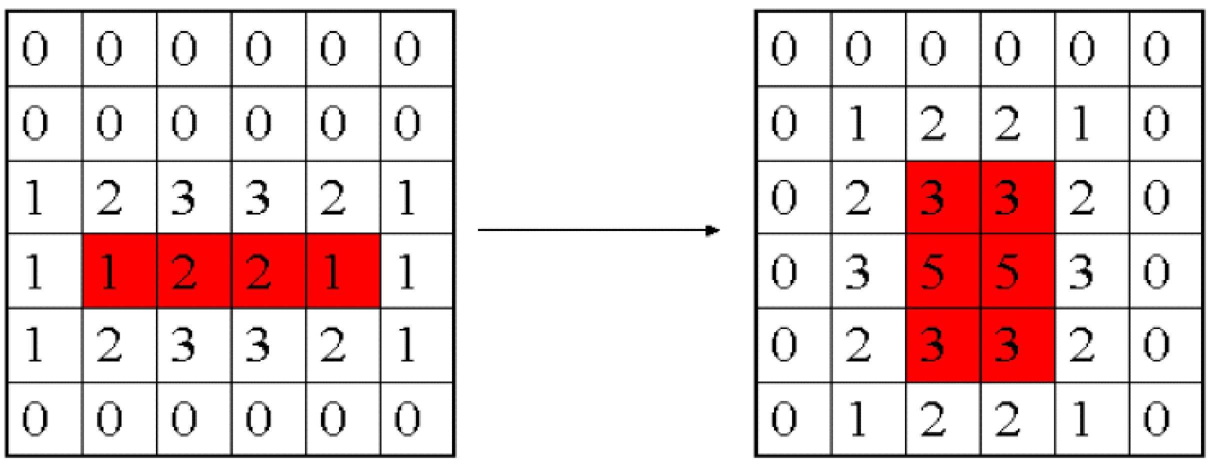
Outline of presentation

- A brief background
- Deep convection parameterization
- Ensemble Prediction and sub-grid variability
- Atmospheric scale interaction

Cellular Automata (CA)

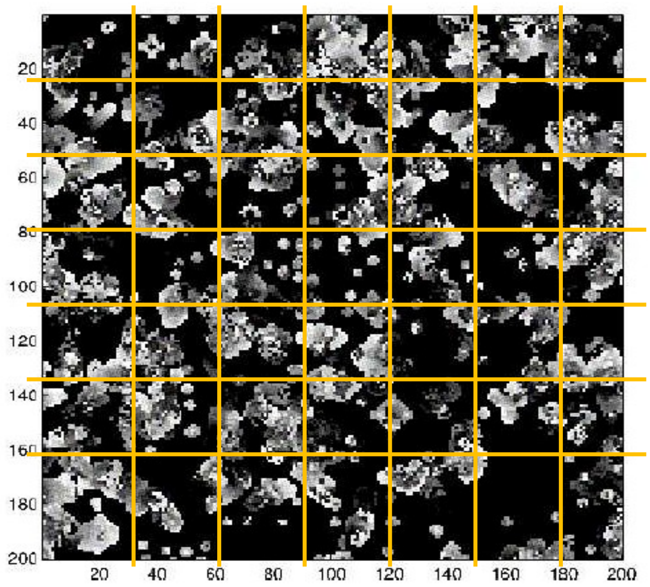
A CA is a dynamical system with a state vector which takes on a number of discrete (often just two) states. This CA state vector is defined on a discrete grid of points in space and time

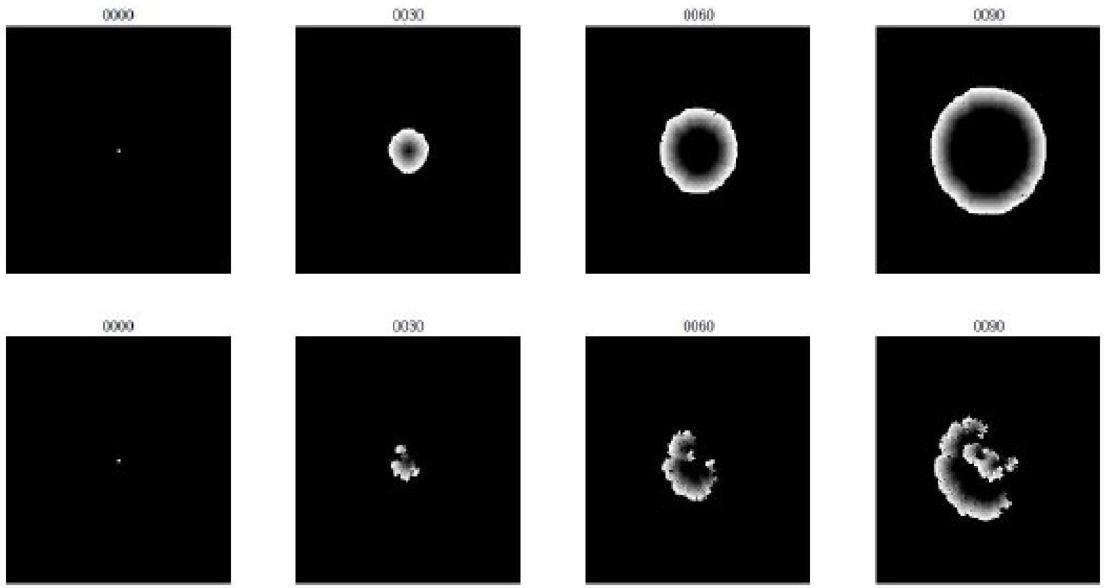
A set of rules are defined to determine the state of a cell at t+1, by using the states of the neighbourhood cells at t.



The ”birth” and ”survival” of a cell state is dependent on the number of ”living” nearest neighbours.

Cellular Automata (CA) in NWP





From Martin Steinheimer, ECMWF

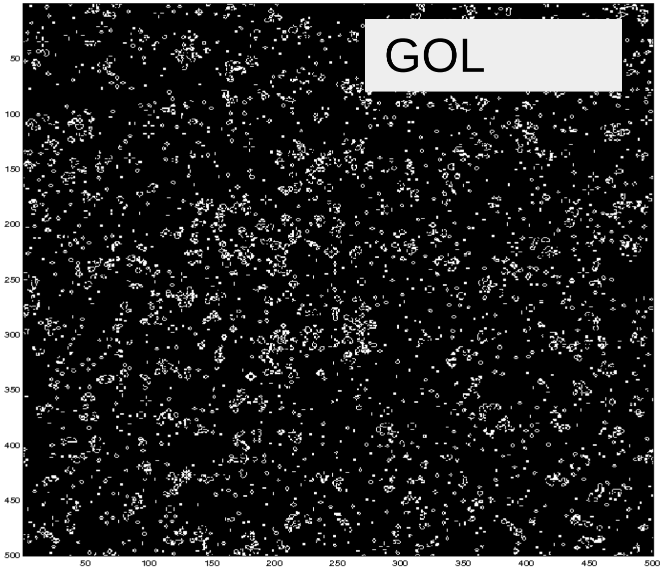
- Bengtsson et al. (2013) used a cellular automaton for the parameterization of convection, which allows for the horizontal transports of heat, moisture and momentum across neighbouring grid-boxes.

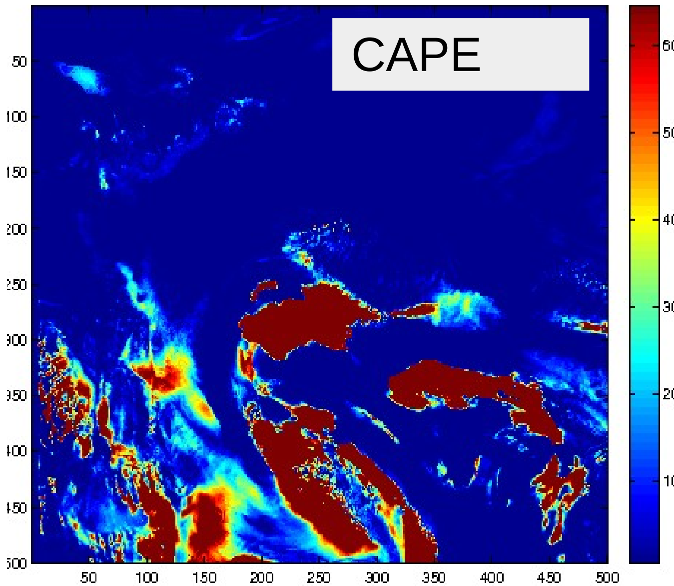
- It possesses many qualities interesting for deep convection parameterization.

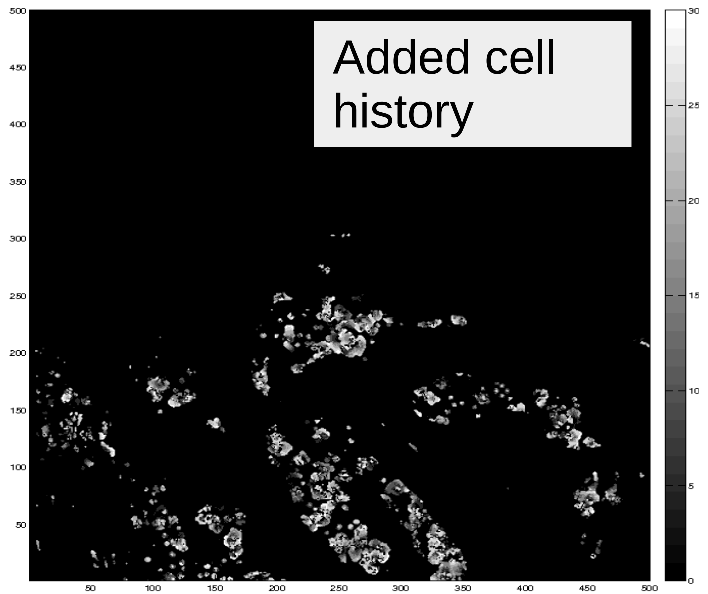
  - Horizontal communication
  - Added memory
  - Stochastisity

Stochastic parameterization of cumulus convection using cellular automata

- Can we use random numbers and self-organizational properties of cellular automata to mimic statistical fluctuation in cloud numbers and intensities?
- Can we allow for horizontal organization and communication between adjacent model grid-boxes in the cumulus parameterization?
- *Bengtsson, L., Steinheimer, M., Bechtold, P. and Geleyn, J.-F. (2013), A stochastic parametrization for deep convection using cellular automata. Q.J.R. Meteorol. Soc., 139: 1533–1543.*







Prognostic updraft mesh-fraction

$$\frac{\partial \sigma_u}{\partial t} \int (h_u - \overline{h}) \frac{dp}{g} = L \int \sigma_u \omega_u^* \frac{\delta q_{ca}}{g} + \alpha_{cvg} L \int CVGQ \frac{dp}{g} + \frac{\sigma_{CA} - \sigma_u}{\tau} * (\int (h_u - \overline{h}) \frac{dp}{g})$$

Storage =
Increase of mesh
fraction

I

Sink =
Gross
condensation
(consumption
by updraft)

II

Source =
resolved
moisture
convergence

III

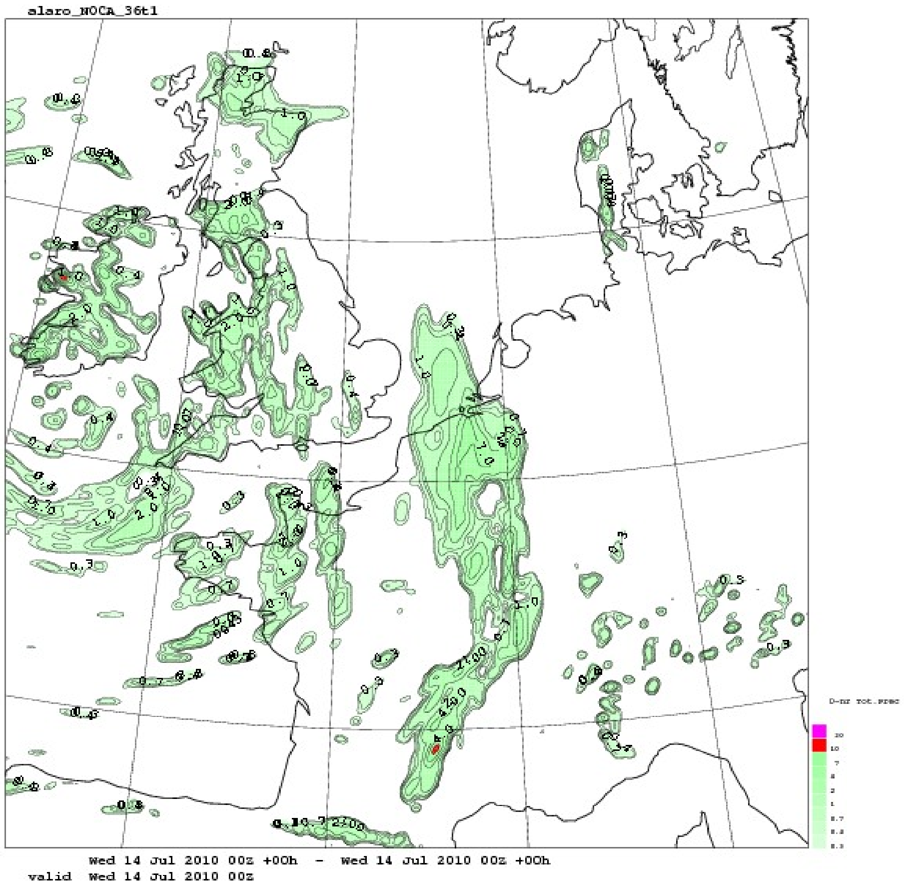
Source/(sink)
organization by
CA

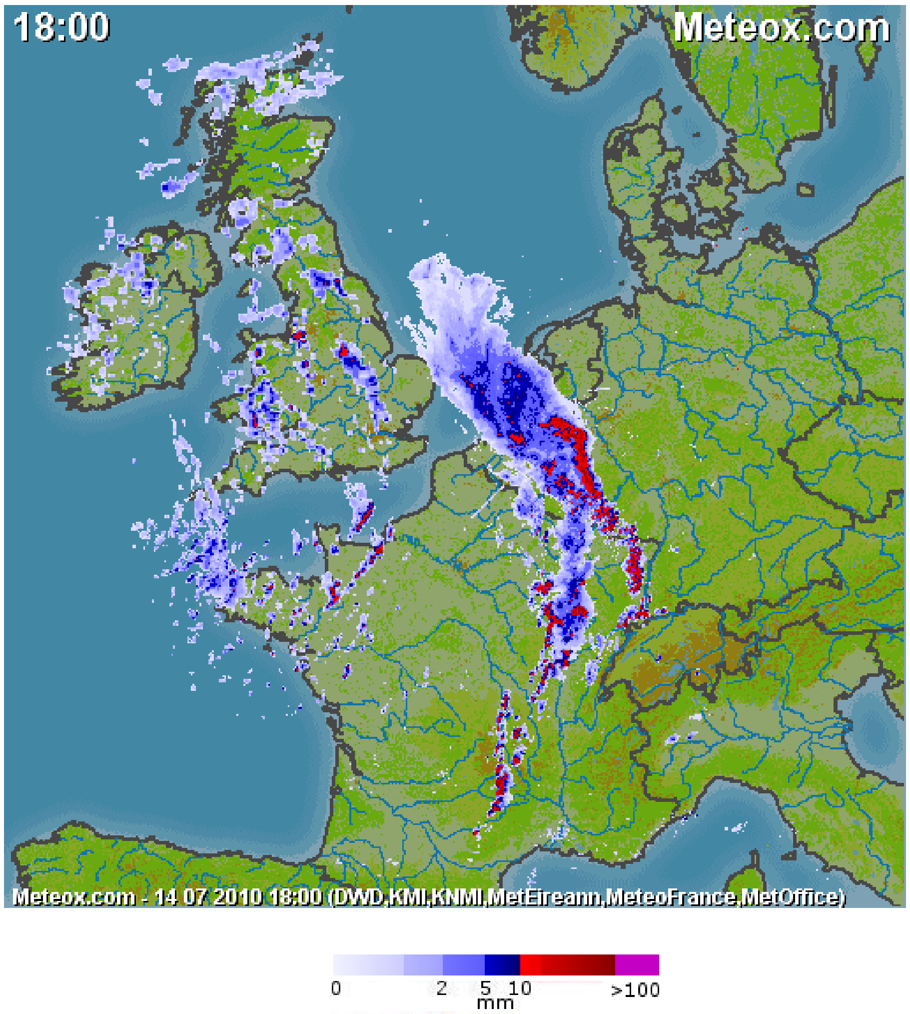
Function of
CAPE
or/and
Low level
moisture
convergence

IV

$$\frac{\sigma_u^+ - \overline{\sigma_u}}{\Delta t} = \frac{\sigma_{CA} - \sigma_u^+}{\tau}$$

Radar image, squalline 14/7-10
16 UTC (or 18 CET)

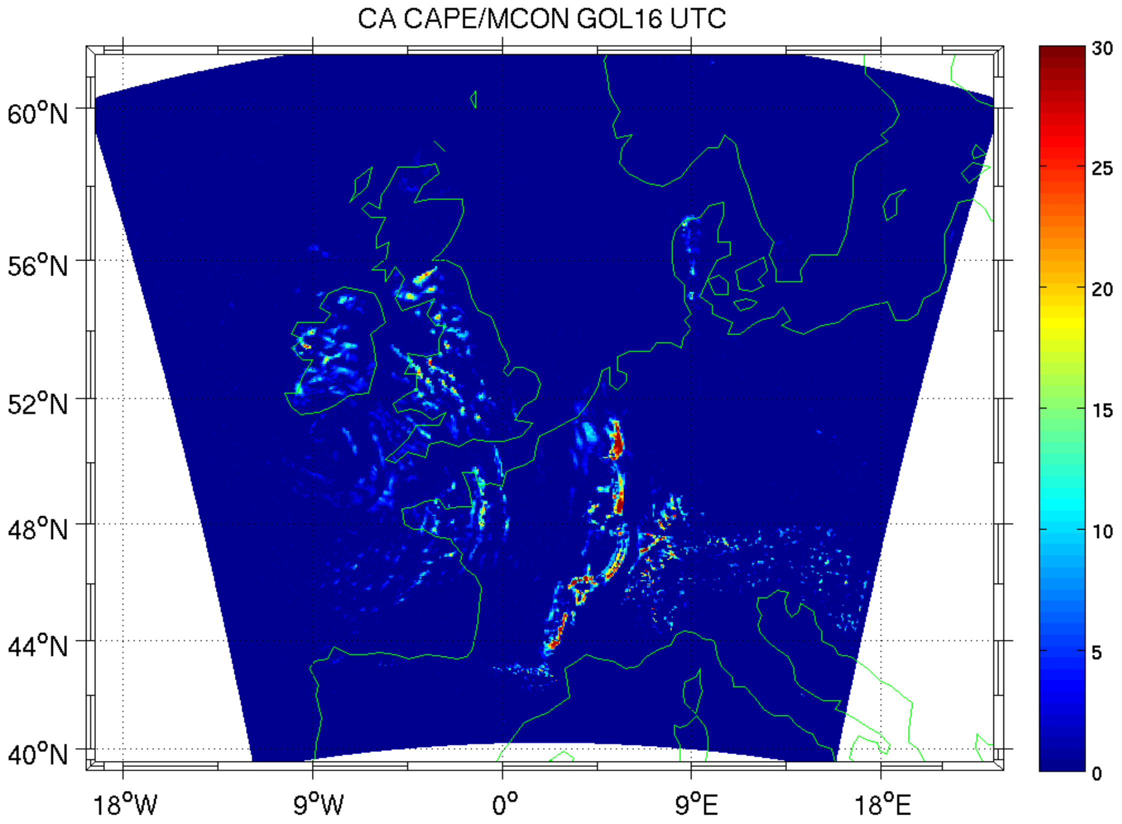




ALARO 36h1.1, total 1h precip.
(No data assimilation, cold start)

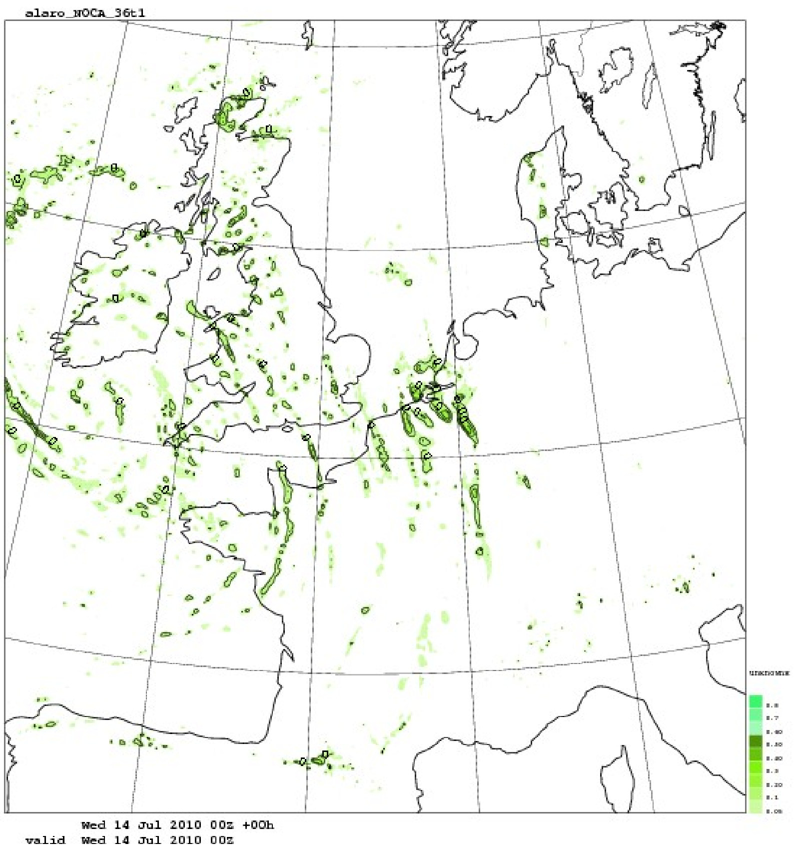
1 hour precip from radar image.

Cellular automata field on NWP grid



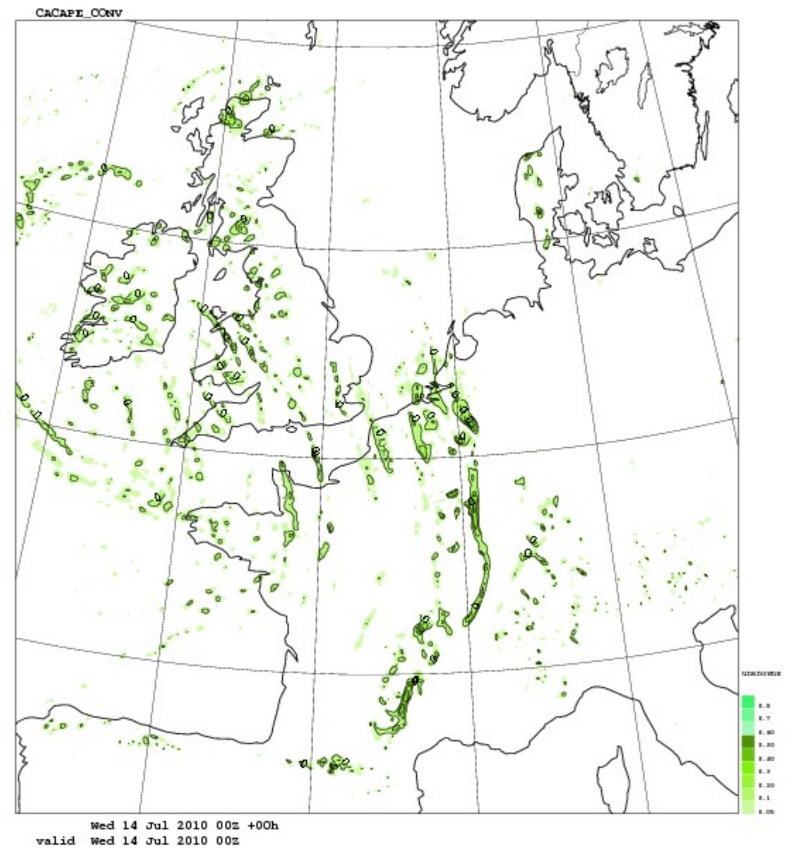
Updraught mesh fraction, 2010-07-14

ALARO reference, 36h1.1



16 UTC

ALARO CA exp, 36h1.1



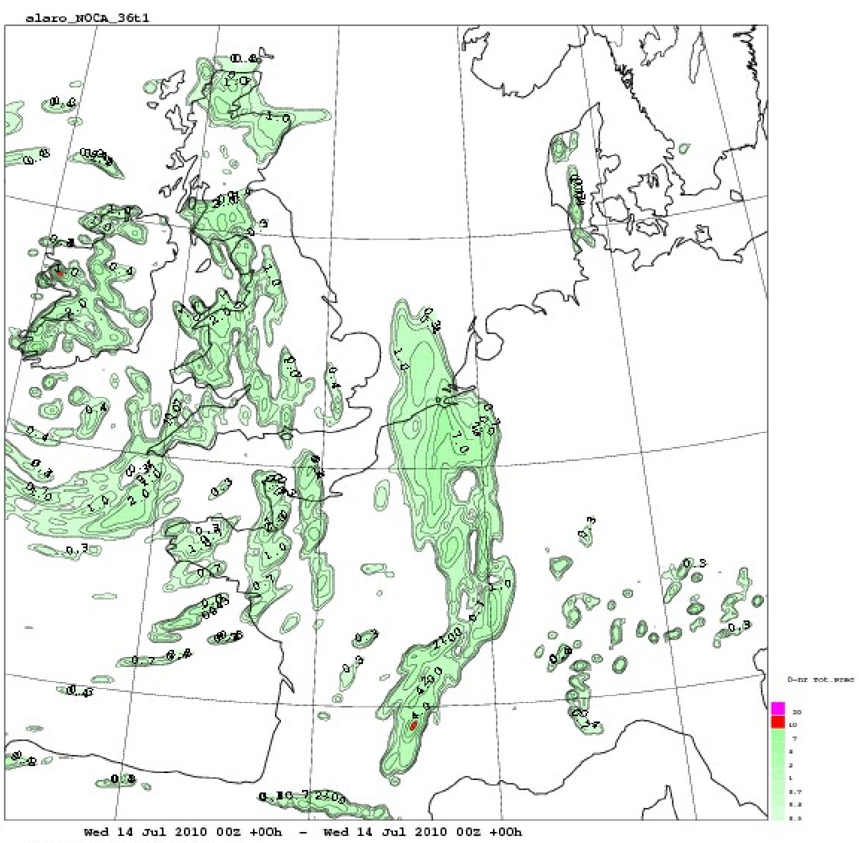
16 UTC

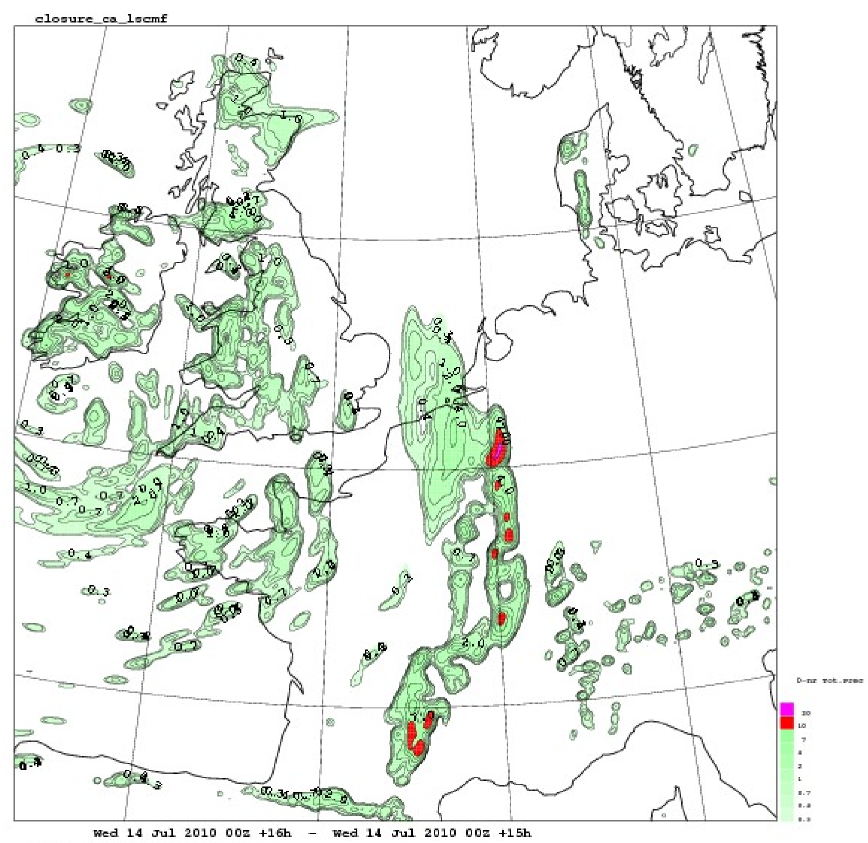
Total precipitation, 2010-07-14

ALARO reference, 36h1.1

ALARO CA-CAPECONV, 36h1.1

LSCMF = FALSE





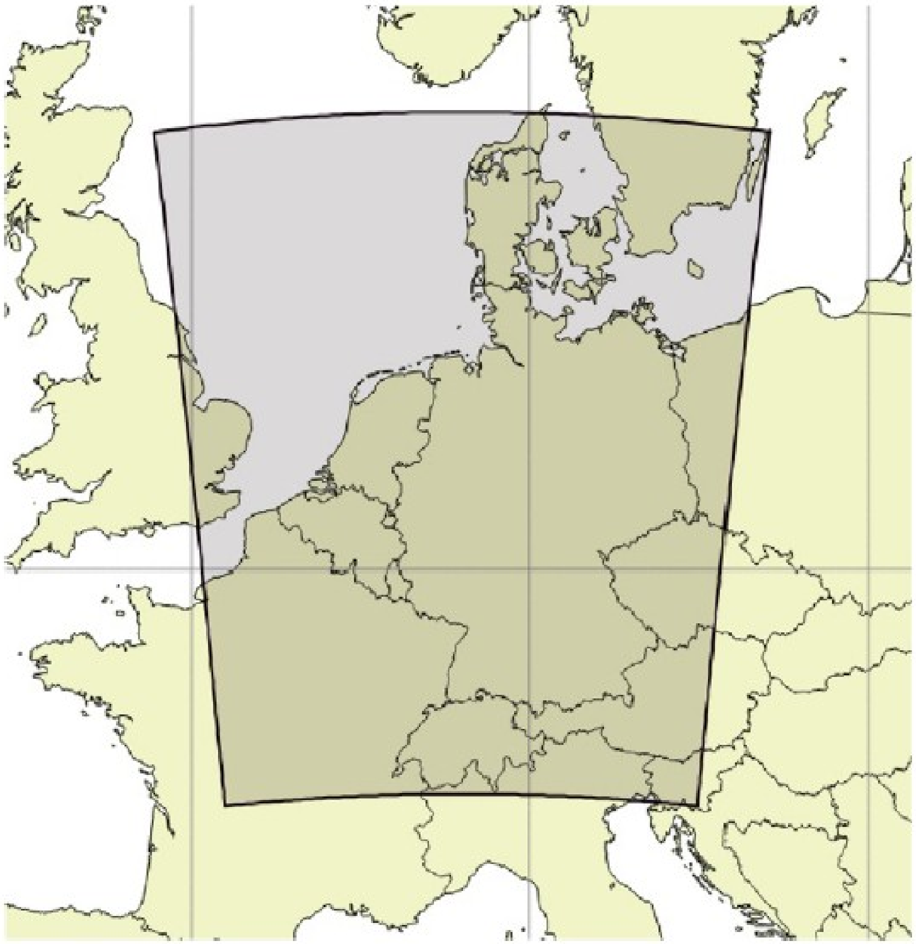
16 UTC

16 UTC

Ensemble Prediction using the stochastic scheme

Can the proposed scheme have an impact on the performance of the ***uncertainty estimates*** given by an ensemble prediction system?

Experiment setup



- 18 day period June, 2012.

  36 h forecasts, initiated 00 and 12 UTC.

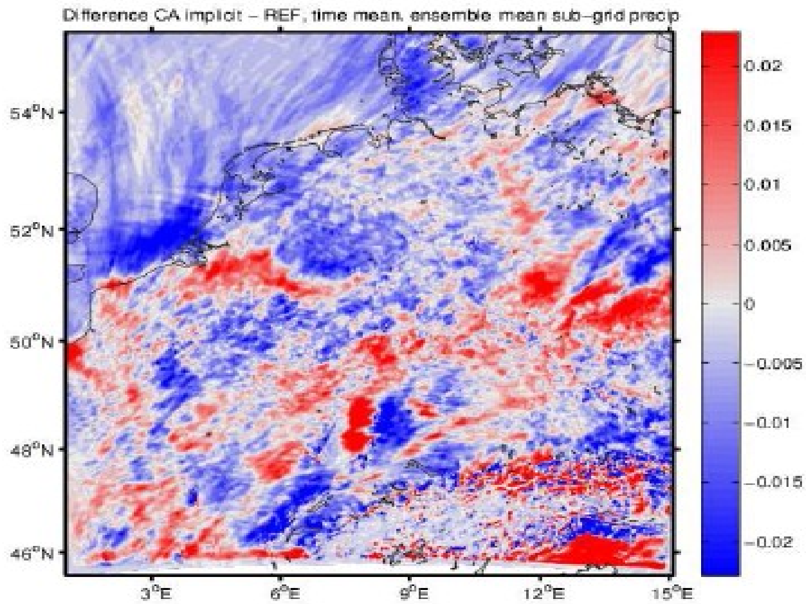
  The control member is using 3D-variational data assimilation, with 6 hour cycling.

  The perturbations come from the boundary and initial conditions updated at 00 UTC and 12 UTC, where each member of HarmonEPS uses a member from the ECMWF EPS with 16 km horizontal resolution. (Courtesy of Martin Leutbecher, ECMWF). All perturbed members use their own surface data assimilation.

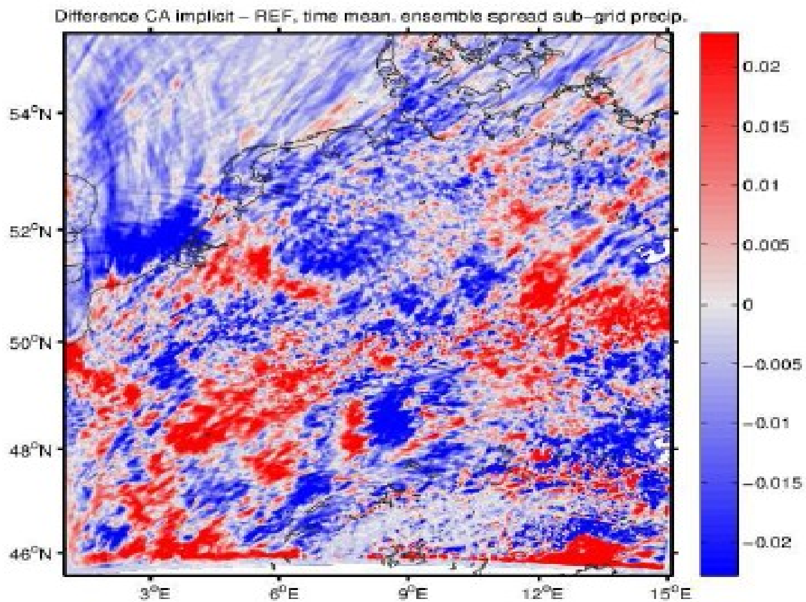
  The reference experiment uses only 10+1 members with ALARO physical parameterization.

  Te cellular automata (CA) experiment uses the exact same initial/lbc perturbations, but each member has a different random seeding in the initialization of new CA cells.

Monthly Mean of 6h *sub-grid* precip.

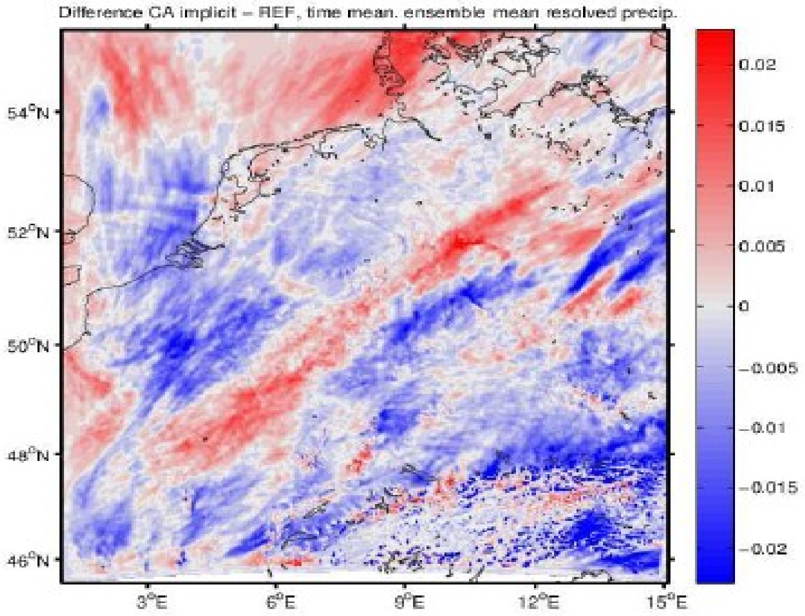


- CA – Reference
  Ensemble Mean

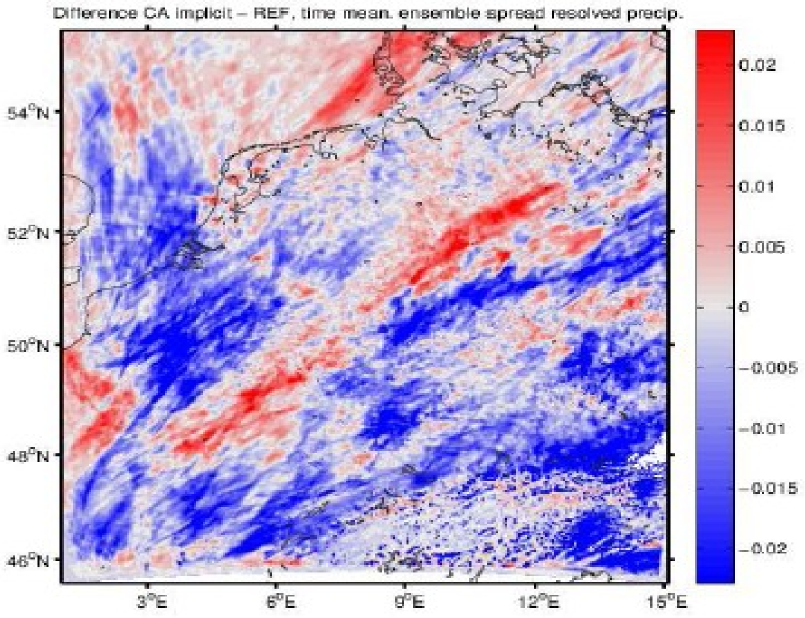


- CA – Reference
  Ensemble Spread

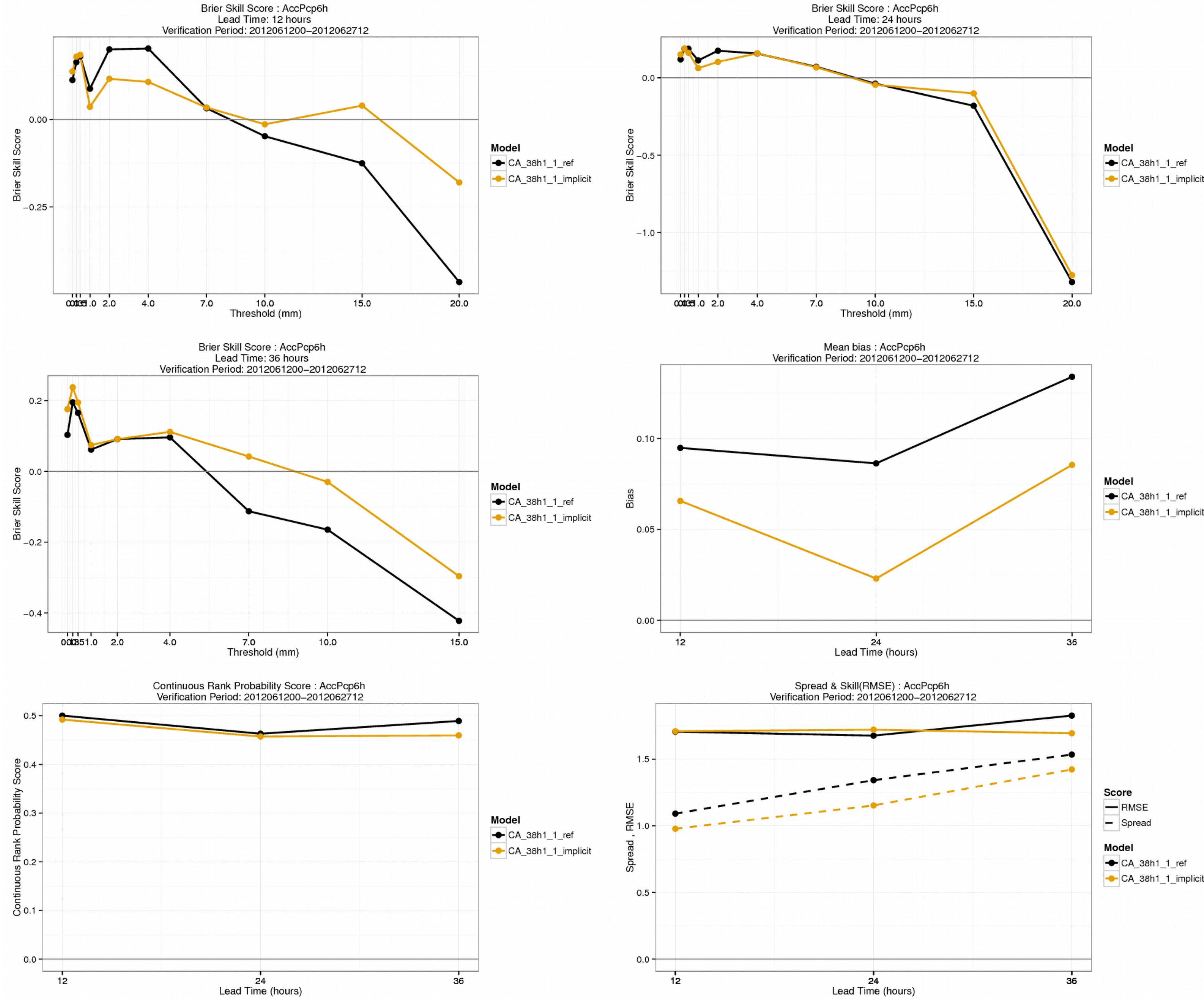
Monthly Mean of 6h *resolved* precip



- CA – Reference
  Ensemble Mean



- CA – Reference
  Ensemble Spread



Brier Skill Score : AccPcp6h
Lead Time: 12 hours
Verification Period: 2012061200–2012062712
Brier Skill Score
Threshold (mm)
Model
CA_38h1_1_ref
CA_38h1_1_implicit
Brier Skill Score : AccPcp6h
Lead Time: 24 hours
Verification Period: 2012061200–2012062712
Brier Skill Score
Threshold (mm)
Model
CA_38h1_1_ref
CA_38h1_1_implicit
Brier Skill Score : AccPcp6h
Lead Time: 36 hours
Verification Period: 2012061200–2012062712
Brier Skill Score
Threshold (mm)
Model
CA_38h1_1_ref
CA_38h1_1_implicit
Mean bias : AccPcp6h
Verification Period: 2012061200–2012062712
Bias
Lead Time (hours)
Model
CA_38h1_1_ref
CA_38h1_1_implicit
Continuous Rank Probability Score : AccPcp6h
Verification Period: 2012061200–2012062712
Continuous Rank Probability Score
Lead Time (hours)
Model
CA_38h1_1_ref
CA_38h1_1_implicit
Spread & Skill(RMSE) : AccPcp6h
Verification Period: 2012061200–2012062712
Spread , RMSE
Lead Time (hours)
Score
RMSE
Spread
Model
CA_38h1_1_ref
CA_38h1_1_implicit

Conclusion EPS simulation

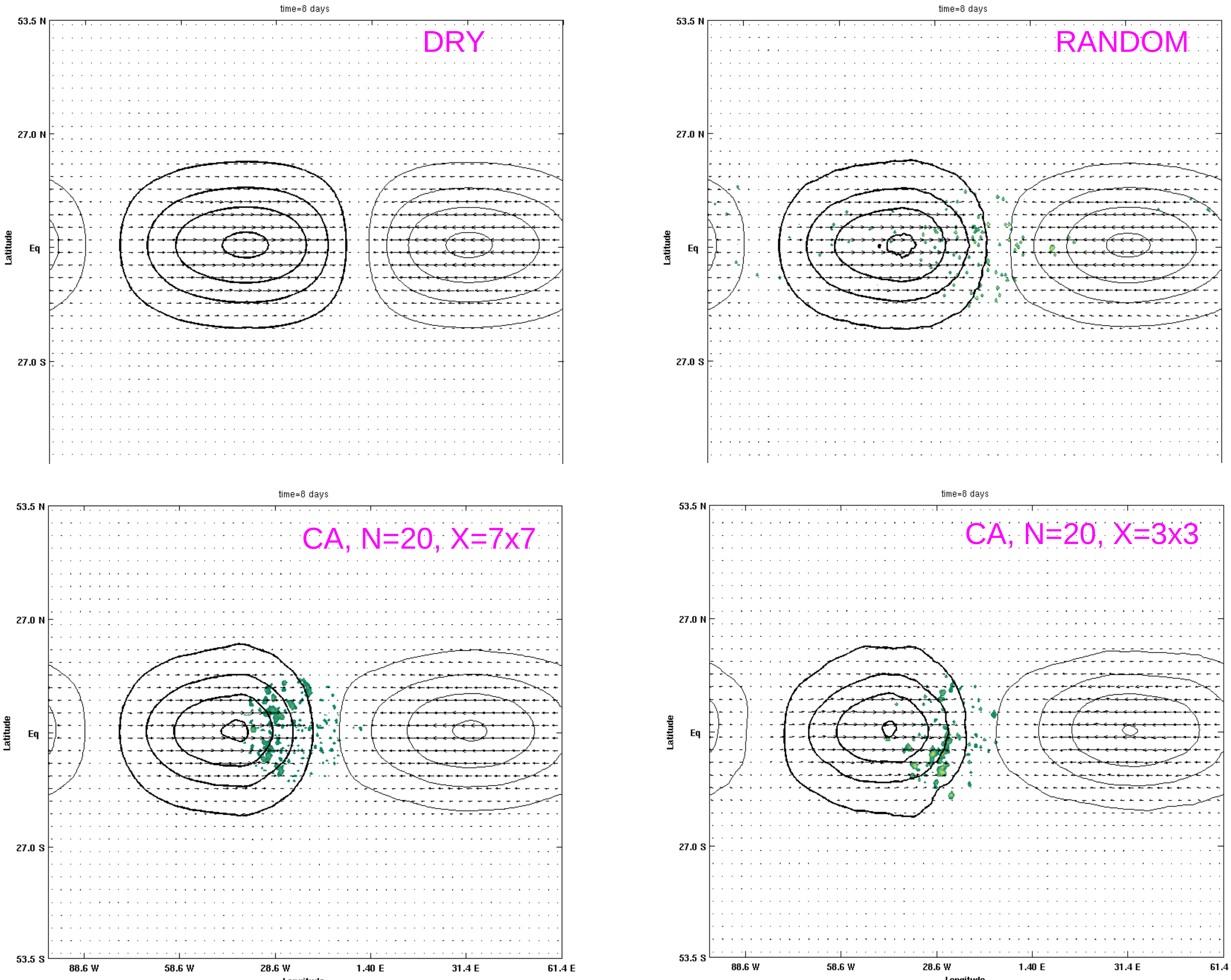
- The inclusion of the stochastic scheme increases the spread of convective precipitation, but the knock-on effects on large-scale precipitation mean that the approach overall reduces the spread in total precipitation.

  -> A stochastic scheme on the sub-grid, does not automatically produce more spread.
- The scheme reduces the model bias in 6h acc. precipitation, which leads to a slightly improved ensemble forecast (more reliable), but not because of increased spread, but rather because of improved skill.
- The influence of the scheme seem confined to the sub-grid scale, no large impact on ensemble spread in the resolved variables, T, q, U, V
- Useful to have cellular automata at 2.5 km grid-spacing?
- In order to really understand the interaction with the dynamics, and “transfer of uncertainty” upscale, would like to study convectively coupled equatorial waves, with/without the cellular automata scheme.

Shallow water simulation with CA

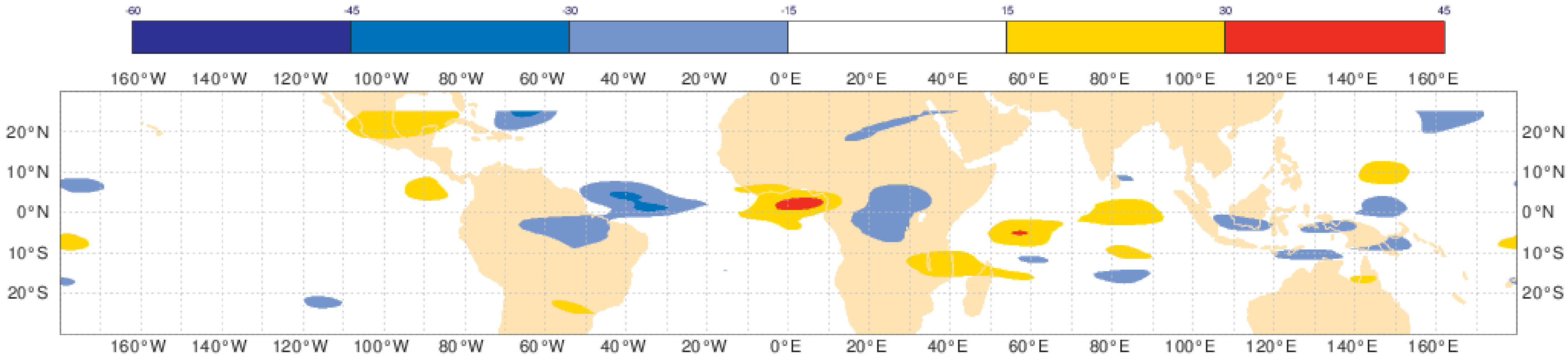
- Initialize shallow water model with wave solutions of Kelvin, EMRG, WMRG, ER, EIG and WIG waves.
- 10 day forecast coupled to “convection” using a CA (tests with different space and time correlations.)
- 10 day forecast coupled to “convection” using random numbers.

Bengtsson, L., Körnich, H., Källén, E., & Svensson, G. (2011). Large-scale dynamical response to subgrid-scale organization provided by cellular automata. Journal of the Atmospheric Sciences, 68(12), 3132-3144.

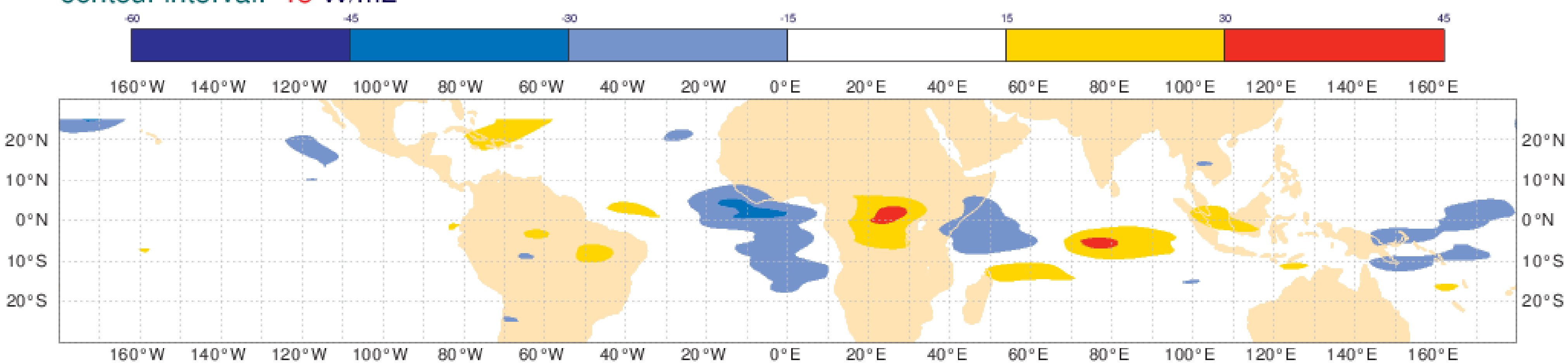

time=8 days
DRY
RANDOM
CA, N=20, X=7x7
CA, N=20, X=3x3
53.5 N
27.0 N
Eq
27.0 S
53.5 S
Latitude
88.6 W
58.6 W
28.6 W
1.40 E
31.4 E
61.4 E
Longitude

Convectively coupled Equatorial waves

Real time monitoring of kelvin waves OLR (ECMWF) 20150210
contour interval: 15 W/m2

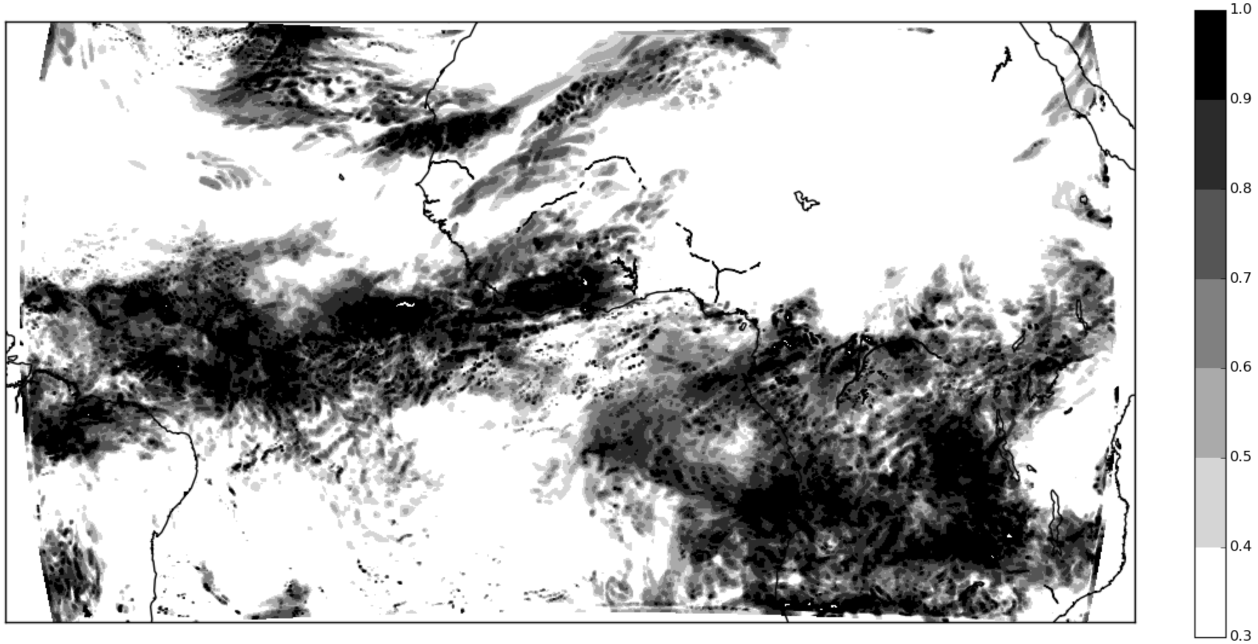


Real time monitoring of kelvin waves OLR (ECMWF) 20150212
contour interval: 15 W/m2



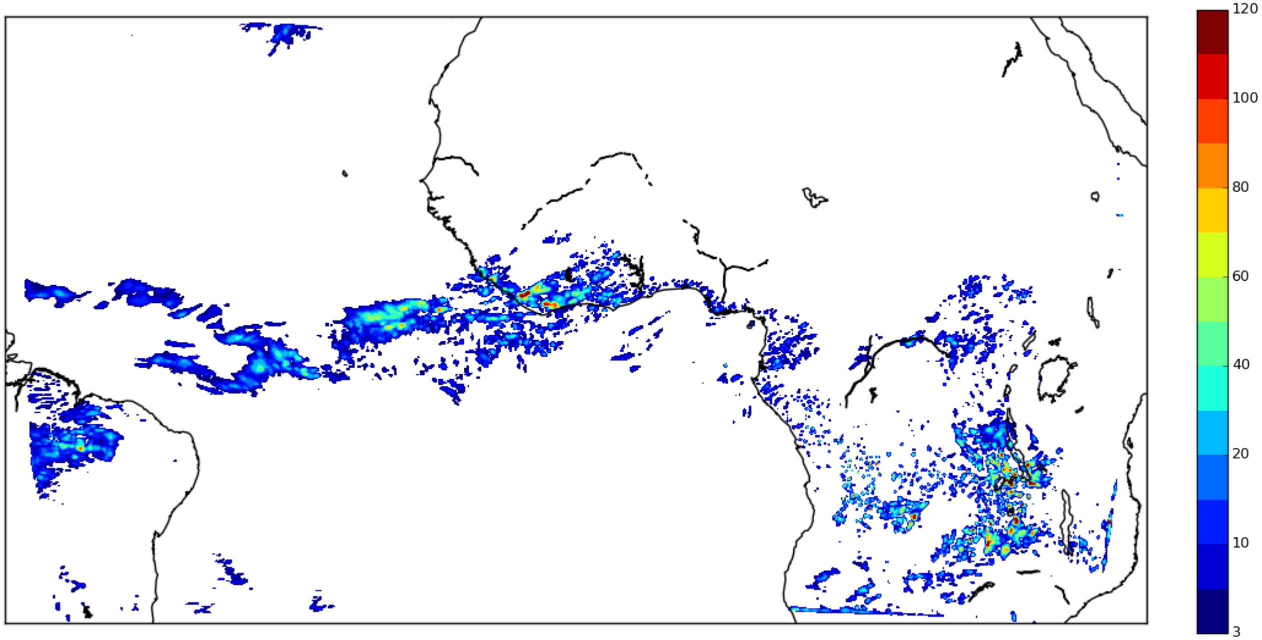
Convectively coupled Equatorial waves

Cloud cover, 2015021100 +24



ALARO-0 reference simulation.

12 h acc precip, 2015021100 +24



Convectively coupled Equatorial waves

Cloud cover, 2015021100 +24

ALARO-0 with CA scheme simulation.

12 h acc precip, 2015021100 +24