Using LES and observations to inform the representation of convective organization and memory in ESMs

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Bulk versus Decentralized parameterization

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BAMS (2003)

BREAKING THE CLOUD PARAMETERIZATION DEADLOCK

BY DAVID RANDALL, MARAT KHAIROUTDINOV, AKIO ARAKAWA, AND WOJCIECH GRABOWSKI

Progress on the cloud parameterization problem has been too slow. The authors advocate a new approach that is very promising but also very expensive computationally.

Deadlock: Refers to our lack of success in overcoming long standing problems in the representation of clouds and convection in Earth System Models (ESMs) used for numerical weather forecasting and climate simulation

18 years on, are we making any progress?

An incomplete list of problems, old and new..

Climate sensitivity

Grey zone problem

Impacts of mesoscale organization

Convective memory and transitions

Can we identify a common factor?

Most first-generation convective parameterizations rely on a bulk approach:

They usually have the form: $\boxed{\overline{A} = F(a, b, c, d, \ldots)}$

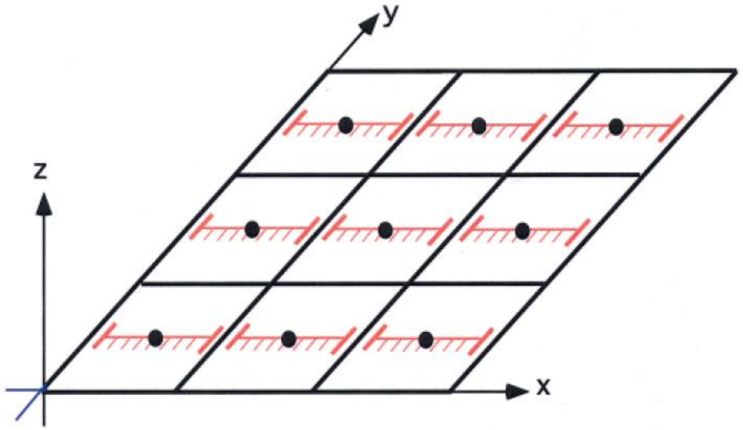
Have been very successful in addressing first-order biases (e.g. Tiedtke, 1993)

However, shortcomings of this deterministic paradigm have become apparent

Subtle but important dependencies can easily be overlooked, while adding complexity (numerical or conceptual) in bulk schemes has not really delivered the giant leap forward that we all hoped for ..

What are the possible alternatives?

Alternatives to bulk



Randall et al (BAMS, 2003)

Option I: Global LES

Convection is mostly resolved

Option II: Machine learning (ML)

Use AI algorithms to identify relations and train subgrid systems on big data

Option III: **Superparameterization**

Implement a 2D grid in each GCM gridbox and semi-resolve subgrid processes

Option IV: **Decentralized approaches**

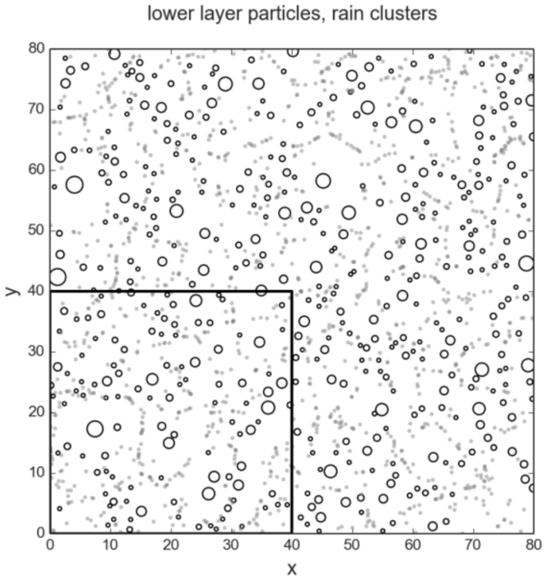
Conceptual models consisting of an ecosystem of multiple interacting objects, representing the smallest building blocks of convection

Decentralized frameworks

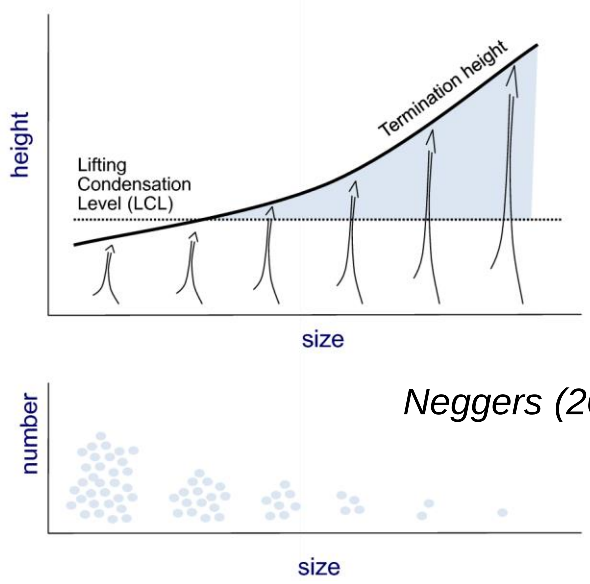
Examples: Population models, Particle models, Multi plume models

The idea:

- An ecosystem of independent but interacting objects
- Let the system evolve freely, instead of superimposing bulk behavior
- Interactions can introduce negative feedback mechanisms which drive equilibration (self-regulating bulk behavior)



Böing et al (2016)



Neggers (2015)

Some characteristics

Pros

- Bulk closures become obsolete: Emergent properties
- Possibly subtle responses to weak perturbations in external forcings
- Yield a deeper understanding of the problem
- Still orders of magnitude cheaper than global LES

Cons

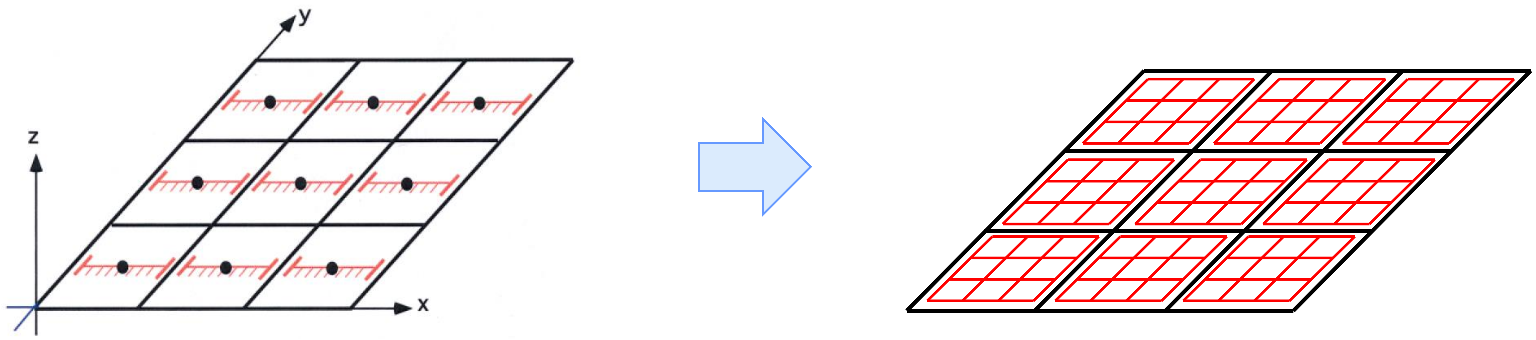
- Stability is not guaranteed
- Rules of interaction are crucial, but need to be parameterized
- Added degrees of freedom add to cost → harms applicability as a parameterization?

Idea

Khouider et al. (2010), Dorresteijn et al (2013, 2015), Bengtsson et al (2020)

Why not combine a 2D grid approach with a decentralized approach?

Step 1: Instead of vertical microgrids, use horizontal microgrids:



Step 2: Let a population of objects live on the microgrid, coupled to a vertical transport module consisting of multiple transporting modes

- A horizontal grid can capture spatial organization and memory
- Potentially computationally efficient
- Can well be trained using ML

Example: BiOMi

JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

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Key Points:

- A scale-aware stochastic number generator based on a Bernoulli process is applied to model object births and advection on Eulerian grids

A Binomial Stochastic Framework for Efficiently Modeling Discrete Statistics of Convective Populations

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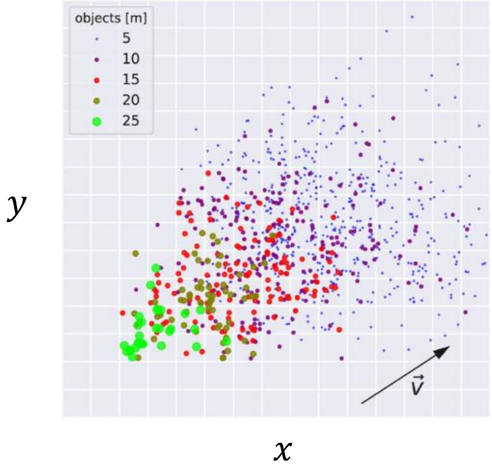
An ecosystem of interacting, mobile convective objects is modeled on a 2D microgrid



Goals:

- Capture forms of spatial organization and memory
- Fully discrete formulation (for the grey zone)
- Stay computationally efficient

Combining concepts from lattice modeling and Lagrangian particle modeling

Inspired by Böing et al (2016)

Ansatz

Given a reference object birth rate $\dot{B}_i$ per unit area and unit time

Number of births per timestep Δt within a large, finite domain of size L:

$$B_i = \dot{B}_i \, L^2 \, \Delta t$$

Assume all births are randomly distributed over N gridcells: $N = \dfrac{L^2}{\Delta x \Delta y}$

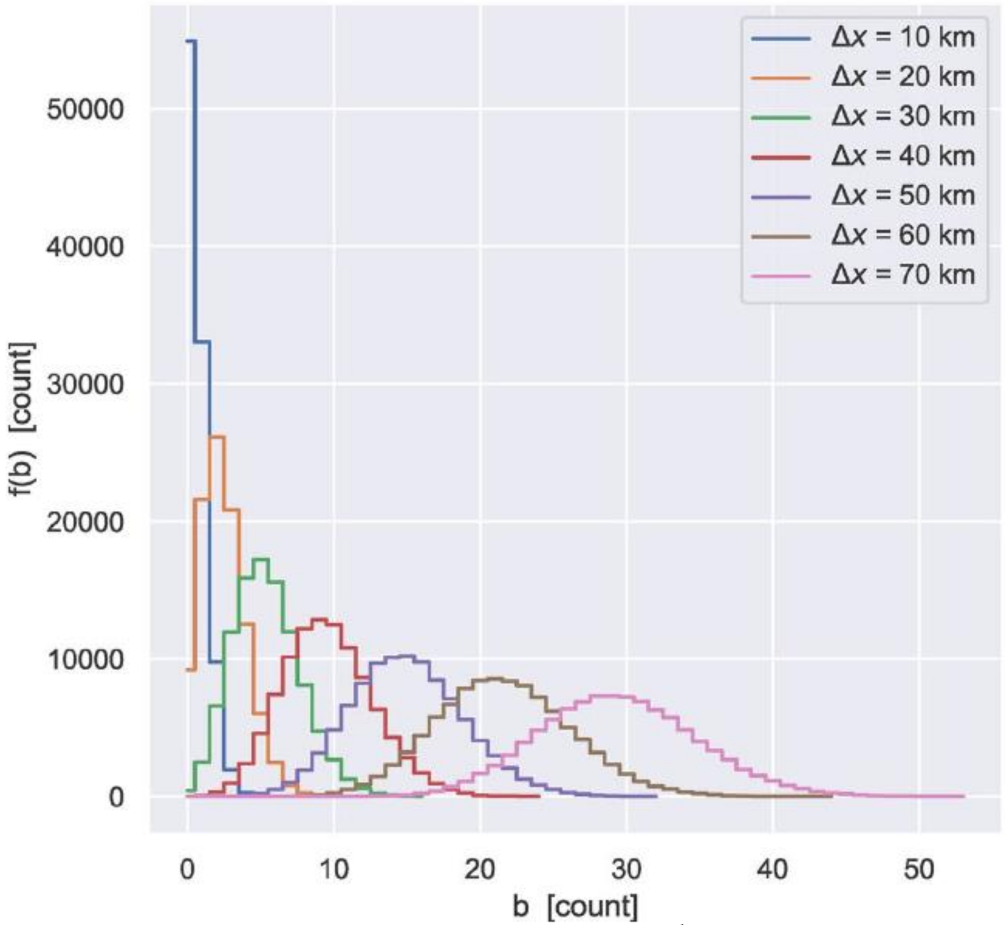
Probability p that a single birth occurs in a specific gridcell: $p = 1 \,/\, N$

Assuming all births are independent yields a set of Bernouilli trials (coin flips). The associated probability mass function is a binomial:

$$f_i(b) = \binom{B_i}{b} p^b \, (1 - p)^{(B_i - b)}$$

Grey zone stochasticity

Is automatically captured through the discrete nature of (sub)sampling the binomial:



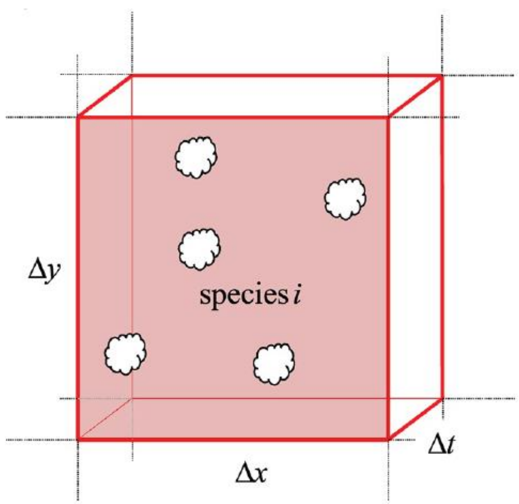
Integer (number of births)

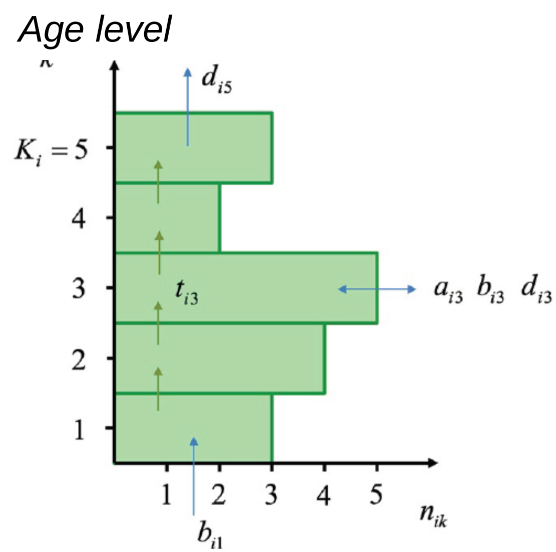
A scale-aware stochastic binomial operator

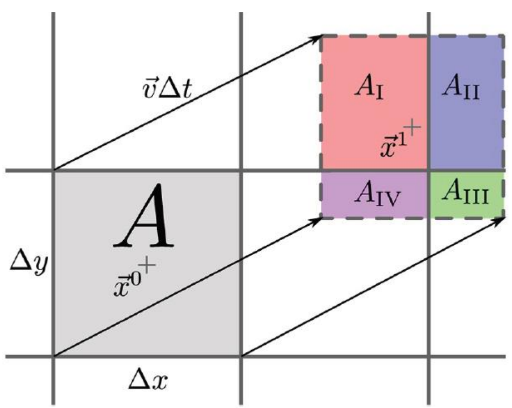
For describing the behavior of a multitude of objects in a cell

This is a defining difference with Lagrangian particle models

Used to describe object births, object demographics, and object movement

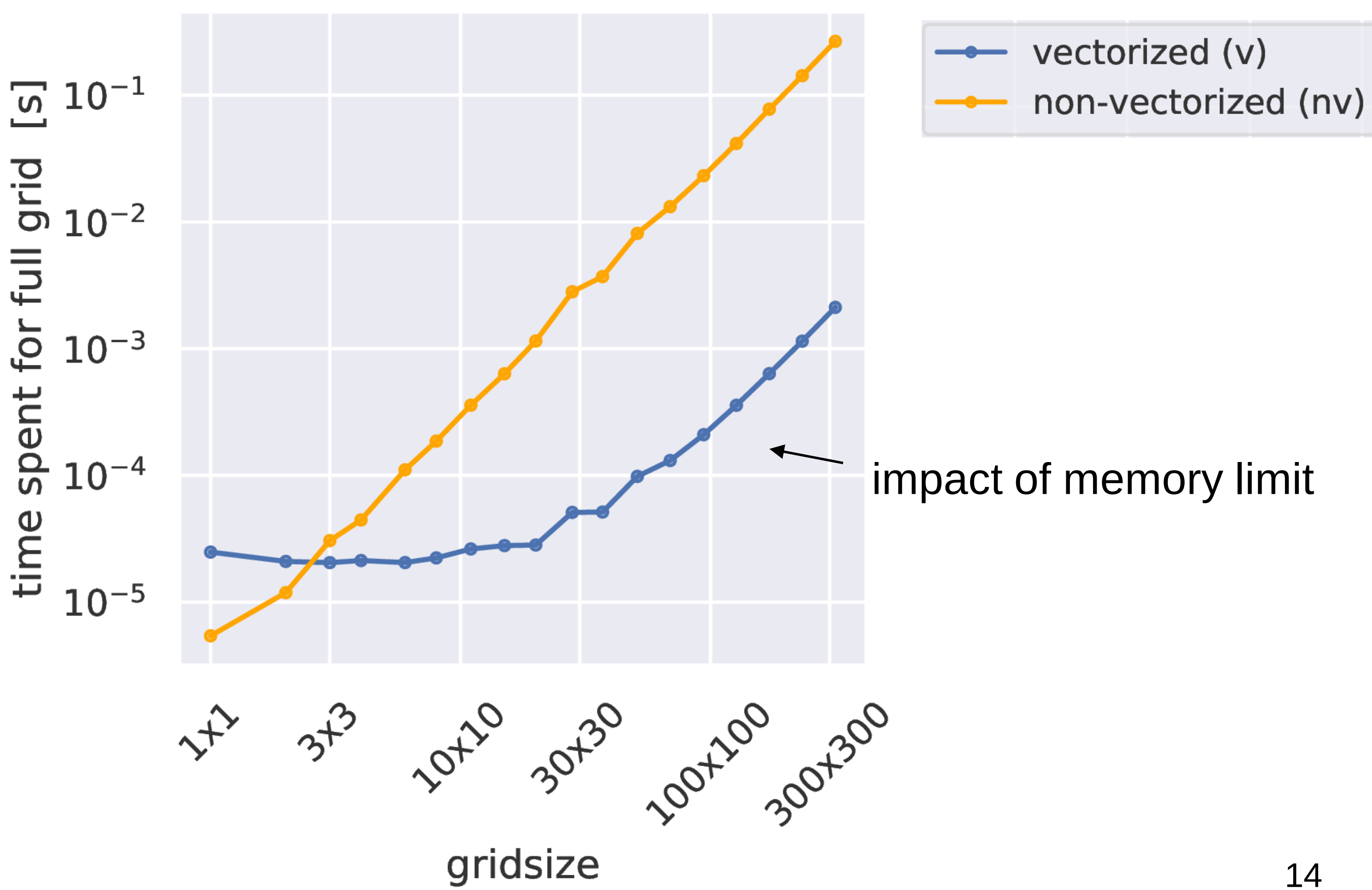






Binomial functions are efficient

Can easily be vectorized, allowing large microgrid sizes at little cost:



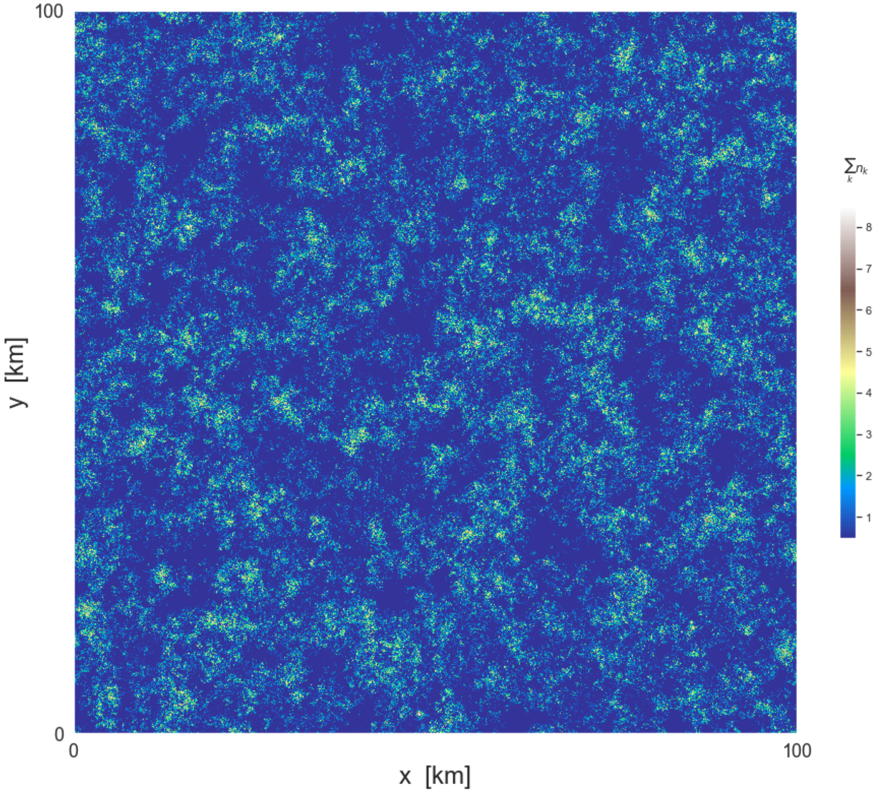
Results

Two simple rules of object interaction, acting through birth probability p.

These represent known physics of **convective thermals**:

pulsating growth and environmental deformation.

Under these rules, memory and spatial organization is apparent on the microgrid:



MODIS true color image of sugar / gravel cloud patterns during EUREC^{4}A (NASA Worldview)

Coupling BiOMi to ED(MF)^n

Eddy Diffusivity Multiple Mass Flux scheme *Neggers, JAMES 2015*

A discretized spectral framework for turbulent-convective transport

The macrophysical properties of size-bins of coherent surface-rooted convective structures are estimated independently

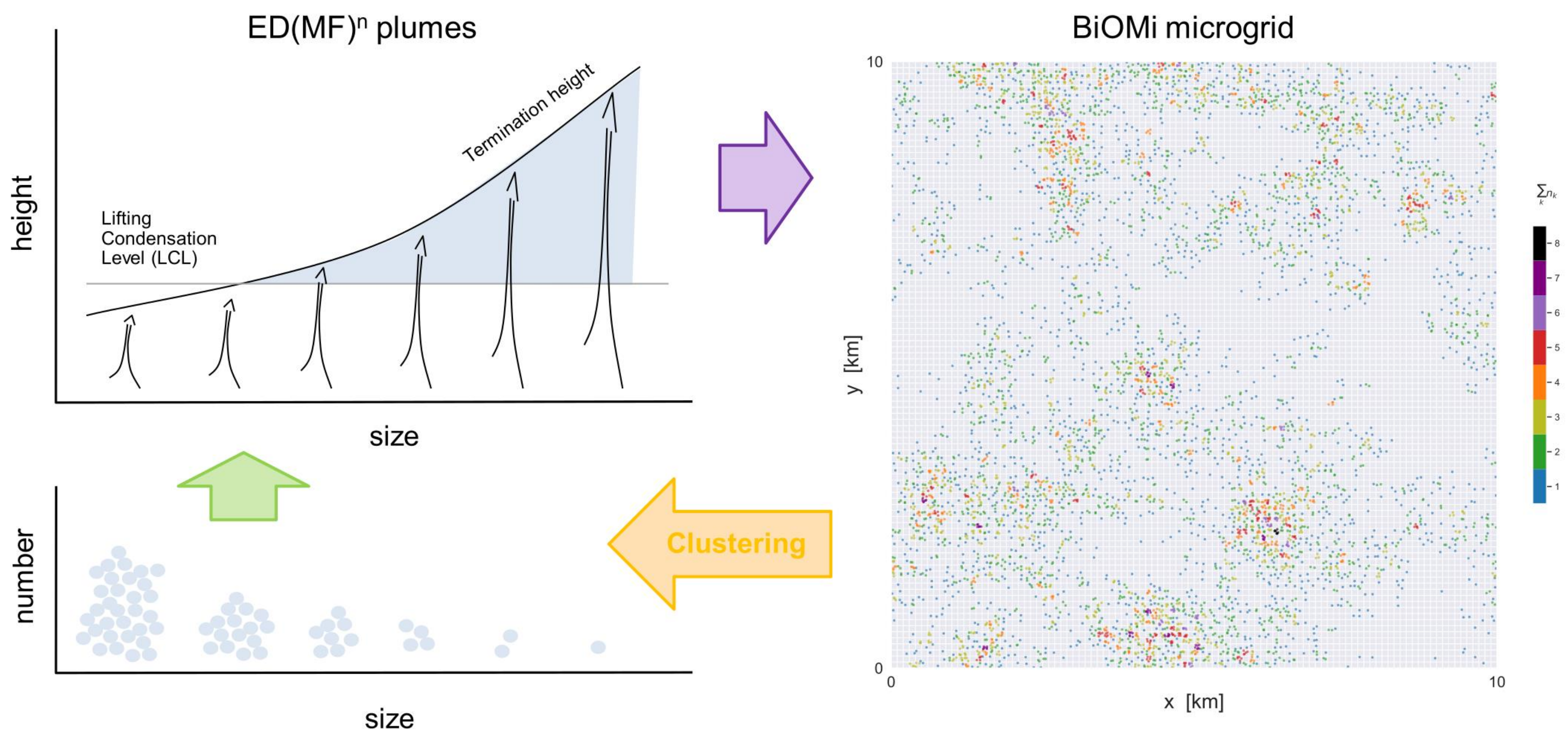
This makes bulk mass flux closures redundant, and allows interactions across the size spectrum

Remaining closures (transport):

- Bin initialization
- Size-dependent entrainment (e.g. Griewank et al., 2019; Peters et al, 2020)
- Size density of object number ← BiOMi

Schematic illustration of the coupling:

An online clustering algorithm is applied to read the size density of cluster number from the BiOMi microgrid, which is then fed to EDMF



Implementation in DALES

Dutch Atmospheric LES (Heus et al., 2010)

BiOMi-ED(MF)^n replaces the vertical component of the subgrid transport scheme

Object birth rate is coupled to the surface buoyancy flux

2x2 grid

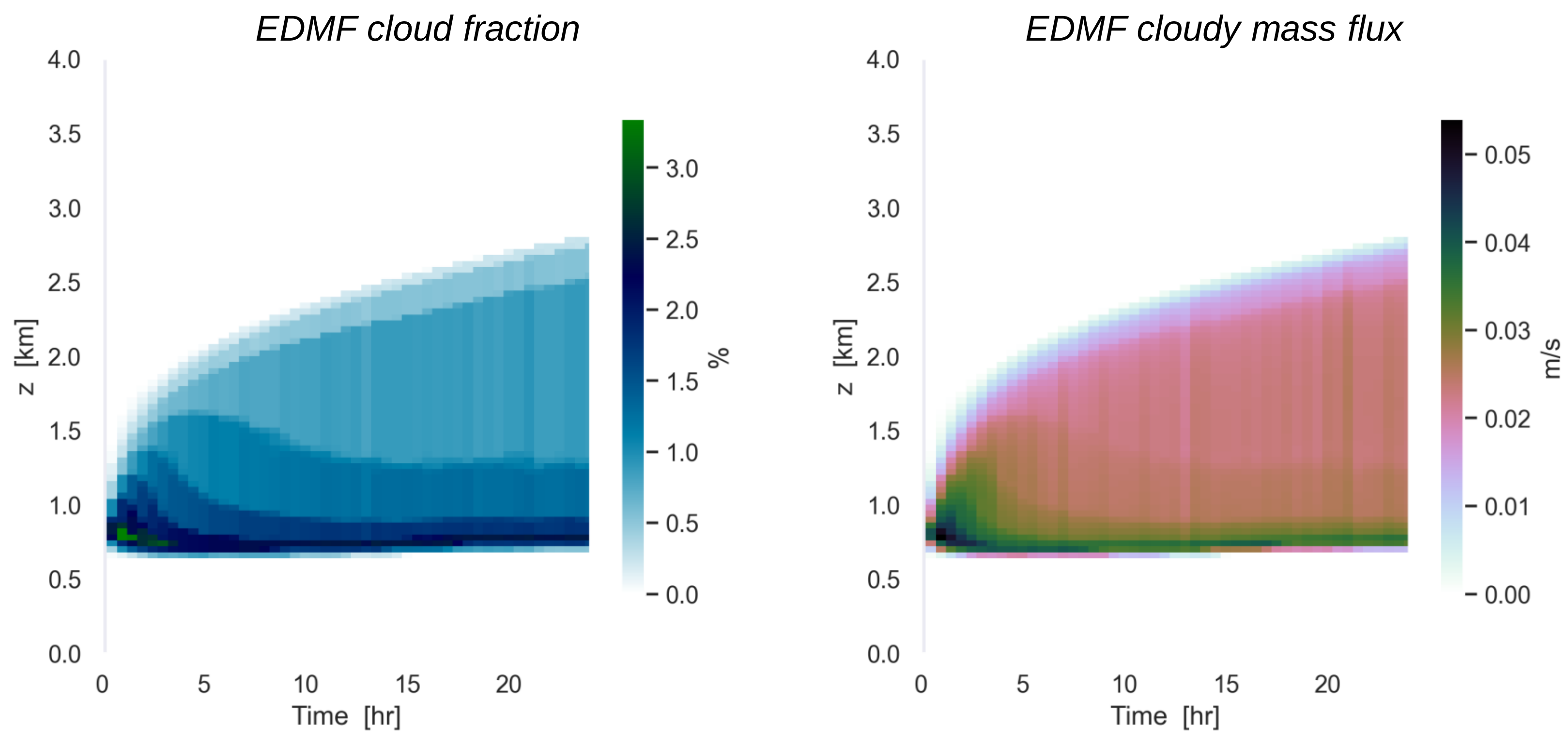
No interaction between microgrids in different LES gridcolumns

Note: Scale-adaptivity (i.e. dependence on LES gridsize) is introduced through the cluster size density that evolves on the BiOMi microgrid

Neggers and Griewank (in preparation)

Results

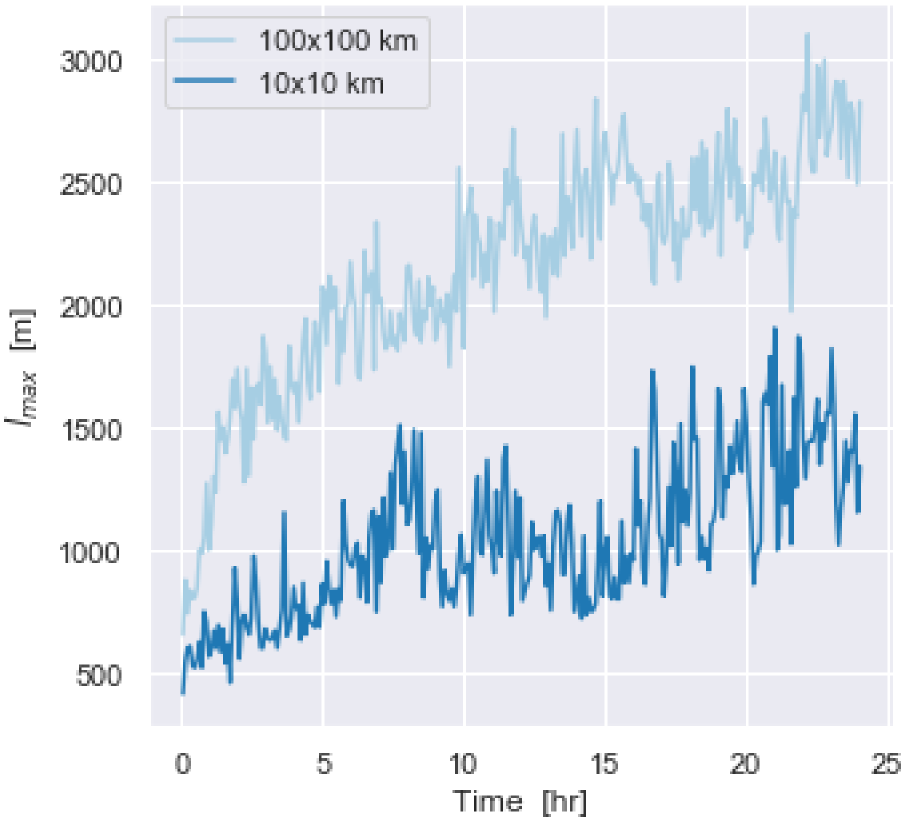
For subtropical marine Trade wind conditions (RICO shallow cumulus case)
DALES gridbox size 100x100 km^2, microgrid size 1000x1000 at 100m spacing



The coupling of EDMF to BiOMi introduces many extra degrees of freedom, which could easily lead to instability / collapse… yet it doesn't!

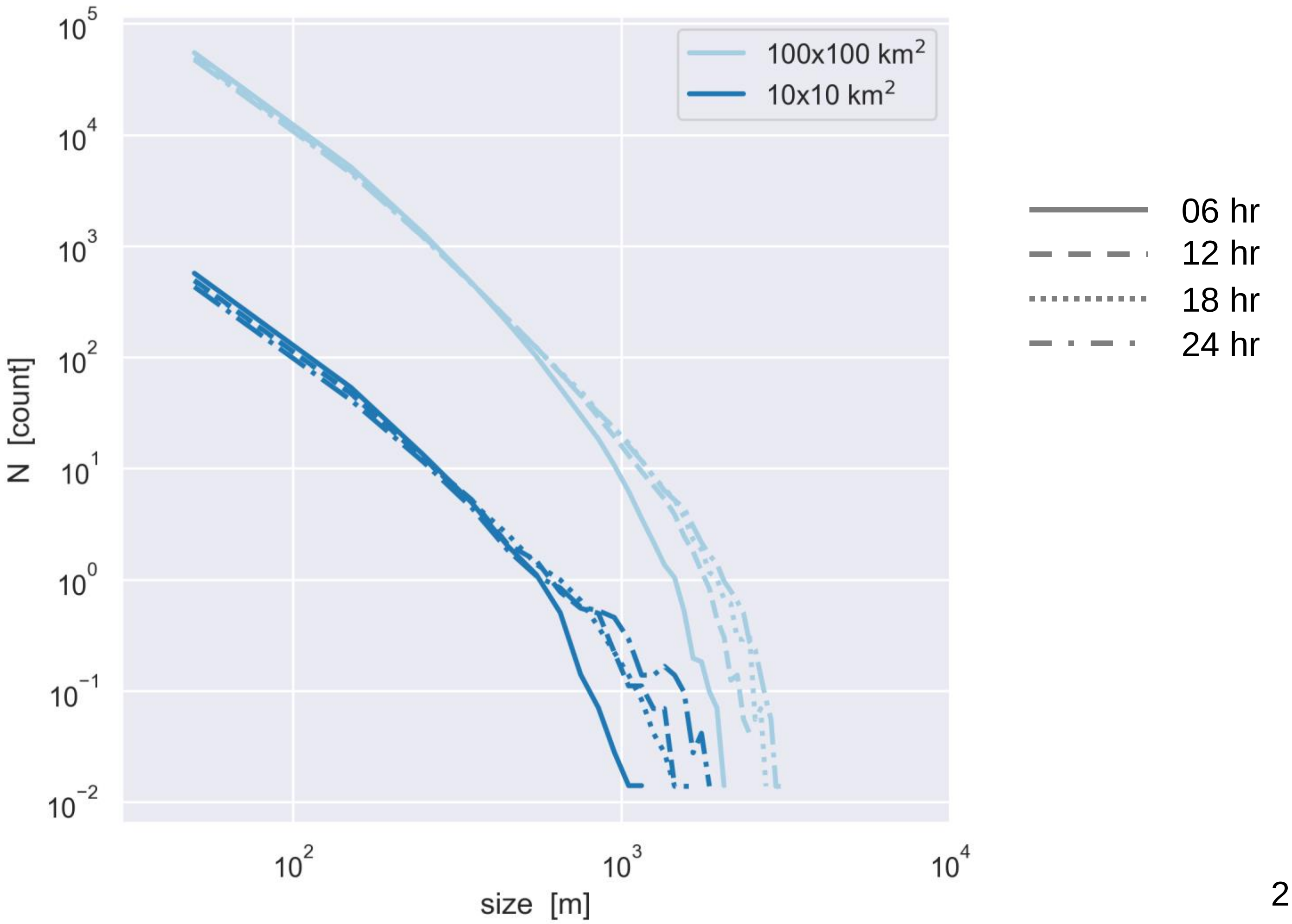
Results

Convective memory: Evolution of largest cluster size on the microgrid



Results

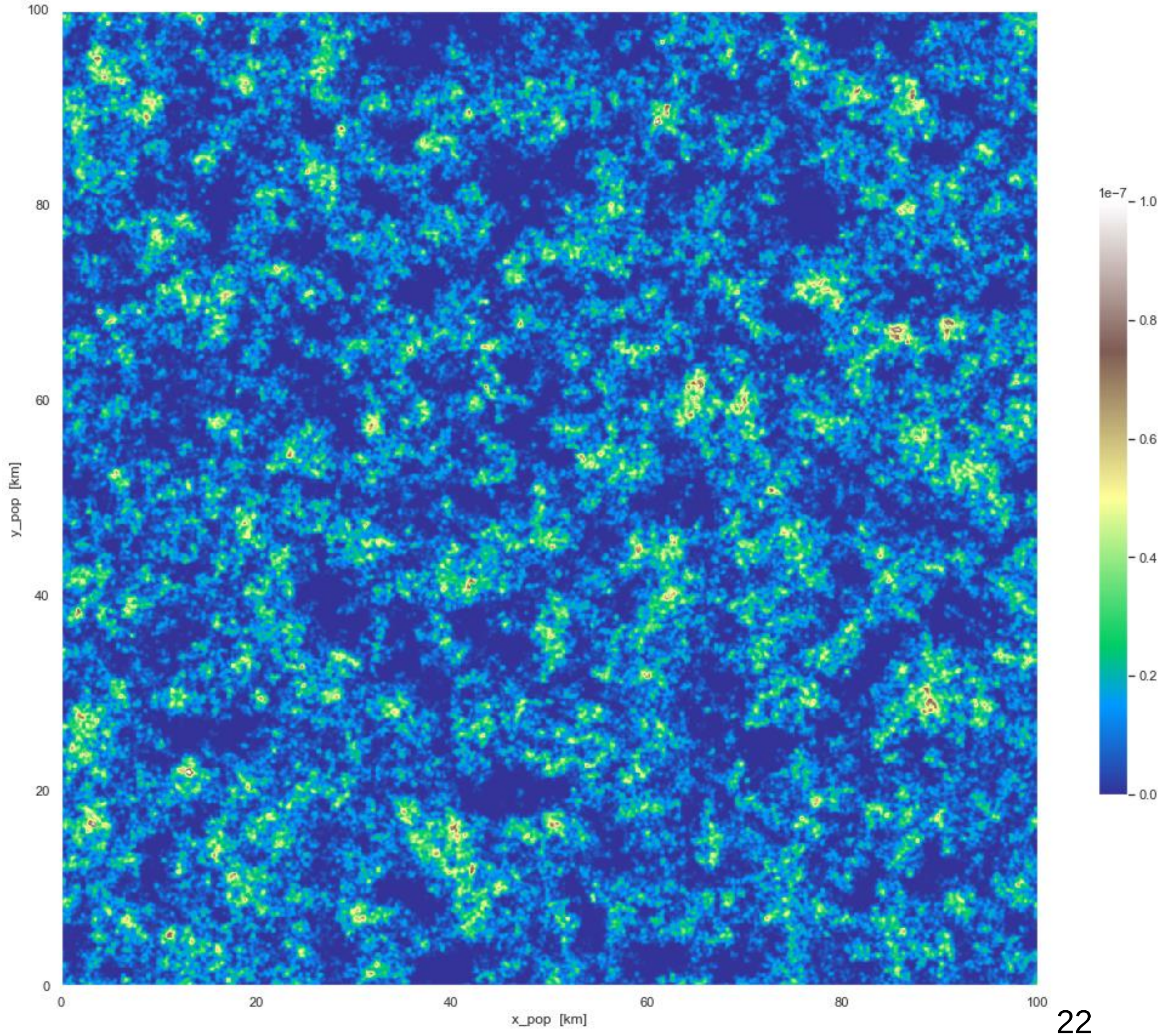
Convective memory: The evolution of cluster size distributions on the microgrid



Results

Spatial organization on the microgrid

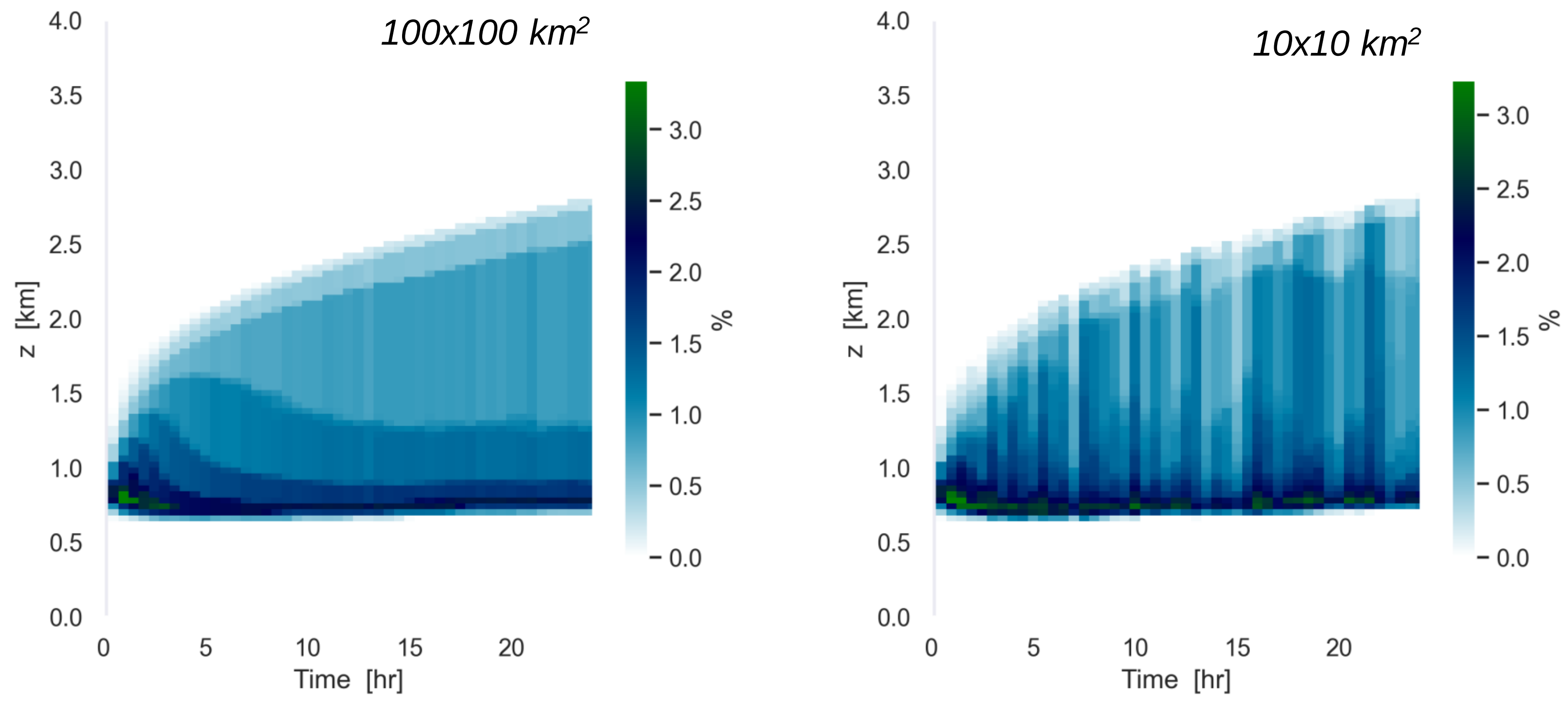
Birth probability p



Results

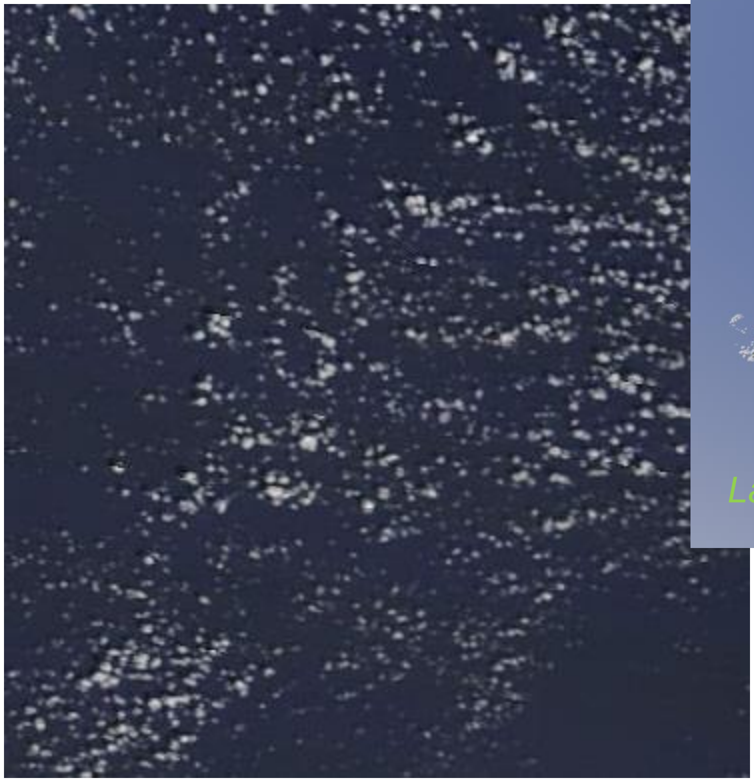
Grey zone behavior: Stochasticity due to subsampling

EDMF cloud fraction



Using LES and observations

To train the BiOMi rules of interaction, making use of ML algorithms
We need many spatial fields for this! Scale up towards multi-year coverage

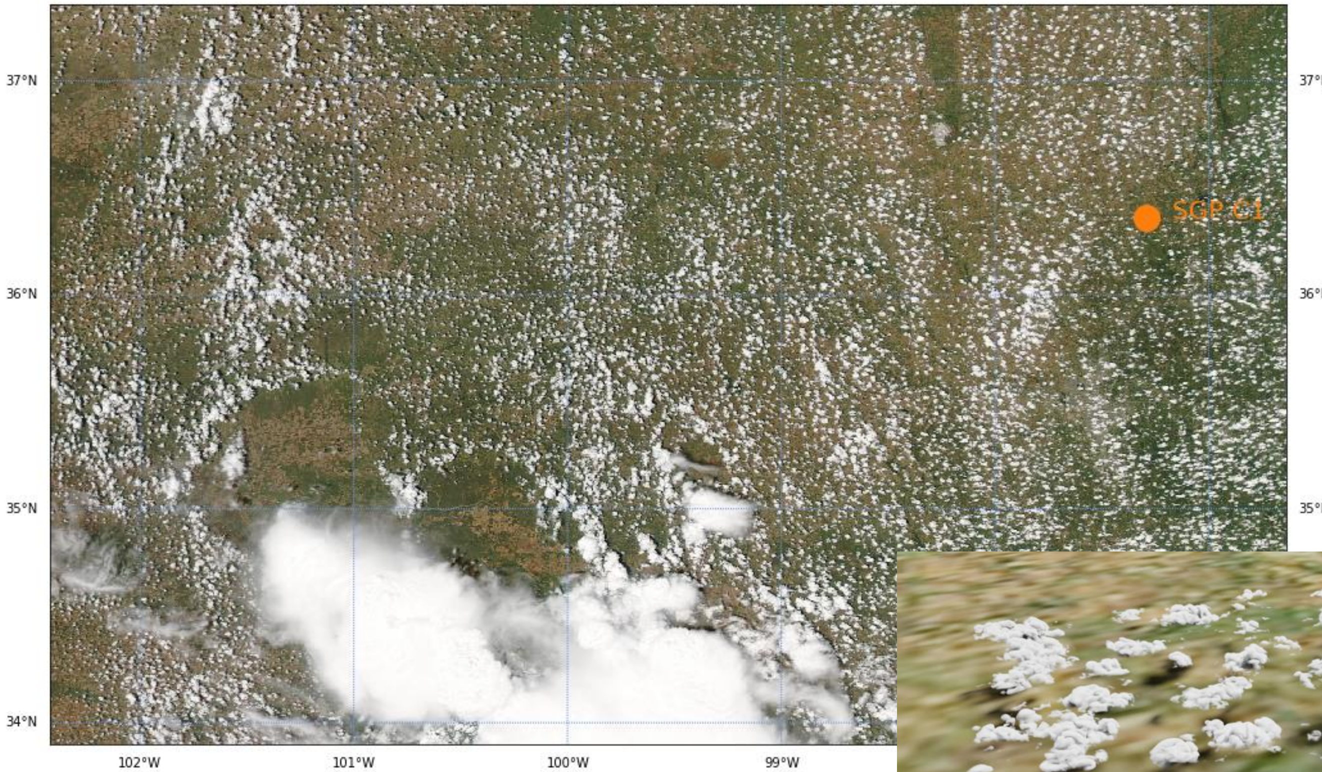


MODIS image during EUREC^{4}A

Lagrangian DALES for EUREC^{4}A

What does it take for BiOMI to reproduce these patterns?

Special focus on cloud pattern evolution during diurnal cycles at continental meteorological sites (SGP, CACTI)



Ray-trace rendering of LASSO cloud simulations during the HI-SCALE field campaign at SGP (2016)

Conclusions

A spatially-aware convective population model, consisting of binomial functions on a microgrid, shows promise in capturing convective memory and spatial organization in an efficient way

Coupling the framework to a transport module illustrates that shallow convective boundary layers can be reproduced, including stochastic effects in the grey zone

Outlook

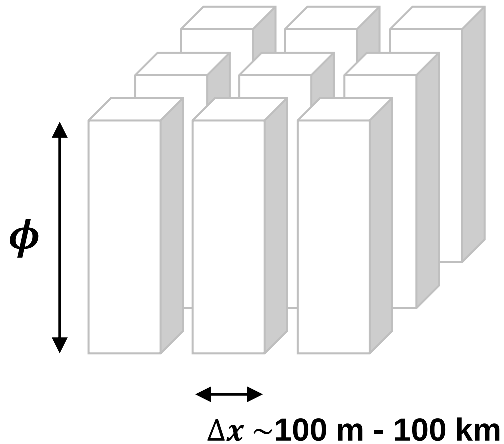
So far this is still a research model! To do’s:

- Train rules of interaction for many cases using LES and obs data
- Play with more rules of interaction (rain, radiation, shear, surface heterogeneity)
- Investigate convection-circulation coupling
- Investigate surface-convection coupling
- Assess responses to idealized climate perturbations

A different way of (mis)using an LES code …

Simple platform for investigating the two-way coupling between parameterized convection and the resolved flow

Few Column Model
(FCM)



Multi Column Model
(MCM)