Objective characterization of mesoscale cloud patterns from graph theory and an Ising-like model (BICIM)

Supplementary Material

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Section 1

Context & Methodology

Observed cloud field organizations

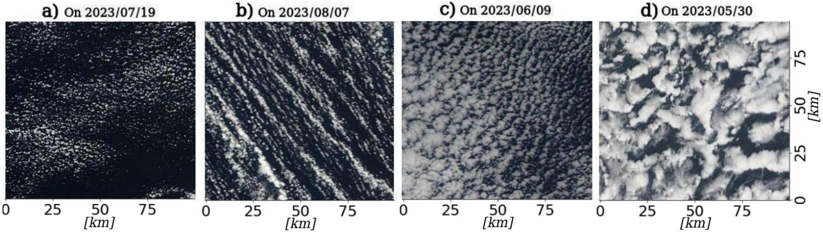


Figure: Example of satellite observations

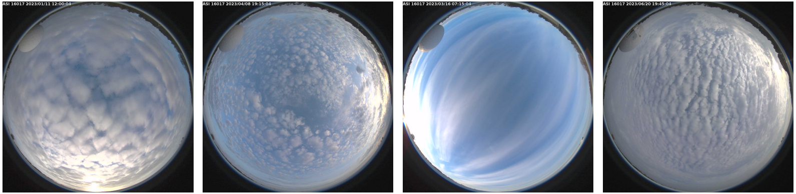


Figure: Example of ground-based observations (from a Sky Camera)

Context: West Coast of Sweden

- Oceans play a major role in the climate system — **70%** of Earth's surface.
- Focus region: **North Sea, West of Sweden** (56°–59°N, 3°–12°E).
- Northern Europe = convergence zone for diverse air masses:
  ↪ mP, mT, cP, mA, cA
- Region strongly influenced by pressure oscillations (e.g., NAO).

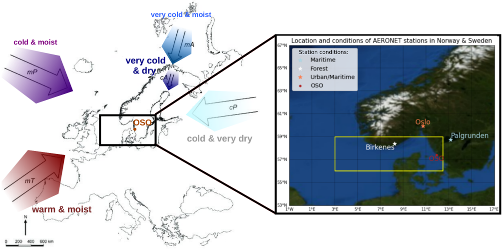


Figure: Left: Air mass types. Right: Study area

- **Onsala Space Observatory (OSO)**: ideal for atmospheric studies
  ↪ Located in "clean" air, land/sea interface

Methodology

① Modelisation (BIdimentional Cloud Ising Model)

→ BICIM simulations & sensitivity tests using OSO measurements as input data
→ Cloud Field Characterization via Graph Theory

② Observations

→ To collect 250 satellite observations (or observations from Sky camera)
→ Cloud Field Characterization via Graph Theory

③ MASCOL

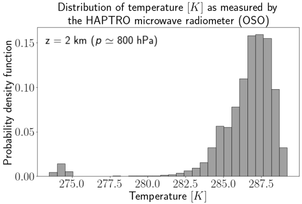
→ Automatic identification of similar cloud field organizations using the MASCOL metric.

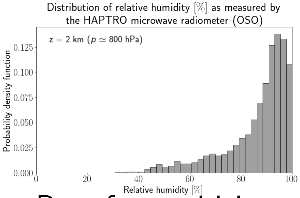
Section 2

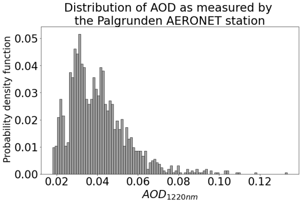
BICIM model

Modelisation – Input Data for BICIM

Input data for BICIM simulations (*I*, *II*, *III* & *IV* $\rightarrow$ see Poster):







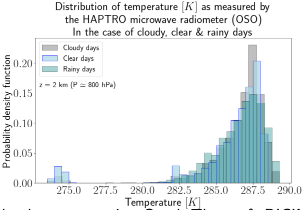
Input Data for sensitivity tests:

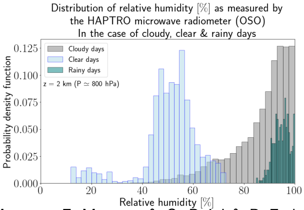
Day classification based on *Wei et al. (2021)*

$\hookrightarrow$ **Clear**: $RH \leq 85\%$ from 0 to 10km

$\hookrightarrow$ **Cloudy**: $RH \leq 85\%$ below 600m, $RH \geq 84\%$ above

$\hookrightarrow$ **Rainy**: 20 min continuous rain with $RH \geq 84\%$ from 0 to 10 km





Wei et al. (2021), Remote Sensing, doi: 10.3390/rs13132527

Modelisation – Sensitivity tests

- The model shows **consistent behavior** across all cases:
  ↪ **100% cloudy grid**: more clouds for "cloudy" input; quick clearing for "clear".
  ↪ **Random grid**: "rainy" case → more clouds at first, then decrease (rain consumes clouds).
- Tests: each flux excluded one at a time:
  ↪ **Conductive flux** $\Phi^{dif} = 0$: Slight delay in flocculation (+25k draws), but similar final state.
  ↪ **Surface flux** $\Phi_s = 0$: small impact

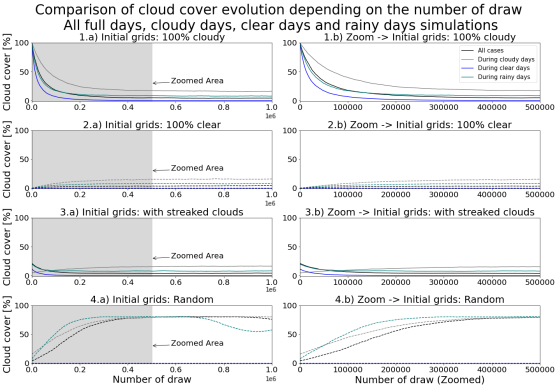


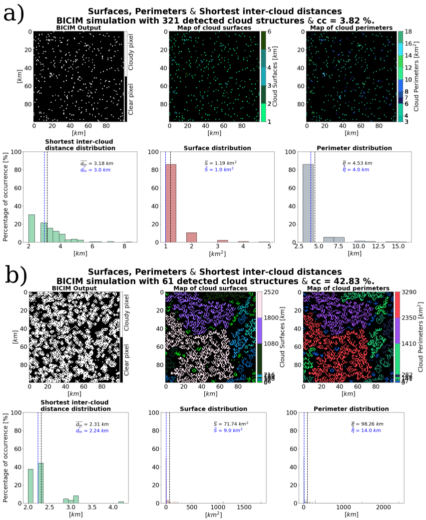
Figure: Cloud cover evolution depending on day type

Section 3

Graph Theory & MASCOL

Graph Theory

- **Graph theory** ⇒ to objectively quantify cloud field organization.
  ↪ N_C: Number of cloud structures
  ↪ CC: Cloud cover (%)
  ↪ Distributions of cloud **surface areas** (S)
  ↪ Cloud **Perimeters** (P_r)
  ↪ **Shortest inter-cloud distances** (d_m)
- Example shown for 2 cloud fields: isolated clouds (a) vs. flocculated field (b):
  ↪ **Case a)**: CC, S, P_r lower; d_m, N_C higher
  ↪ **Case b)**: CC, S, P_r higher; d_m, N_C lower
- These metrics (CC, N_C, S, P_r, d_m) form the basis of our automatic identification method.



Mascol metric

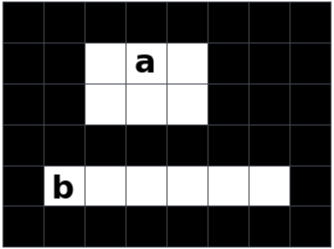


Figure: $S_a = S_b = 6$ km^2, but $P_{r,a} < P_{r,b}$ $\Rightarrow \frac{S}{P_r^2}$ higher for cloud a.

- Ratio S/P_r^2 informs about cloud compactness.
- Higher value $\Rightarrow$ more compact cloud.
- Lower value $\Rightarrow$ more spread-out shape.

Same cloud patterns, different scales $\rightarrow$ different CC and N_C

- Similar cloud shapes can have different spatial impact.
- Weighting CC and N_C emphasizes scale consistency.

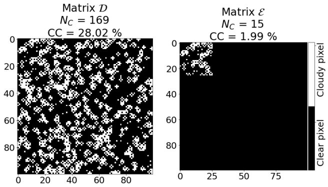


Figure: Cloud fields with similar structures but different scales.

MASCOL

Metric for Assessing Similarity between Cloud Organization Layouts (MASCOL):

$$\mathcal{M} = \alpha KS_{S/P_r^2} + \beta KS_{d_m} + \gamma D_{CC} + \delta D_{N_C} \qquad (\alpha = \beta = 1, \gamma = \delta = 2)$$

- Cloud cover and number of clouds weighted more heavily (scale-sensitive)
- $\mathcal{M} = 0$: identical fields; $\mathcal{M} = 6$: totally different fields

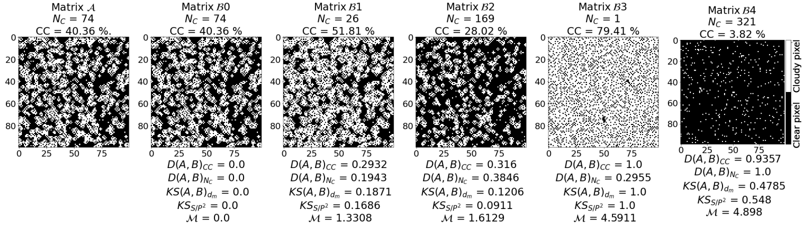


Figure: Example matrices with increasing $\mathcal{M}$ vs reference matrix $\mathcal{A}$.

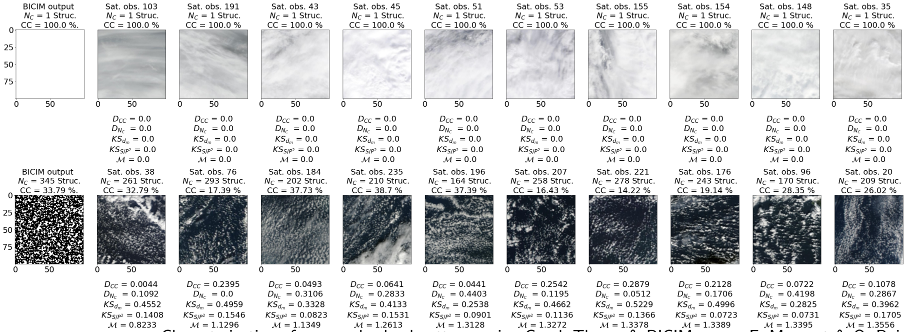
Section 4

First Results

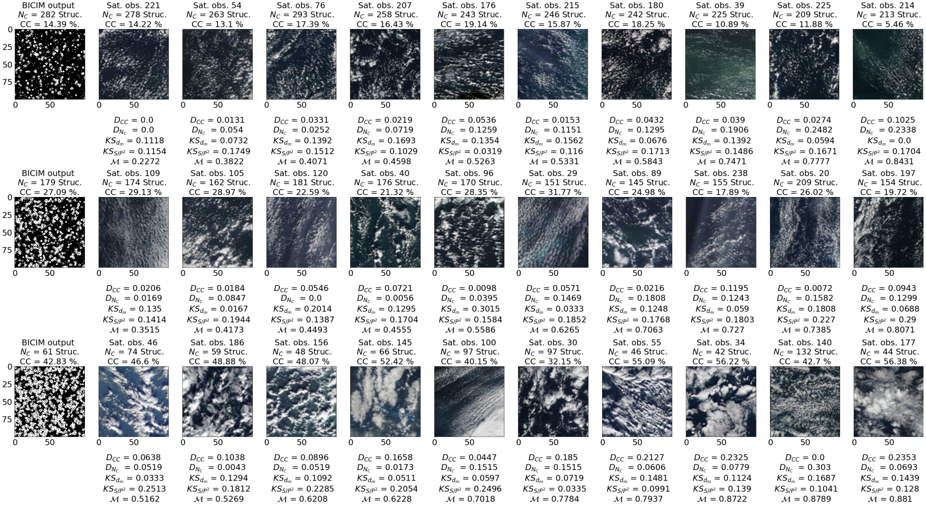
First Results

- BICIM is used as a **reference**.
- We compare model outputs to satellite observations.
- **9 example outputs** from selected for comparison.

- Observations:
  - ↪ **250 satellite images** from NASA Worldview
  - ↪ Region: $56^\circ N$–$59^\circ N$, $3^\circ E$–$12^\circ E$
  - ↪ Timeframe: June 1–October 31, 2023
- Methodology applied to both model and observations.



First Results



First Results

- 9 categories of cloud fields from BICIM are defined (as an ex.).
- Satellite observations with $\mathcal{M} \leq 1.5$ are matched to the most similar category (minimal $\mathcal{M}$).
- If no match ($\mathcal{M} > 1.5$ for all), the observation is labeled as *Unclassified*.

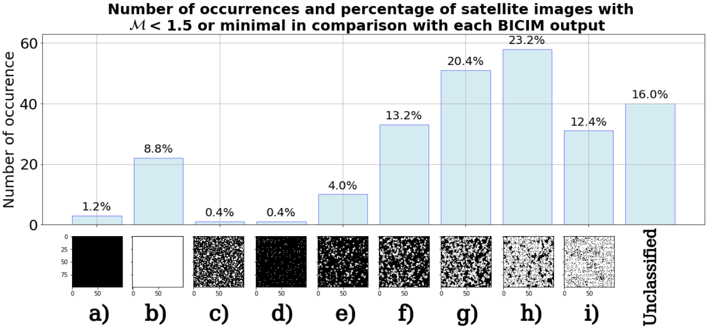


Figure: Number of satellite observations best matched (minimal $\mathcal{M}$) to each output. Last bar: unmatched observations.

Section 5

Summary

Summary

① Modelisation (BIdimentional Cloud Ising Model)

→ capable of generating cloud fields and reproducing their specific organizations
⇒ CC, N_C, S, P_r and d_m using Graph Theory

② Observations

⇒ CC, N_C, S, P_r and d_m using Graph Theory

③ MASCOL ($\mathcal{M}$)

→ Automatic identification of similar cloud field organizations

⇒ MASCOL allows for the *fast* ($\leq$ 10 min) and *objective* identification of cloud organizations.
⇒ It is easily *adaptable* → possible to extend the region and study period.