Tracking clouds in geostationary satellite data

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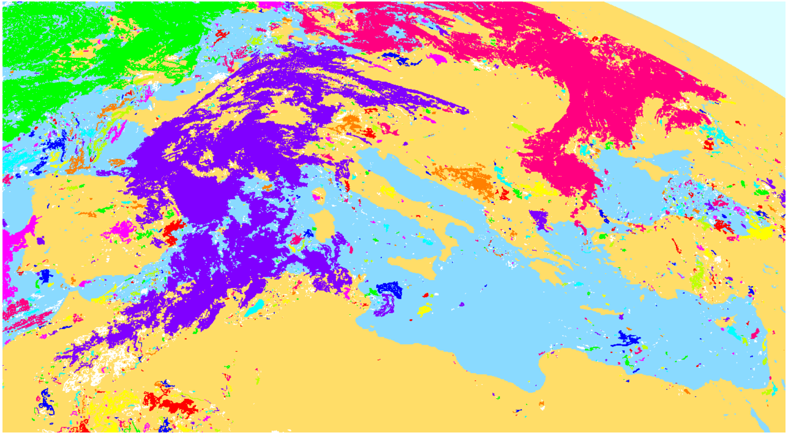
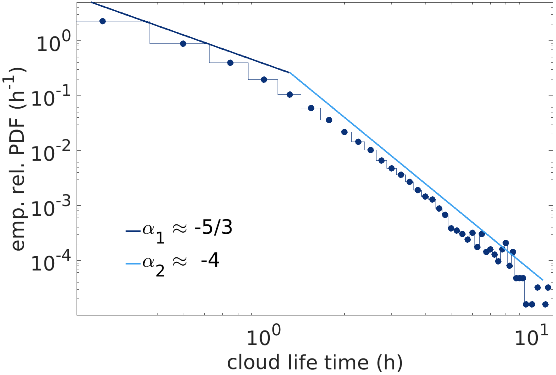
Our cloud tracking in geostationary satellite data enables the reliable tracking of clouds of all sizes. Including the overlap in the matching criterion leads to nearly all cloud cover being tracked.

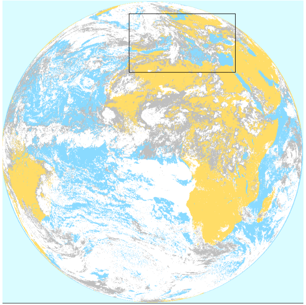


- working to better understand the radiative effect of clouds and aerosol-cloud interactions
- cloud properties to look at
    - cloud cover, size and lifetime, height, temperature, ...
    - e.g. height has a big influence on the cloud radiative effect
- goal: investigate properties of individual trajectories coupled with statistical analyses

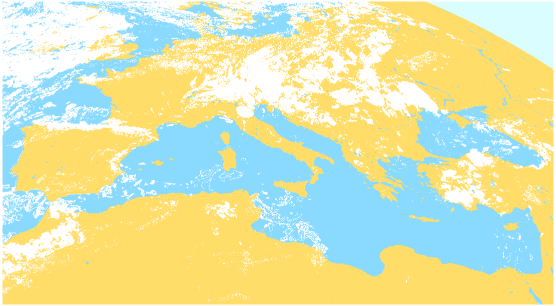


Cloud life time spectrum [Seelig et. al 2021]

- most important for tracking: cloud mask
- CLAAS = *Cloud property dataset using SEVIRI* [Benas et. al 2017], available since 2004 and ongoing
  - classification of pixels into *cloud free*, *cloud contaminated*, or *cloud filled*
- works with any comparable data



land sea mask plus cloud mask



one region we are investigating

How we track clouds

1. identify clouds

2. predict position of each cloud in next timestep using Particle Image Velocimetry [Raffel et. al 2007]

3. find best match for each cloud using predicted positions and observed positions
   - our new approach uses overlapping pixels in sequence with centroid-distance for matching
   - also used in [Coopman et al. 2019, Vila et al. 2008] and others

4. repeat for all consecutive timesteps


```
blobs =

  struct with fields:

       area: [89×1 double]
      centr: [89×2 double]
      bound: [89×4 double]
    ellipse: [1×1 struct]
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step 1: cloud mask to blobs

step 3: overlapping clouds

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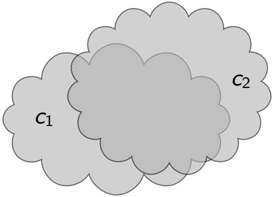

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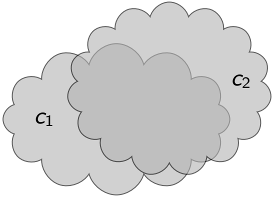
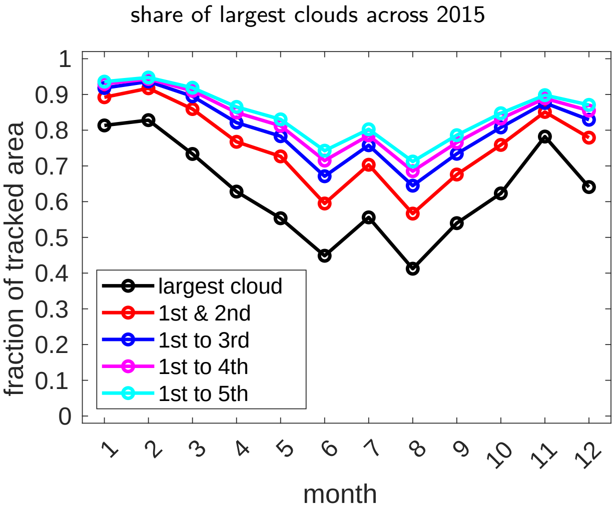
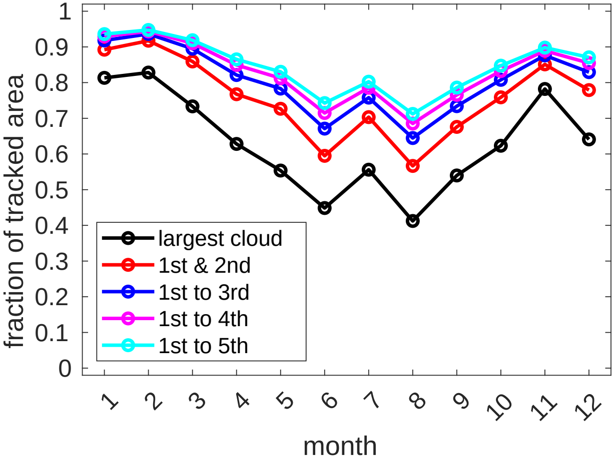


step 3: overlapping clouds



- **overlap matching** works well for large clouds and cloud clusters
- for smaller, relatively isolated clouds the **distance matching** performs better
- new approach tracks clouds of all sizes reliably
- in this region 96% of cloud area is tracked

share of largest clouds across 2015



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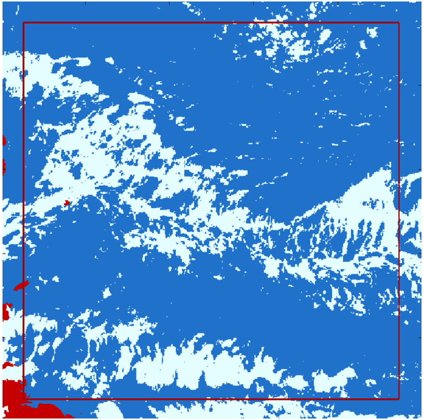
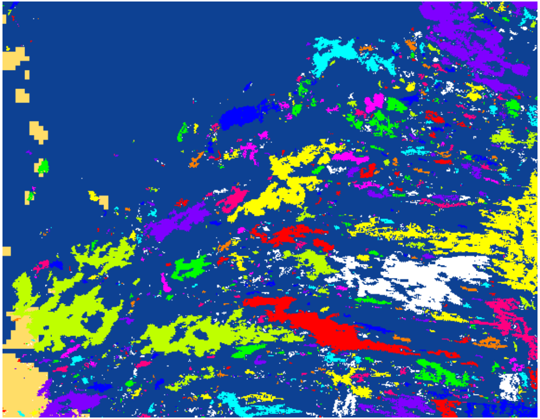
- we also work with observed data from EUREC^{4}A and model data from ICON



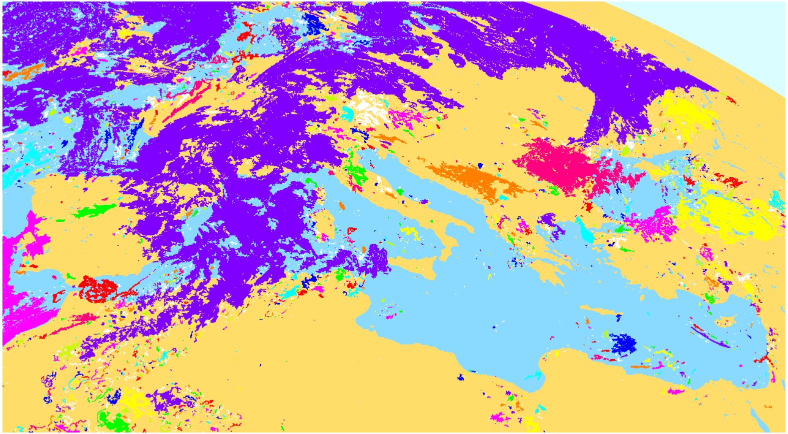
data from EUREC^{4}A campaign [eurec4a.eu]



ICON with 2km resolution

Improve cloud identification

- large cloud clusters are currently treated as one big cloud
- could use cloud top height or pixel-connectivity to split them up



Conclusion

Our cloud tracking routine is able to track nearly all cloud cover and clouds of all sizes reliably in geostationary satellite and model data.

More information in

Seelig et al. (2021) "Life cycle of shallow marine cumulus clouds from geostationary satellite observations", in JGR: Atmospheres, doi: 10.1029/2021JD035577

Contact

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Thank you for your attention!

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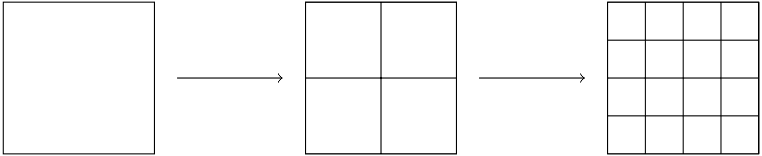
DAAD Deutscher Akademischer Austauschdienst
German Academic Exchange Service

References

- Seelig et al. (2021) ”Life cycle of shallow marine cumulus clouds from geostationary satellite observations”, in JGR: Atmospheres, doi: 10.1029/2021JD035577
- Benas et al. (2017) ”The MSG-SEVIRI-based cloud property data record CLAAS-2” in Earth System Science Data, 9(2):415–434, doi: 10.5194/essd-9-415-2017
- Raffel et al. (2007) ”Particle Image Velocimetry - A Practical Guide”, Springer Verlag, doi: 10.1007/978-3-540-72308-0
- Vila et al. (2008) ”Forecast and Tracking the Evolution of Cloud Clusters (ForTraCC) Using Satellite Infrared Imagery: Methodology and Validation” in Weather and Forecasting, 23(2), p. 233-245, doi: 10.1175/2007WAF2006121.1
- Coopman et al. (2019) ”Detection of Mixed-Phase Convective Clouds by a Binary Phase Information From the Passive Geostationary Instrument SEVIRI” in Journal of Geophys. Res.: Atmospheres 124, 5045-5057. doi: 10.1029/2018JD029772
- EUREC^{4}A campaign: www.eurec4a.eu

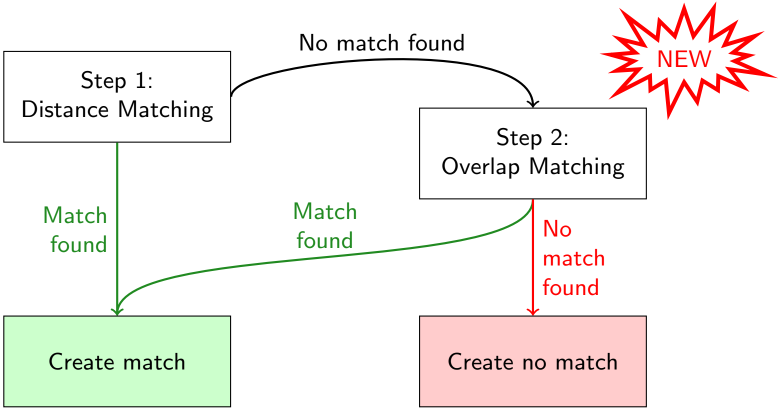
Additional slides coming now!

- 'where are these clouds generally moving?'
- use cross correlation between two consecutive timesteps to compute a velocity field
- use multiple iterations with shrinking windows to include 'local' movements and cover clouds of different sizes
- predicted positions = actual positions + velocity field

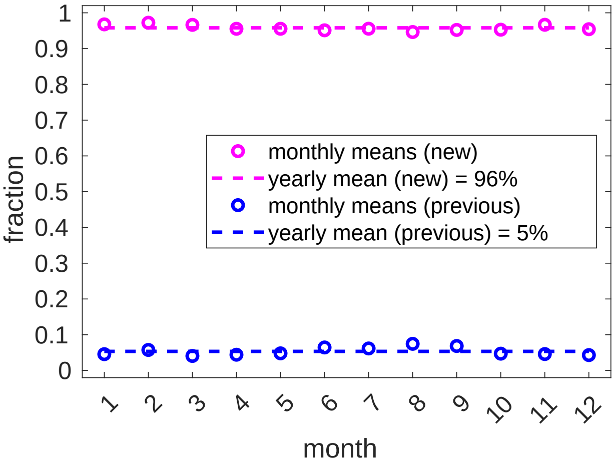


Shrinking grid sizes in multiple iterations

- compare predicted positions from the first timestep and observed positions from the second timestep via two matching criteria
- match with ‘best’ cloud, but create no match if threshold is not passed



- new approach tracks large clouds reliably
- tracks 96% of cloud area
- old approach tracked 5% of cloud area
- large difference is mostly due to the largest clouds being tracked reliably



average tracked cloud fraction across 2015

- large cloud clusters currently are treated as one big cloud
- they could be split up by using cloud top height or pixel-connectivity