Cloud detection using SEVIRI IR channels

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Overview

- Motivations
- Constraints
- Algorithm
- Results
- Comparisons
- Improvements
- Comparisons
- Further work

Motivations

- Scene identification only relying on visible channels
- SEVIRI data affected by sun glint over ocean
- Sun glint saturating 0.6 & 0.8 μm channels

▶ Degraded cloud mask within sun glint area

▶ Cloud mask unavailable at night time

Constraints

- GERB aim is to study climate
- GERB products must remain stable

- Limited use of *uncontrolled* ancillary data
- Independence to NWP data

- Implementation of an IR cloud detection scheme instead of using MPEF or NWCSAF

Physics

- SEVIRI IR 10.8, 8.7 & 12.0 μm channels are most sensitive to clearsky & clouds
- SEVIRI IR 3.9 μm channel is most sensitive to low water clouds
- Clouds are characterized by lower radiances (temperatures) than clearsky surfaces (warmer) except for snow & sea ice surfaces
- Aerosols are *generally* lowering IR radiances
- IR radiances are varying with viewing zenith angle, history (precipitation, cloud shadow) and state of atmosphere (profiles)

► Visible & IR cloud masks will have discrepancies due to different measurement sensitivities

Assumptions

- Considering time–series of pixel–based BTs
- Temporal window for time–series set to 60 days
- Samples in time–series can be grouped into 3 classes:
  1. thick cold clouds (low BTs)
  2. thin or low clouds (high BTs)
  3. clearsky conditions (highest BTs)
- Tails of upper classes are overlapping
- No realtime ancillary data such as NWP fields

▶ Cannot be applied to snow & sea ice surfaces

Scheme

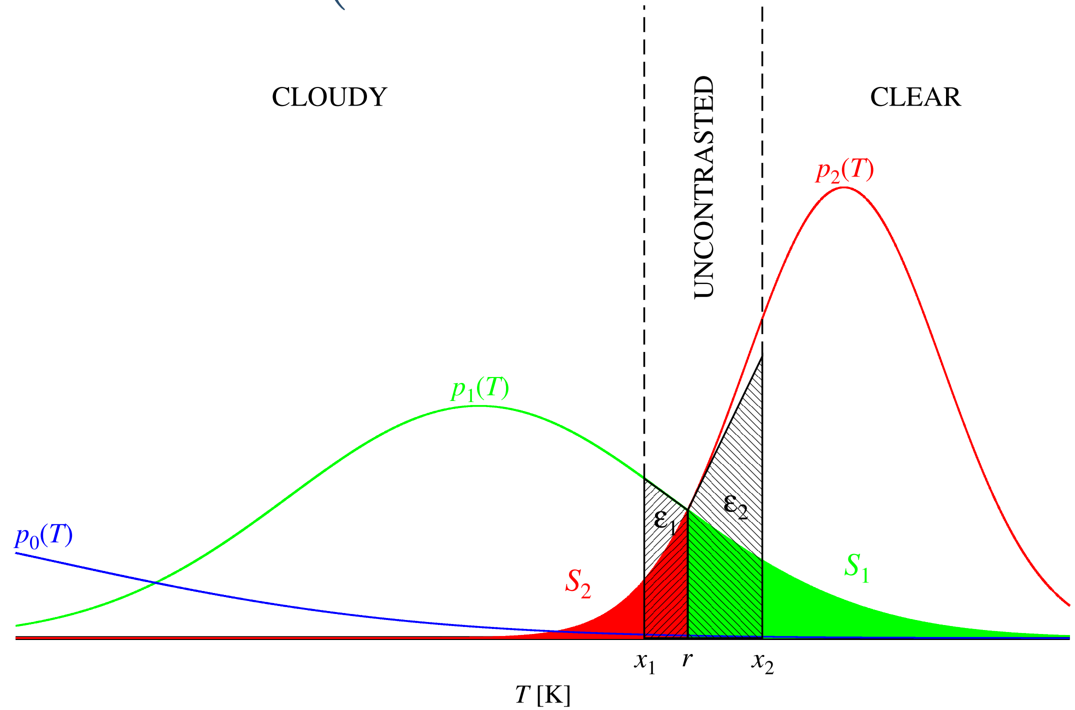
- Perform a *modified* k–means clustering:

  1. Initialize the μ_n and σ_n for the 3 clusters
  2. If initialization fails goto step 1 with 2 clusters and so on...
  3. Classify all 60 BTs according to their nearest cluster with $d(T, \mu_n, \sigma_n)$
  4. Update μ_n and σ_n
  5. Repeat from step 3 until all μ_n do not significantly change ($\Delta\mu_n < 0.01$ K)

- ▶ Metric $d(T, \mu_n, \sigma_n) = (T - \mu_n)^2/\sigma_n^2 + \ln \sigma_n^2$ if values in each class follow $p_n(T) = N(\mu_n, \sigma_n)$
- ▶ Initialization driven by physics (climatology)

Scheme

Final classification (of the most recent sample):



- Equality of the probabilities of no good classification: $\epsilon_1 + S_1 = \epsilon_2 + S_2$
- Equality of probabilities of uncontrasted and false classifications: $\epsilon_1 + \epsilon_2 = S_1 + S_2$

$\Rightarrow S_1 = \epsilon_2$ and $S_2 = \epsilon_1$

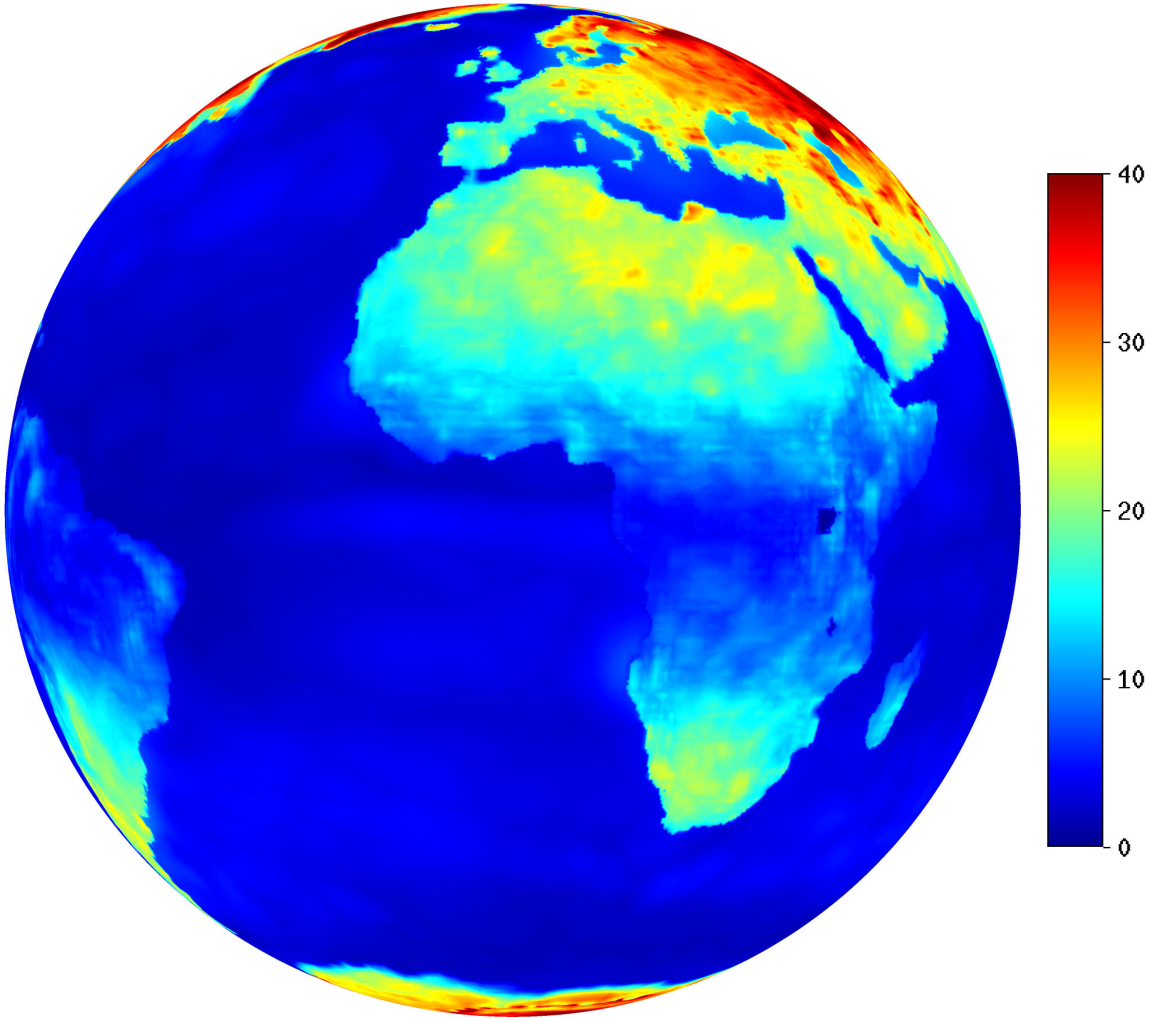
Initialization

- Assume that clearsky class is Δ wide
- Cloudy classes evenly distributed over remaining T range
- Δ is only needed for starting the clustering
- Single cluster case associated to clearsky

Δ is estimated from climatology:

- 10 years of 6–hourly ERA–40 surface skin temperatures T_s
- Compute $\delta_t = T_s^{(59)} - T_s^{(2)}$ at pixel level (x, y)
- $\Delta(x, y)$ is the median of 10–years seasonal $\delta_t(x, y)$

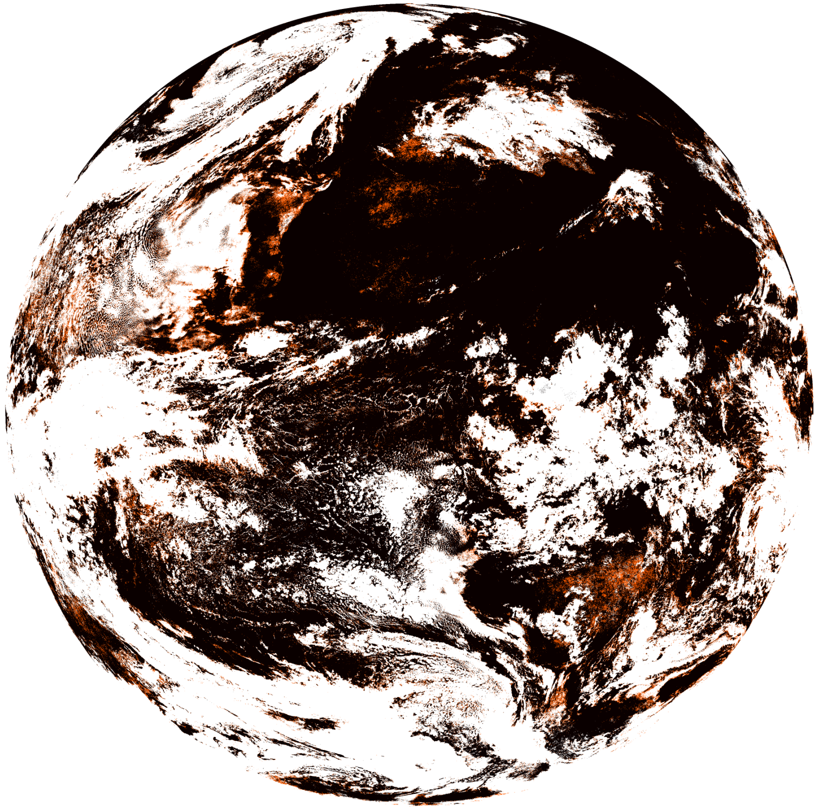
Initialization



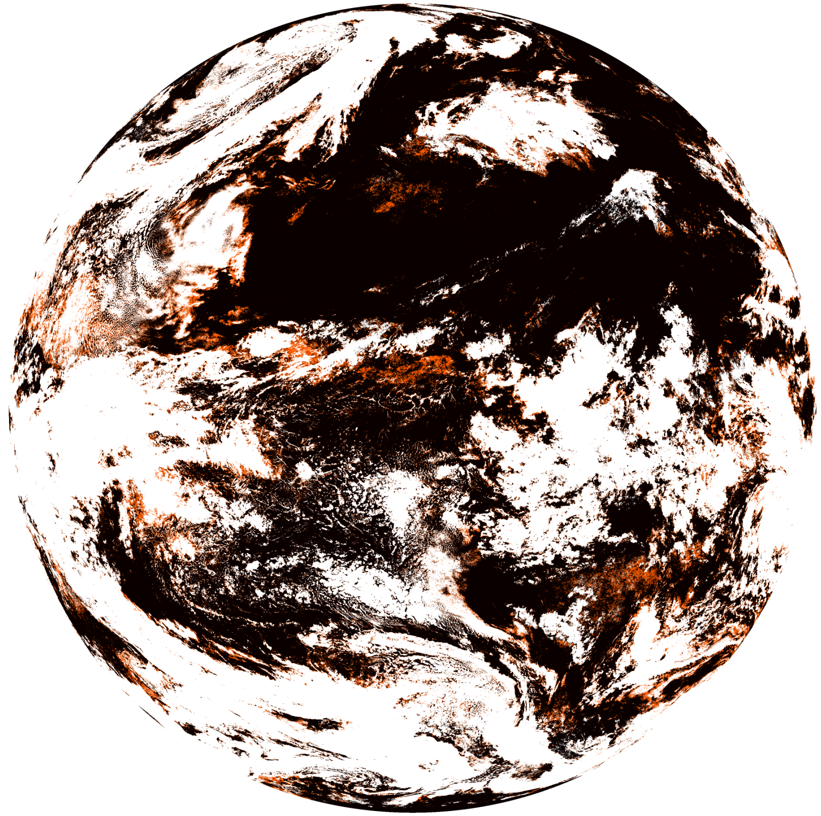
Δ_{MAM} [K] at 00:00 UTC

Results (single channel)

3.9 μm



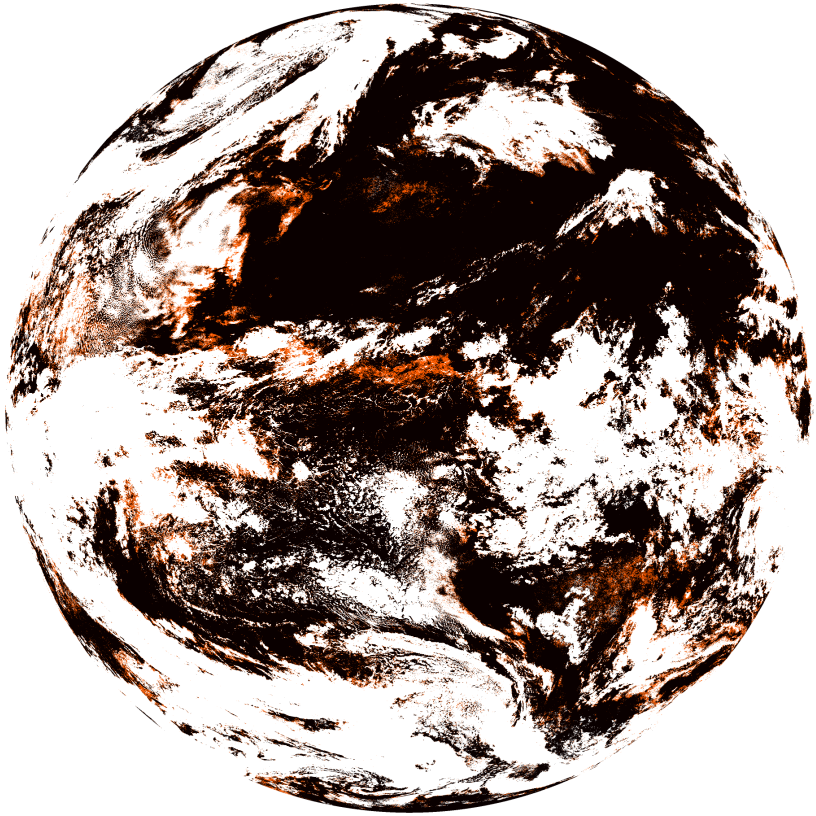
8.7 μm



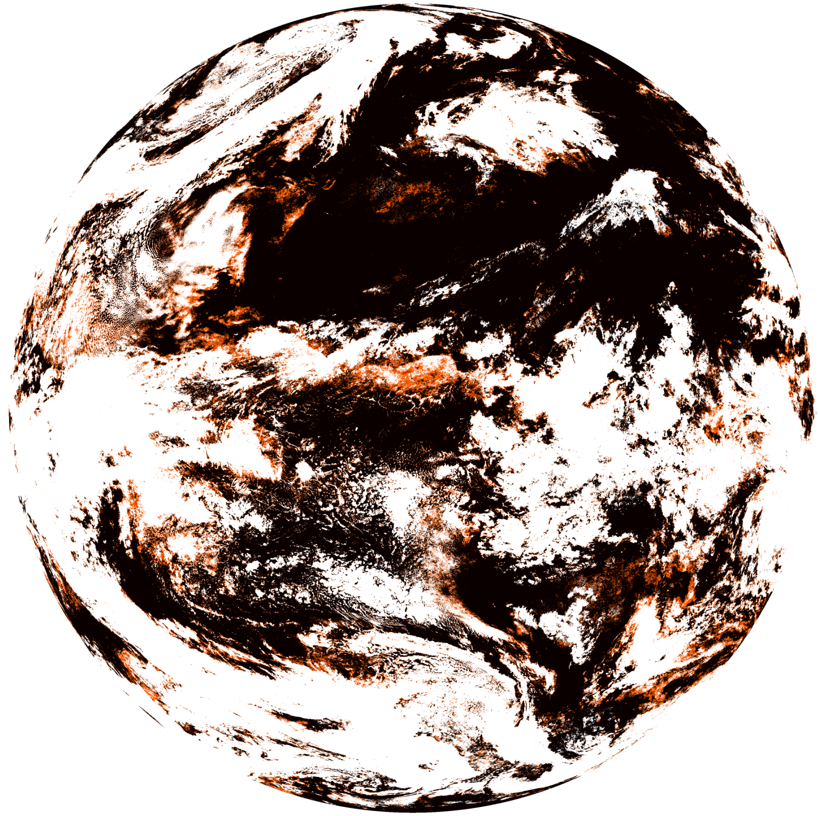
March 11 2007 at 00:00 UTC

Results (single channel)

10.8 μm



12 μm



March 11 2007 at 00:00 UTC

Comparisons (single channel)

- Reference is MPEF & NWCSAF common cloud mask (March 2007 at 00:00 UTC)

	Day	11	12	13	14	15	16	17
Band	Common [%]	86.90	88.04	87.52	87.71	87.38	87.37	88.05
3.7	POD [%]	89.68	90.69	90.68	90.25	88.99	88.84	86.55
	fcs [%]	5.17	4.42	4.91	5.04	6.06	5.76	7.30
	fCL [%]	0.92	0.78	0.70	0.78	0.80	1.01	1.15
8.7	POD [%]	91.44	92.46	92.69	91.99	91.08	91.20	89.56
	fcs [%]	3.20	2.67	2.98	2.66	3.02	3.06	3.61
	fCL [%]	1.26	1.11	0.98	1.23	1.72	1.53	1.93
10.8	POD [%]	91.16	92.06	92.33	91.50	90.90	91.07	89.82
	fcs [%]	2.90	2.47	2.65	2.39	2.52	2.55	2.82
	fCL [%]	1.55	1.47	1.42	1.86	2.30	2.05	2.52
12	POD [%]	89.46	90.71	91.20	89.93	89.28	89.70	88.71
	fcs [%]	2.96	2.56	2.50	2.32	2.28	2.32	2.52
	fCL [%]	2.81	2.61	2.49	3.23	4.06	3.28	3.89

fcs = false clearsky, fCL = false cloudy

Comparisons (single channel)

Limitations:

- Cloud masks sensitive to specific clouds
- Cloud masks cannot be "simply" merged
- 10.8 μm gives most consistent results
- Low water clouds systematically missed ($\Delta \approx 1$K)

Suggestions

NWCSAF algorithm uses threshold on:

- $T_{10.8} - T_{3.9}$ for low water clouds
- $T_{12} - T_{3.9}$ for low water clouds (ocean)
- $T_{10.8} - T_{12}$ for thin cirrus and cloud edges
- $T_{8.7} - T_{10.8}$ for thin cirrus

▶ Note that 3.9 μm channel only used at night

Algorithm

Low water clouds ”improved” detection (night):

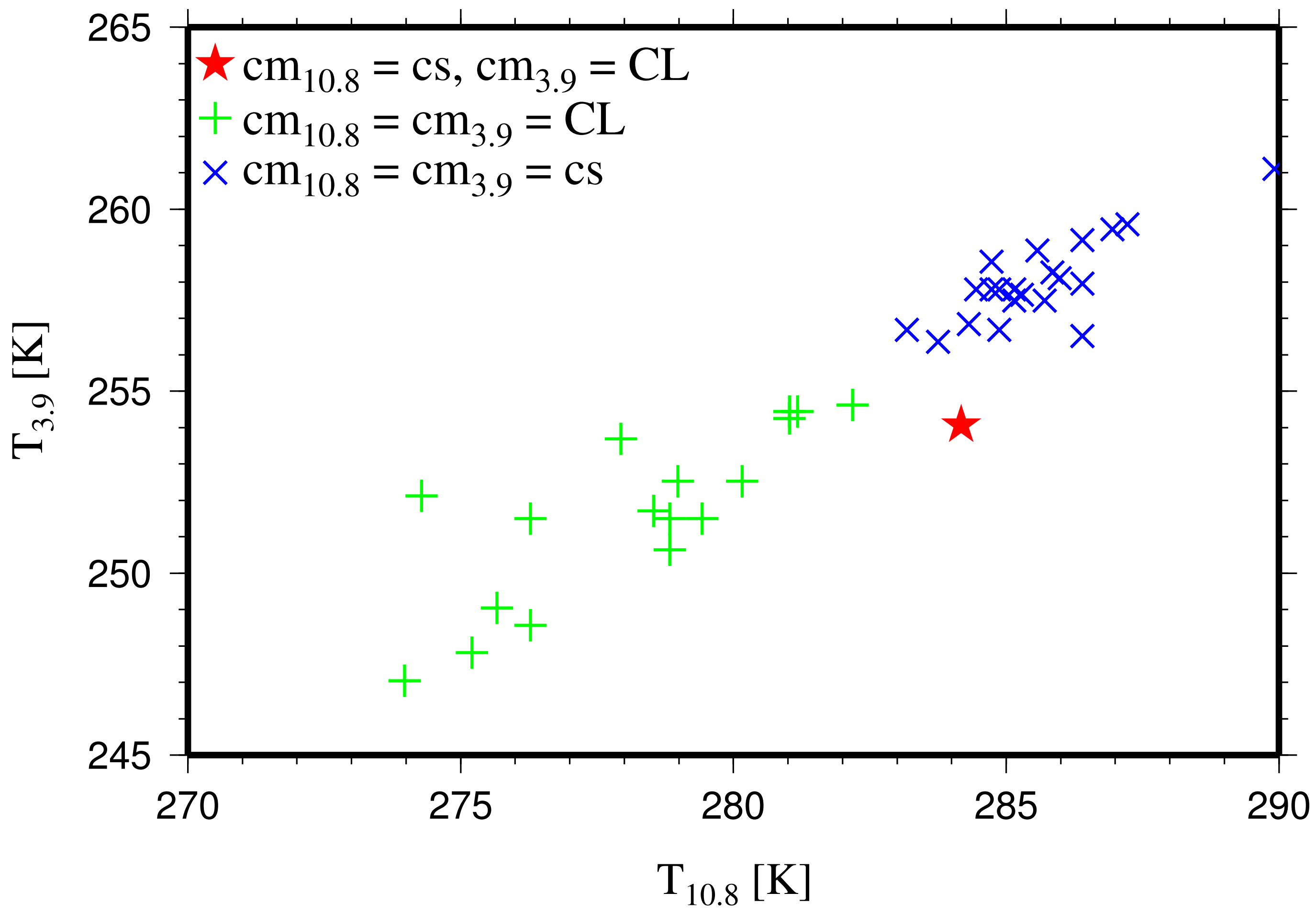
- Use 10.8 μm cloud mask for reference
- Use joint 3.9 & 10.8 μm 1D clustering results

For pixels with discordant 3.9 & 10.8 μm cloud masks:

1. Compute 2D MLE $(\mu_{\mathbf{n}}, \mathbf{\Sigma}_{\mathbf{n}})$ on joint common:
   - clearsky class
   - low contrast cloudy class
2. Classify most recent sample pair $\mathbf{T}^{\star}$ according to nearest 2D cluster with $d(\mathbf{T}, \mu_{\mathbf{n}}, \mathbf{\Sigma}_{\mathbf{n}})$

▶ Metric:
$d(\mathbf{T}, \mu_{\mathbf{n}}, \mathbf{\Sigma}_{\mathbf{n}}) = (\mathbf{T} - \mu_{\mathbf{n}})^t \mathbf{\Sigma}_{\mathbf{n}}^{-1} (\mathbf{T} - \mu_{\mathbf{n}}) + \ln |\mathbf{\Sigma}_{\mathbf{n}}|$
if values in each class follow $p_n(\mathbf{T}) = N(\mu_{\mathbf{n}}, \mathbf{\Sigma}_{\mathbf{n}})$

Algorithm



- 2D MLE assigns most recent pixel ★ to cloudy

Comparisons (3.9 & 10.8 μm bands)

- Reference is MPEF & NWCSAF common cloud mask (March 2007 at 00:00 UTC)

	Day	11	12	13	14	15	16	17
Band	Common [%]	86.90	88.04	87.52	87.71	87.38	87.37	88.05
	POD [%]	93.18	93.80	93.74	93.65	92.57	92.58	90.73
	fcs [%]	3.14	2.78	3.16	2.83	3.20	3.18	3.54
	fCL [%]	1.50	1.38	1.25	1.57	1.78	1.76	2.11
	POD [%]	91.16	92.06	92.33	91.50	90.90	91.07	89.82
10.8	fcs [%]	2.90	2.47	2.65	2.39	2.52	2.55	2.82
	fCL [%]	1.55	1.47	1.42	1.86	2.30	2.05	2.52

fcs = false clearsky, fCL = false cloudy

Further work

- Algorithm improvement for low water clouds applicable to day–time (3.9 μm) ?
- Improvements with other channel combinations (NWCSAF–like) ?
- Comparisons during day time
- Multidimensional k–means clustering ?
- ECMWF surface skin temperatures should be converted to TOA temperatures according to atmospheric path
- Use of asymmetrical distributions $p_n(T)$ instead of $N(\mu_n, \sigma_n)$
- Length of time–series varying according to pixel