Statistical downscaling of water vapour satellite measurements from observations of tropical ice clouds

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Image from T. Peake

Overview

Microphysical processes driving **cloud- and water vapour-related distribution and variability** in the troposphere are not well known:

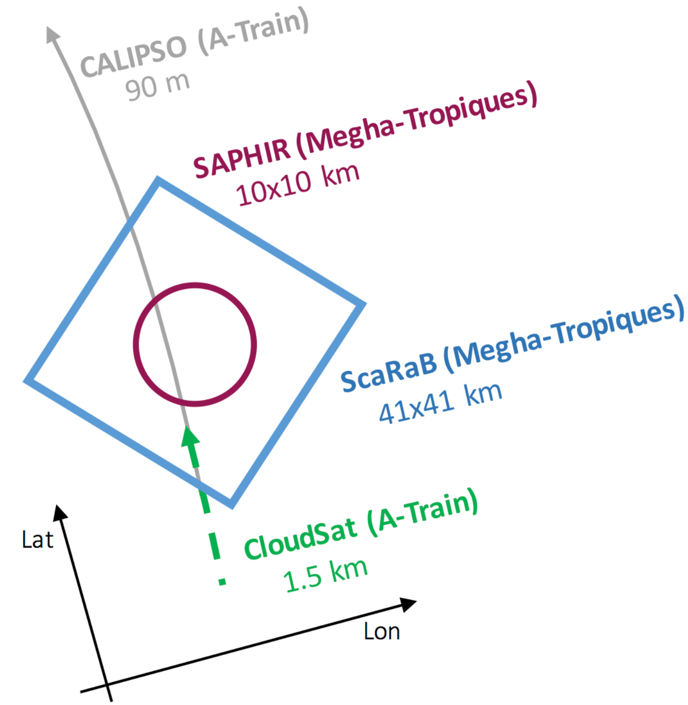
⇒ represent an important source of uncertainty in climate models

⇒ **tropical ice clouds** are of particular interest being intimately connected to water vapour

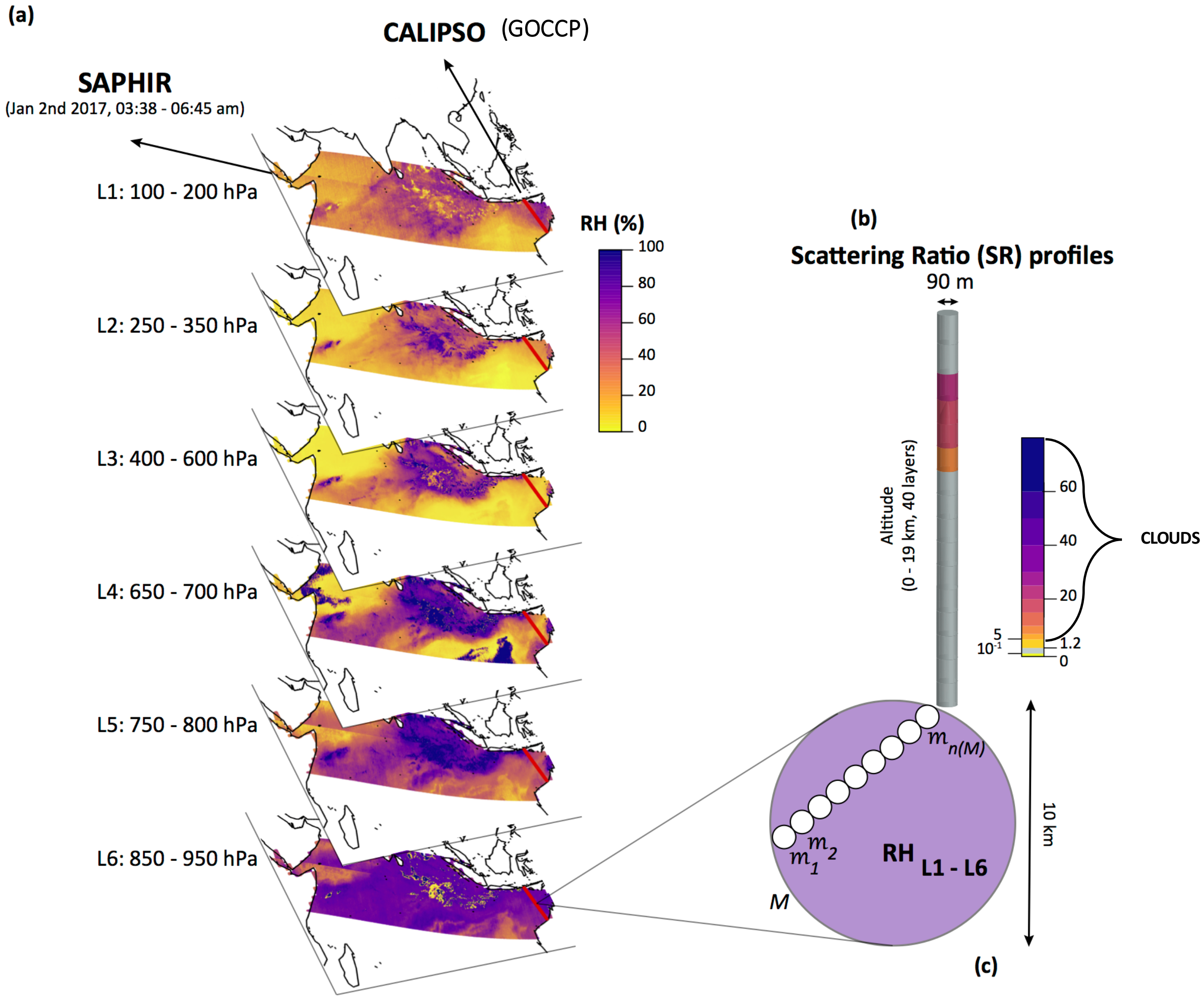
- Reanalyses exhibit noticeable biases in the tropical water and energy budget on the vertical (e.g. GEWEX)
- Satellites can describe both the micro-physical properties **(CALIPSO/CloudSat)** and the moisture structure **(SAPHIR)** in the whole troposphere but

⇒ clouds are heterogeneous variables, humidity is a continuous field

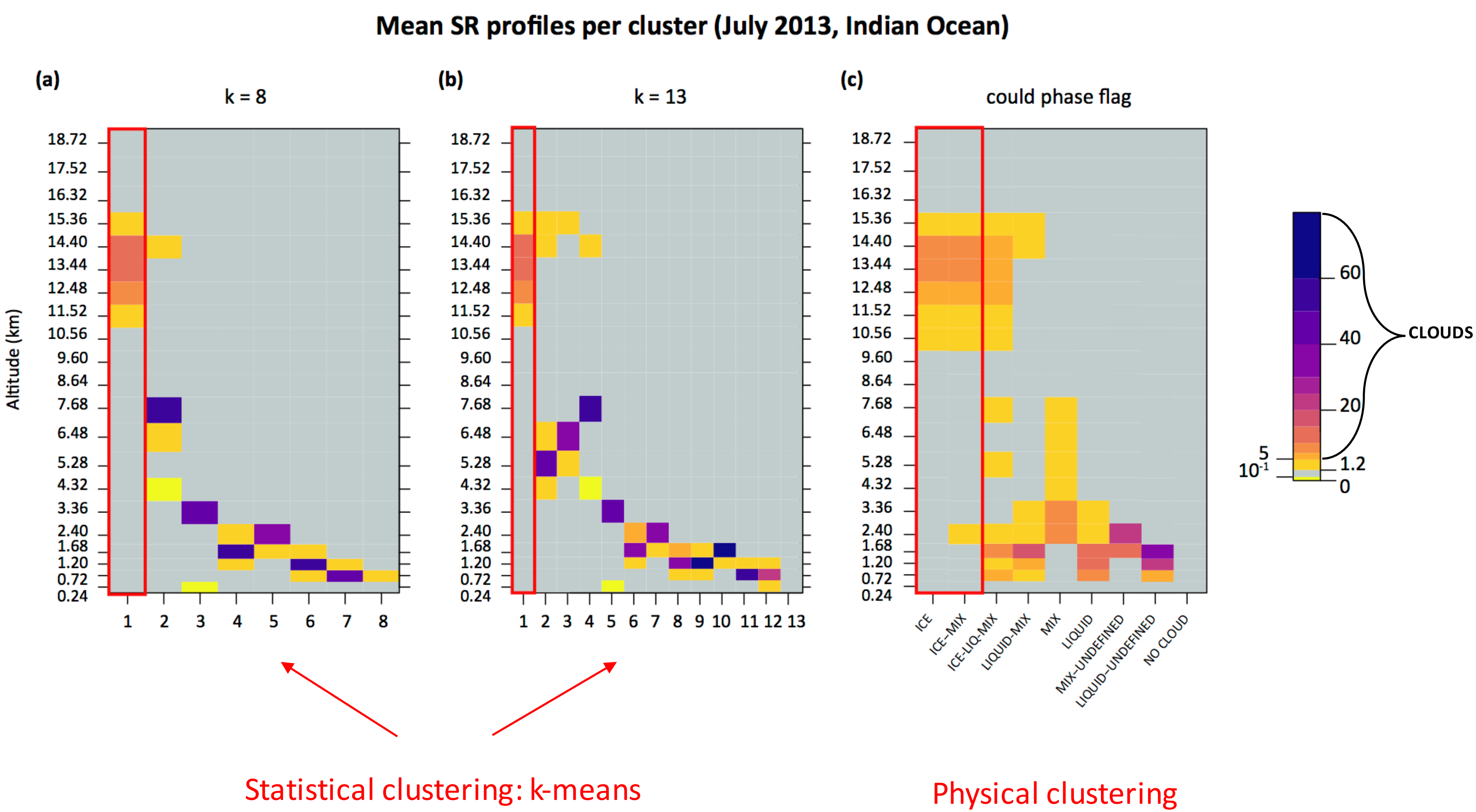
⇒ different instruments with different spatial resolution view the Earth differently



Objective: Simulate at the scale of cloud measurements (`downscaling') the water vapour structure associated to tropical ice clouds from their microphysical properties



Selection of ice clouds



$$RH_l \sim \Phi(SR_1, SR_2, ..., SR_p)$$

Model	Model type	Spatial Correlation	Prediction type
GAM (Wood, 2011)	Semi-parametric	–	Conditional mean
GAM with GMRF smoother (Wood, 2011)	Semi-parametric	Neighbour structure	Conditional mean
Geoadditive (Kammann & Wand, 2003)	Semi-parametric	Exponential correlation function	Conditional mean
RF (Breiman, 2001)	Non-parametric	–	Conditional mean
QRF (Meinshausen, 2006)	Non-parametric	–	Conditional quantiles

An iterative algorithm is then used to optimize the regression ensuring the 'mass balance' (Malone *et al.*, 2012)

Predictive skills:

Observed value

Forecast for the *i*-th ensemble member

$$CRPS(y) = \frac{1}{K}\sum_{i=1}^{K} |\, x_i - y \,| - \frac{1}{2K\,(K-1)}\sum_{i=1}^{K}\sum_{j=1}^{K} |\, x_i - x_j \,|$$

(Ferro, 2008)

$$CRPSS = 1 - \frac{CRPS_{mod}}{CRPS_{ref}}$$

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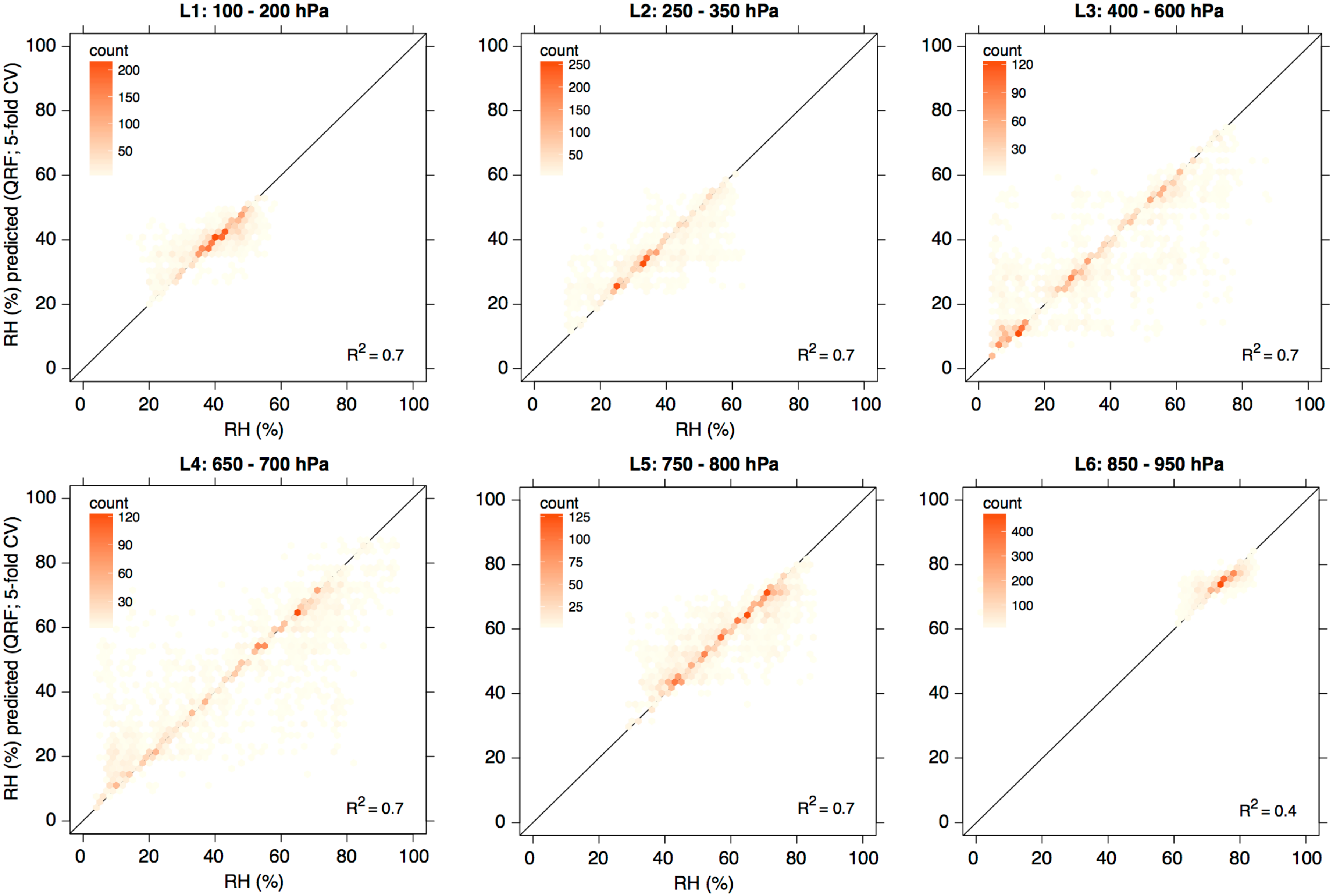
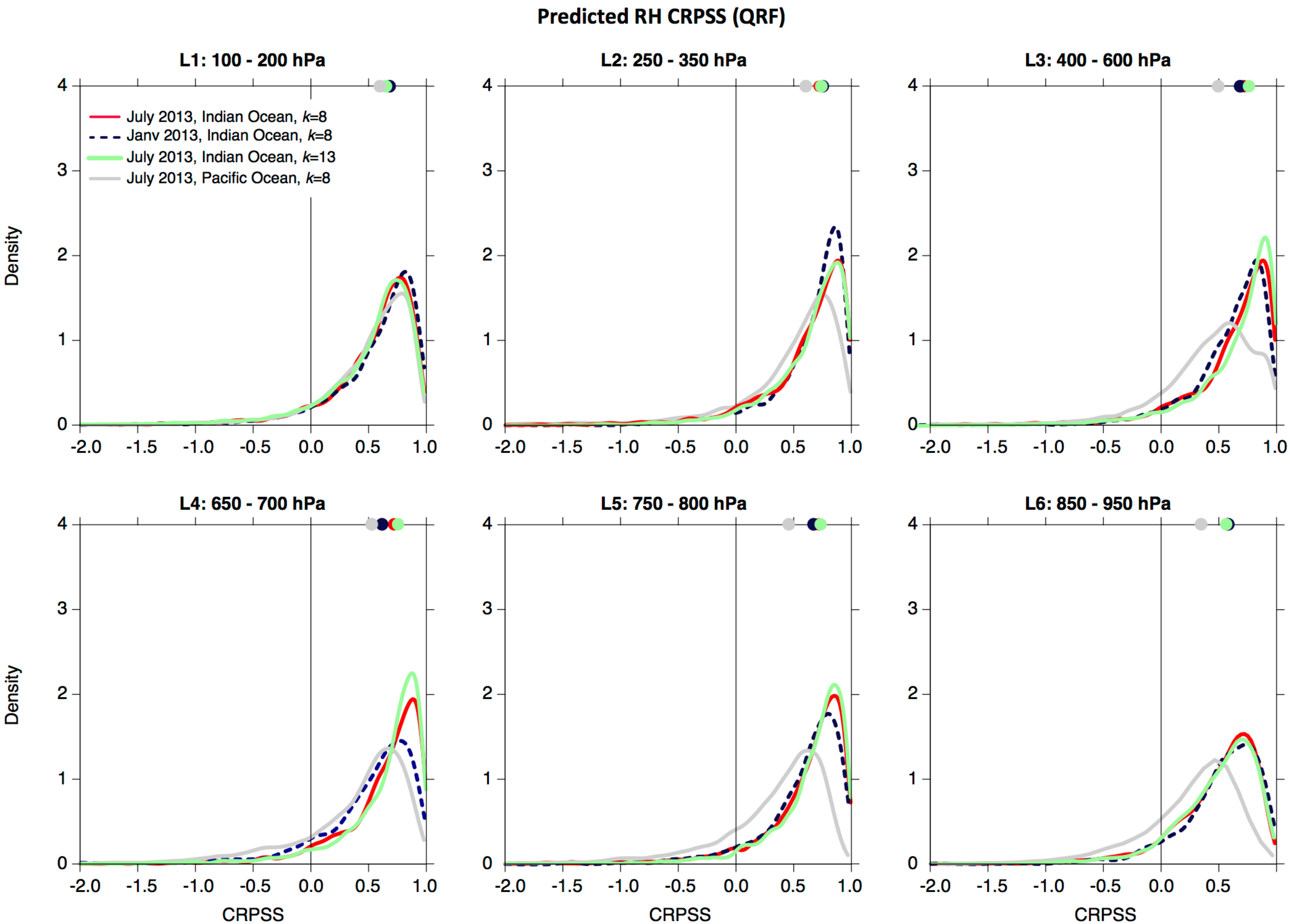
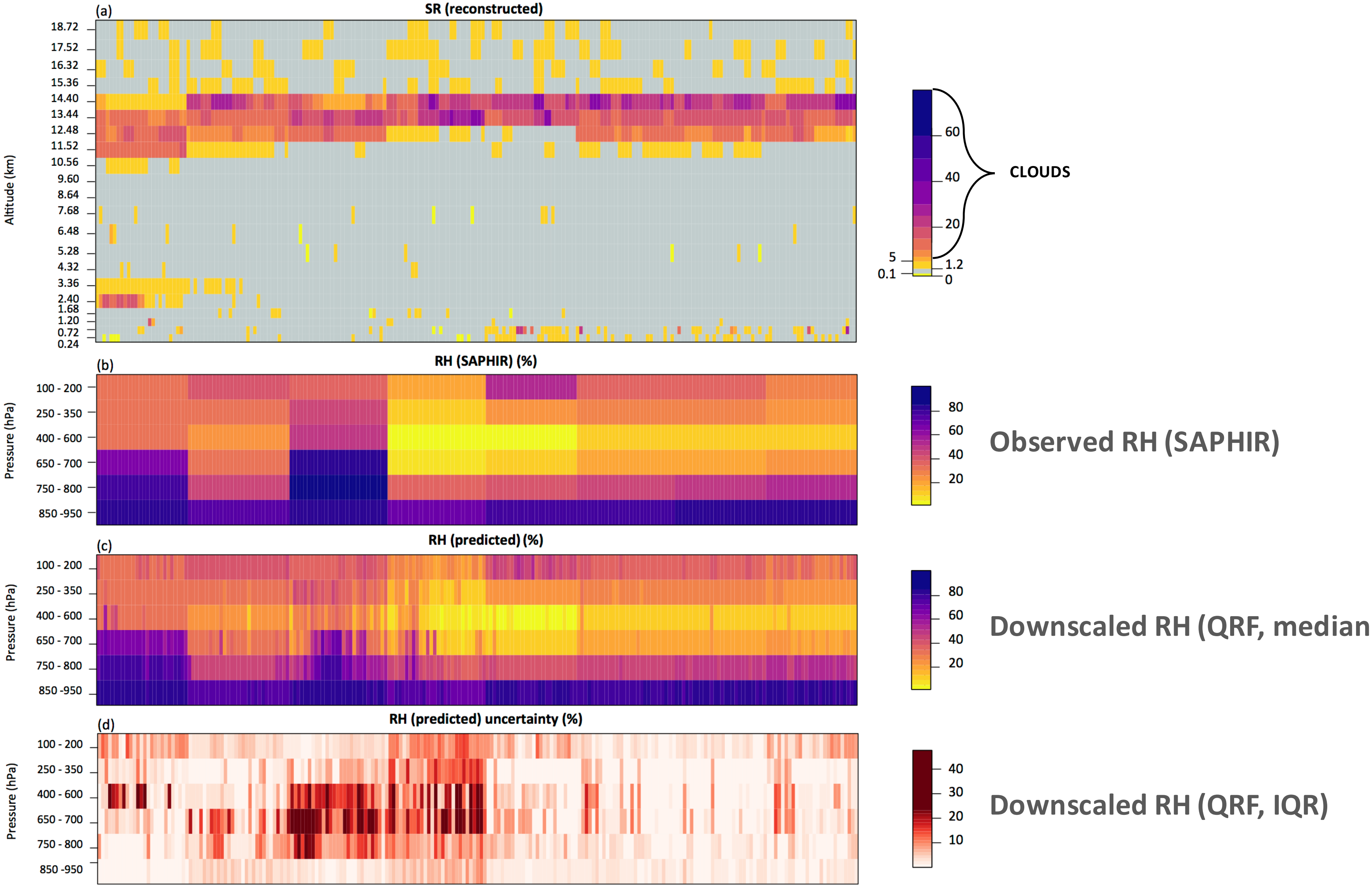
Predicted vs. observed RH (July 2013, Indian Ocean)

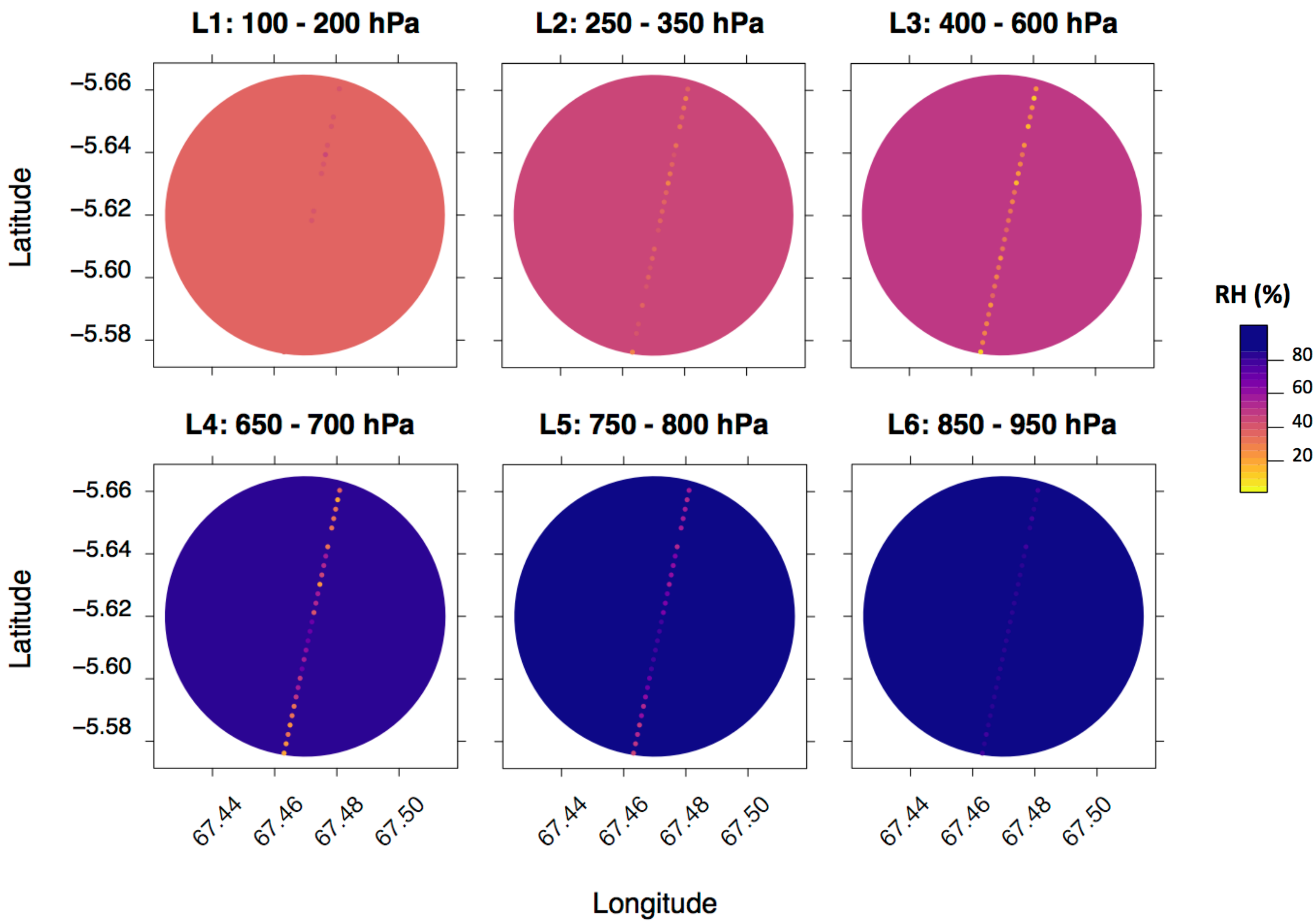



Predicted RH CRPSS (QRF)
L1: 100 - 200 hPa
L2: 250 - 350 hPa
L3: 400 - 600 hPa
L4: 650 - 700 hPa
L5: 750 - 800 hPa
L6: 850 - 950 hPa
July 2013, Indian Ocean, k=8
Janv 2013, Indian Ocean, k=8
July 2013, Indian Ocean, k=13
July 2013, Pacific Ocean, k=8
Density
CRPSS
0
1
2
3
4
-2.0
-1.5
-1.0
-0.5
0.0
0.5
1.0

Results


(a)
SR (reconstructed)
Altitude (km)
18.72
17.52
16.32
15.36
14.40
13.44
12.48
11.52
10.56
9.60
8.64
7.68
6.48
5.28
4.32
3.36
2.40
1.68
1.20
0.72
0.24
60
40
20
5
1.2
0.1
0
CLOUDS
(b)
RH (SAPHIR) (%)
Pressure (hPa)
100 - 200
250 - 350
400 - 600
650 - 700
750 - 800
850 -950
80
60
40
20
Observed RH (SAPHIR)
(c)
RH (predicted) (%)
Pressure (hPa)
100 - 200
250 - 350
400 - 600
650 - 700
750 - 800
850 -950
80
60
40
20
Downscaled RH (QRF, median)
(d)
RH (predicted) uncertainty (%)
Pressure (hPa)
100 - 200
250 - 350
400 - 600
650 - 700
750 - 800
850 -950
40
30
20
10
Downscaled RH (QRF, IQR)

High resolution spatial inhomogeneities in the water vapour field cannot be observed by SAPHIR



Future work and perspectives

⇒ Extended the method to other types of clouds (additional covariates might be required: e.g. for liquid clouds, include the radar reflectivity as measured by CloudSat)

⇒ A 10-year long high resolution water vapour-clouds dataset (2006-2017)

1. <u>Climate-related studies</u>

- how small scale water cycle processes behave when exposed to strong variations in large scale circulation regimes such as those associated to El Niño cycles
- ‘evaluate’ how small scale water vapour inhomogeneities affect the water vapour in reanalyses
- put the results of past and current field experiments into a larger scale context
- guide the parametrization of unresolved subgrid-scale water vapour/clouds processes n climate models
- evaluate the description of water vapour/cloud interactions in regional models
- test the validity of the fixed anvil temperature and estimate the changes to long-wave fluxes with warming, for example using simulated CALIPSO profiles from model variables
- quantify the limits of current and future space missions by characterizing the spatial inhomogeneities in water vapour fields that cannot be observed by present satellites

2. <u>Statistical framework to re-scale observables from different instruments</u>

Conclusions

⇒ The water vapour response for ice cloud profiles in the tropics is well predicted from their micro-physical properties, using instantaneous satellite measurements

⇒ Process studies require water-vapour observations at smaller scale than SAPHIR pixels (<10 km)

⇒ By providing a method to generate pseudo-observations of relative humidity (at high spatial resolution) from simultaneous co-located cloud profiles, this work will be of great help to revisit some of the current key barriers in atmospheric science

QUESTIONS!

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ANSWERS?