Horizontal emissivity structure of UT cloud systems & resulting heating

(A-Train synergy)

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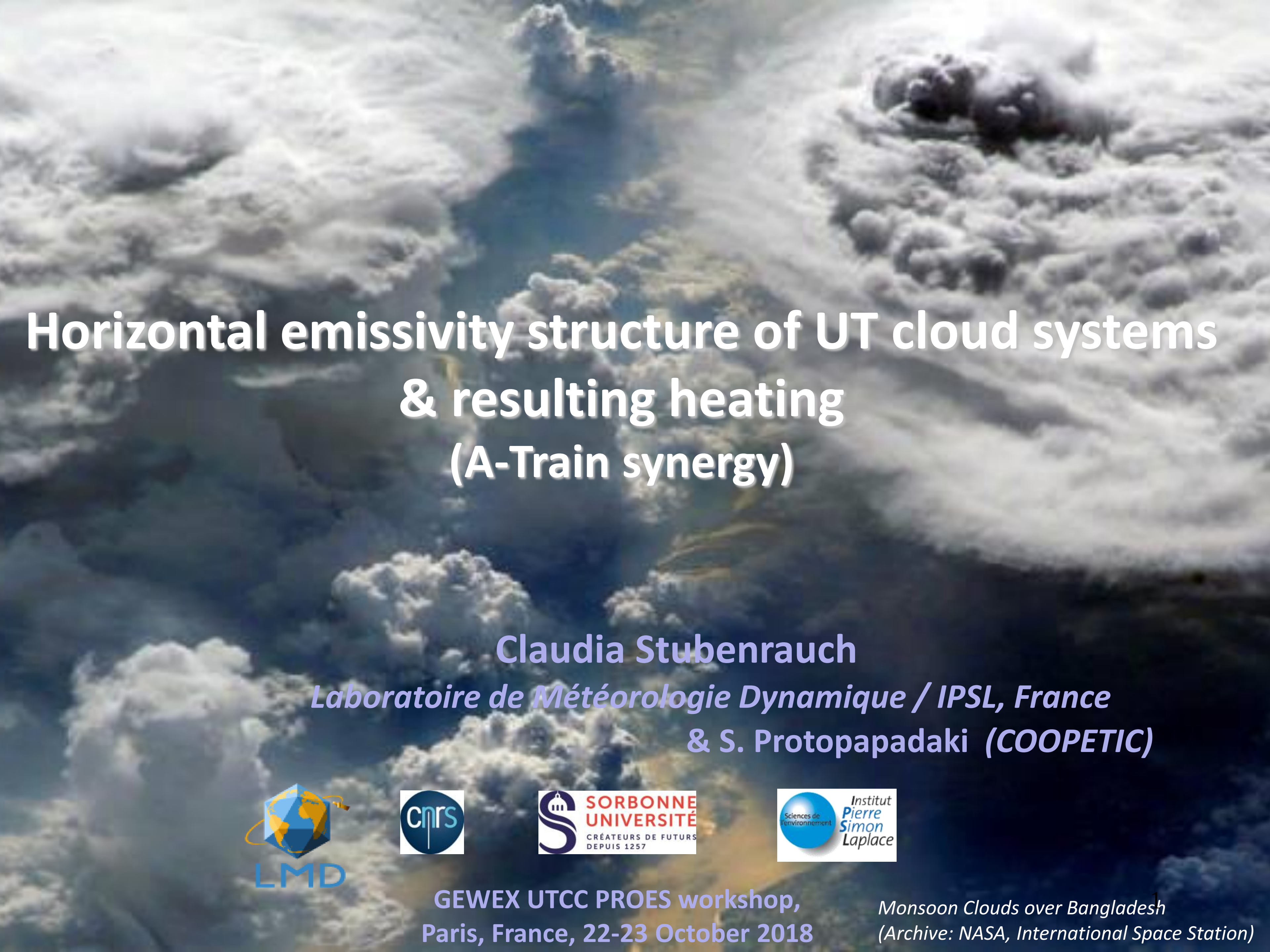
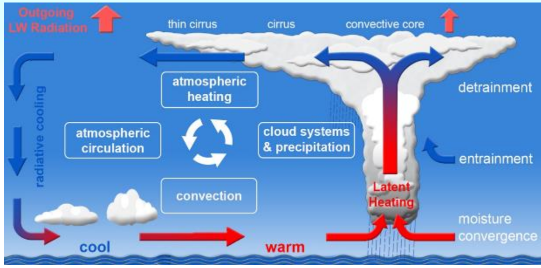


Monsoon Clouds over Bangladesh
(Archive: NASA, International Space Station)

Motivation & Approach



critical to climate feedback of UT clouds :

cirrus radiative heating in upper troposphere

Cirrus anvils might regulate convection as they stabilize the atmospheric column by their heating *(Stephens et al. 2008, Lebsock et al. 2010)*

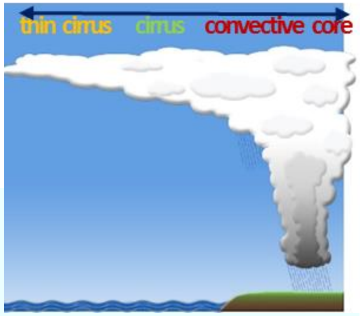
tropical convective regions: > 50% of total heating UT heating due to cirrus *(Sohn 1999)*
-> widespread impact on large-scale atmospheric circulation *(Schumacher et al. 2004)*

Heating will be affected by:

- areal coverage
- emissivity distribution
- vertical structure (layering)

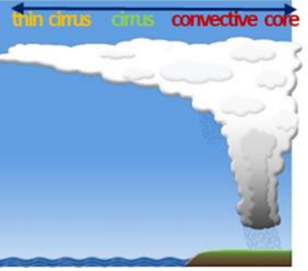
Climate warming : change in convective intensity & coverage, height of convective systems & emissivity structure of the anvils ? This then affects the heating gradients!

Goal: understand relation between convection & radiative heating induced by cirrus anvils



Method:

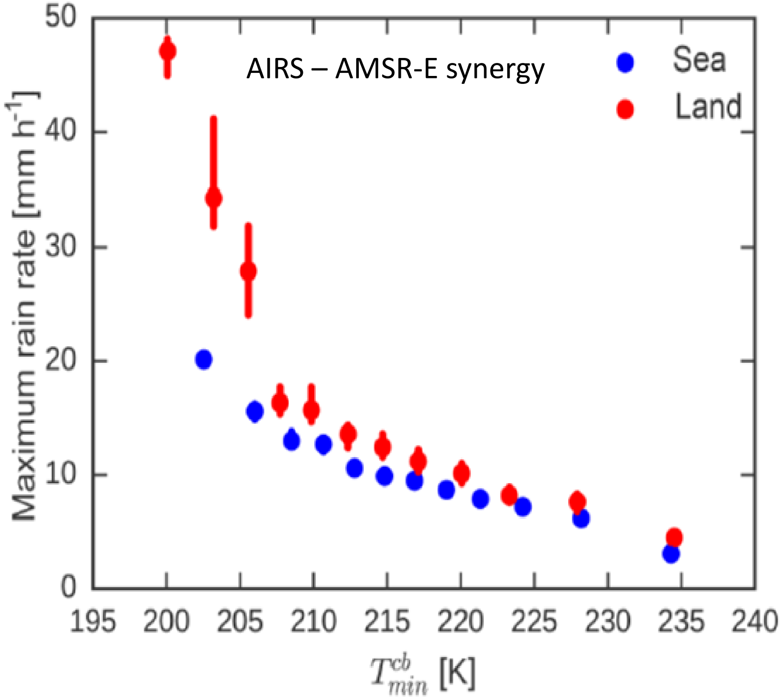
1) IR Sounders provide cloud height & emissivity; sensitive to cirrus
2) Cloud System Concept relates the anvil properties to processes shaping them
3) expand radar-lidar nadir track vertical structure laterally across UT cloud systems



link anvil structure to convective depth

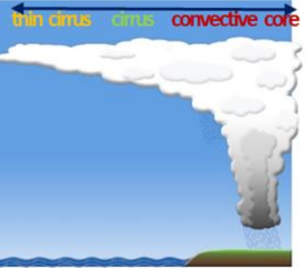
Protopapadaki et al. ACP 2017

15 years AIRS; ***tropical UT cloud systems*** (p_{cld}-$p_{tropopause}$ < 250 hPa or p_{cld} < 440 hPa);
convective core (Cb): ε_{cld}>0.98; ***mature systems***: Cb fraction within system 0.1 – 0.3



Deeper convective cores -> stronger max rain rate
-> T^{cb}_{min} good proxy for convective strength

increasing convective depth



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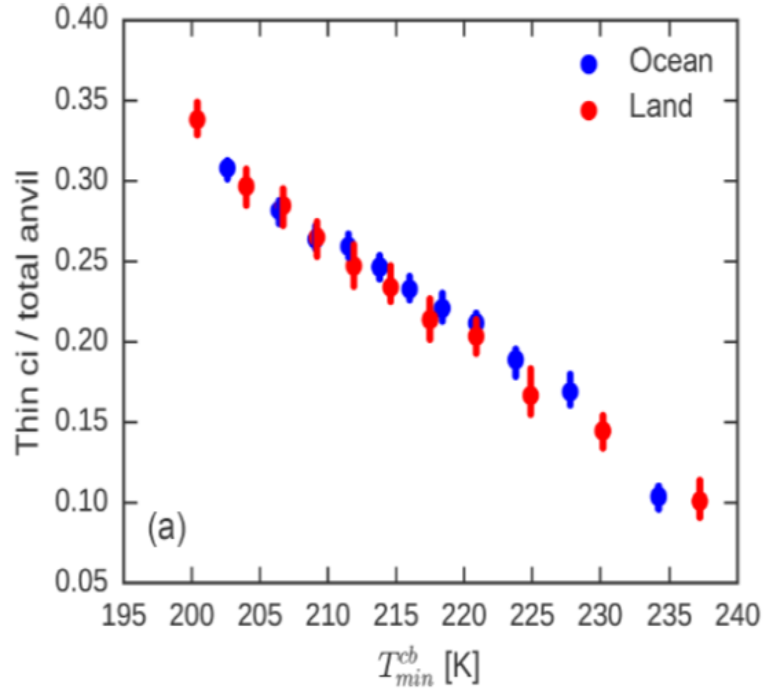


Deeper convective cores -> stronger max rain rate
-> T^{cb}_{min} good proxy for convective strength

Deeper convection leads to relatively more thin cirrus within larger anvils
(similar land / ocean)

relation robust *using different proxies :*
T_{min}^{Cb} / LNB(max mass)

increasing convective depth

Why ?
H1: UT environmental predisposition (at higher altitude larger RH, T stratification)
H2: UT humidification from cirrus outflow

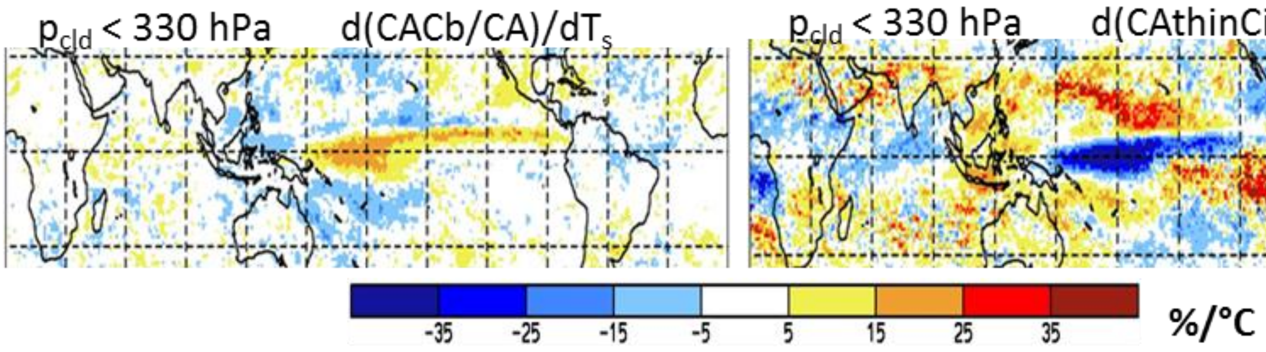
Does the relationship change in a warmer climate ?

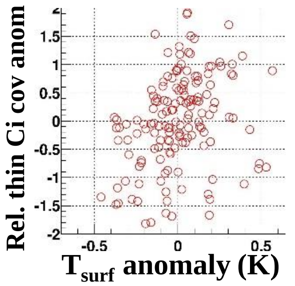
CRM

GCM

How do tropical UT clouds change with global T_{surf} ?

Stubenrauch et al. ACP 2017





Changes in occurrence of Cb & thin Ci relative to total cloud per °C warming show different geographical patterns *-> change in heating gradients*

& UT cloud systems ?

preliminary

av. coverage of all UT cloud systems: 25.6%

$dcov/dT_s = -1.3 \pm 0.6$ %/°C

79% of coverage from convective systems, 6% from thin ci systems

48% of convective systems are cold convective systems ($T_c < 210K$)

$d[cov_{cold\ conv}/cov_{conv}]/dT_s = +18 \pm 5$ % /°C

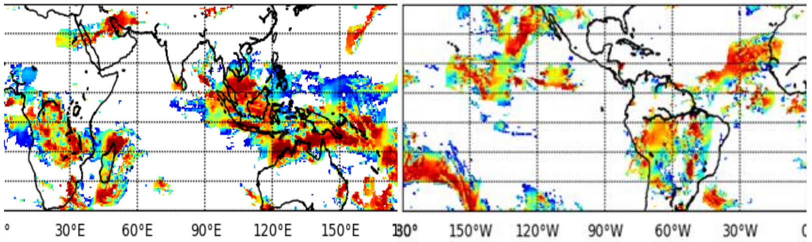
$dT_c/dT_s = -2.1 \pm 0.5$ °C /°C

$d(thci/anv)/dT_s = 0.041 \pm 0.008$ /°C

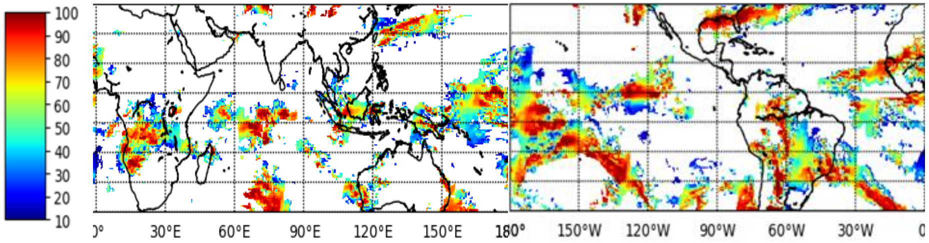
$d\varepsilon_c/dT_s = -0.035 \pm 0.005$ /°C

warming ->
larger area covered by cold convective systems & more thin ci within anvil

Contrast cold *(La Nina)* & warm *(El Nino)* tropics

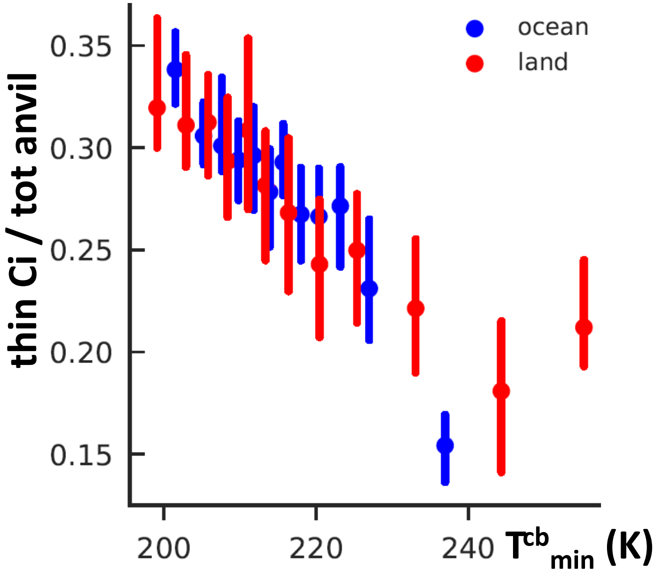


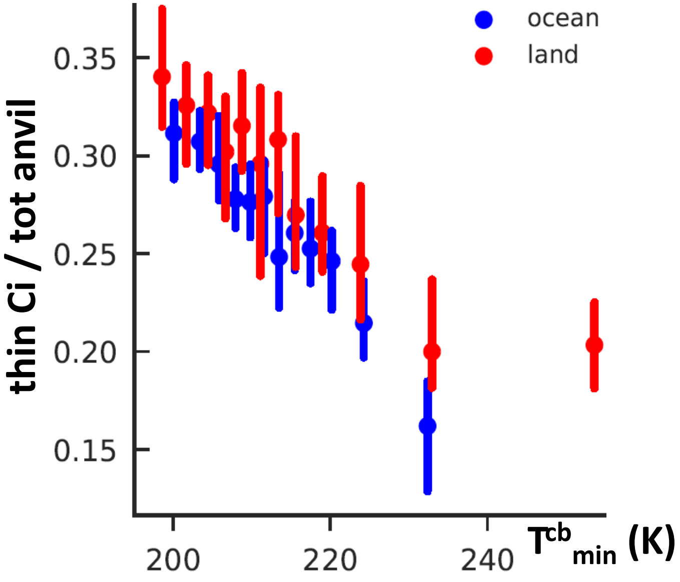
Jan 2008 ΔT_{surf} = -0.46°C



Jan 2016 ΔT_{surf} = +0.47°C

Warmer El Nino period :
larger area covered by cold convective systems & more thin ci within anvil

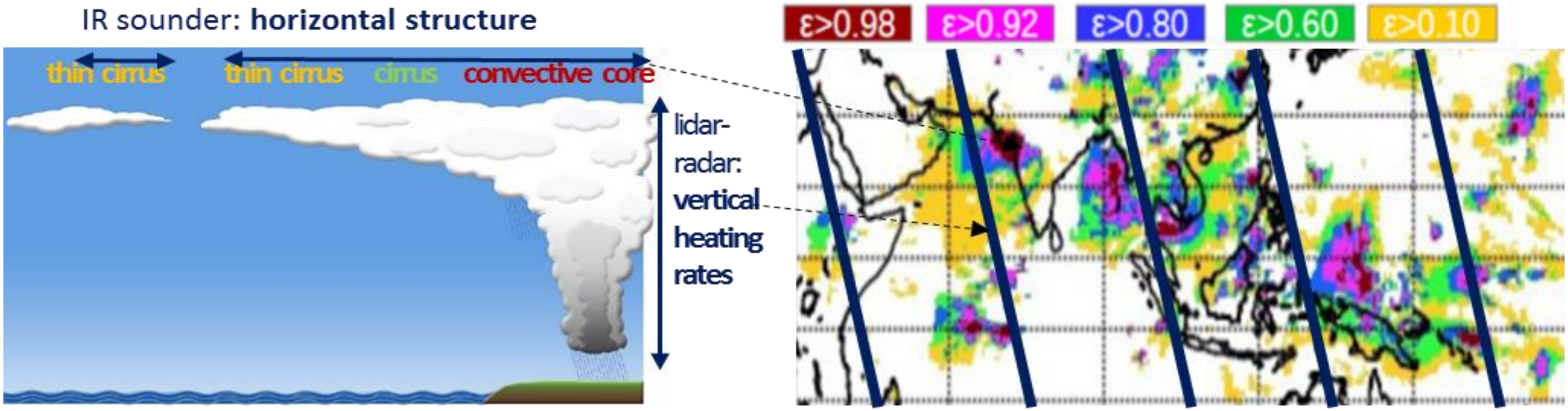




-> Graeme's talk tomorrow

link heating rates to convective depth

via a complete 3-D description of UT cloud systems & their environment (from ERA5)



1) *along nadir tracks:*
categorize CloudSat FLXHR-lidar vertical structure & heating rates wrt cloud type (p_{cld} & ε_{cld}), for different atmospheric situations

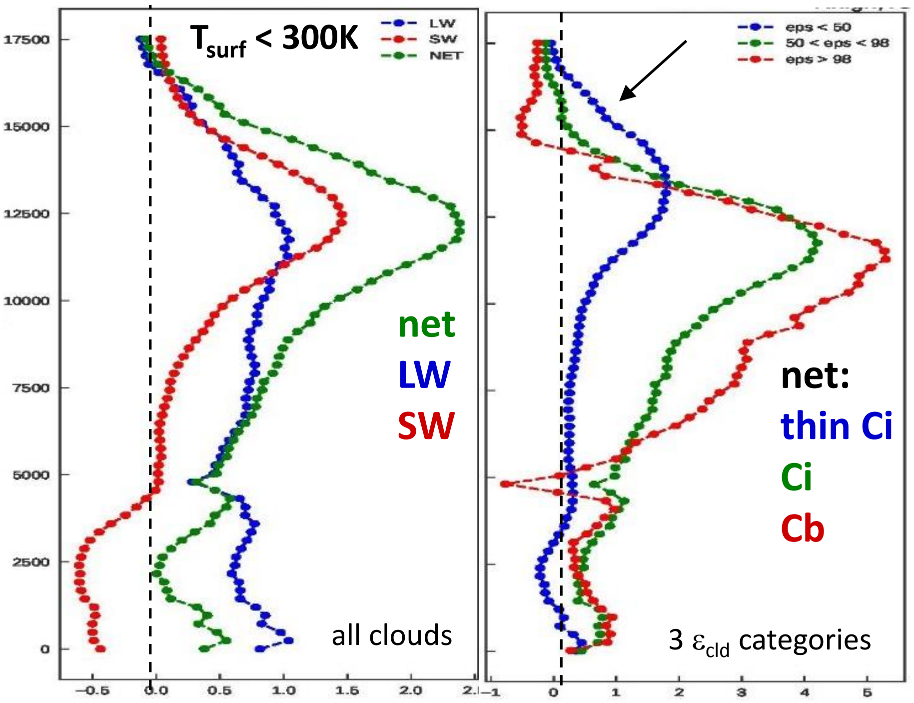
2) *expand nadir track info across UT cloud systems & environment:*
develop optimized 'non-linear regression models':
deep neural network learning techniques relate most suitable cloud & atmospheric properties from IR sounders & meteorological reanalyses to vertical structure & heating rates

1) heating rates sampled along track

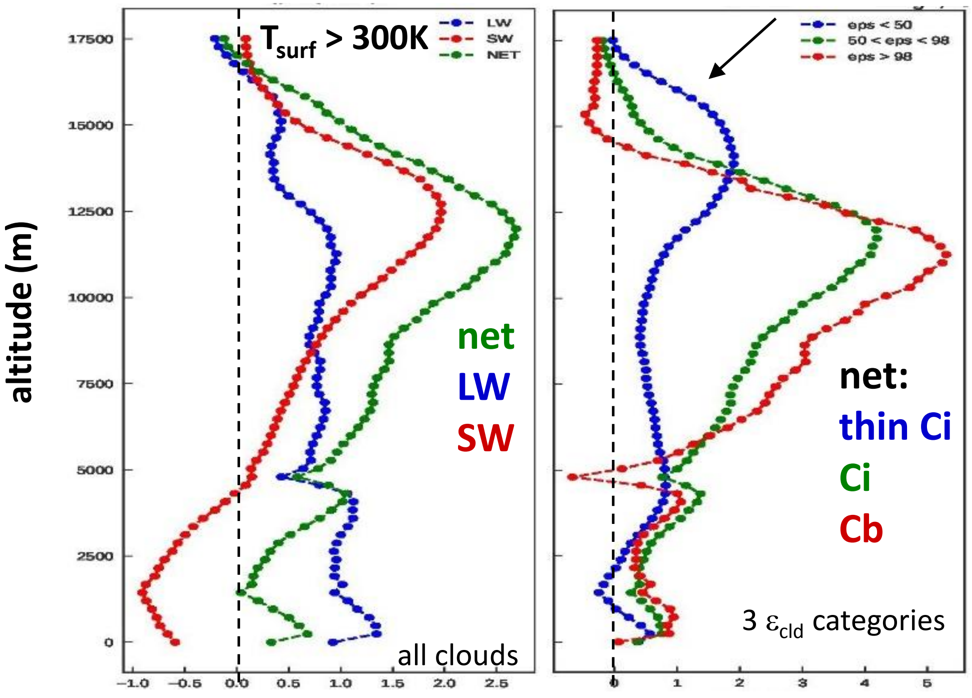
AIRS UT clouds collocated to Lidar-CloudSat FLXHR heating rates wrt to ε_{cld}, p_{cld},

tropics, AIRS p_{cld} < 200 hPa, nadir track statistics

preliminary



cloud – clear sky heating rate (K/day)



K/day

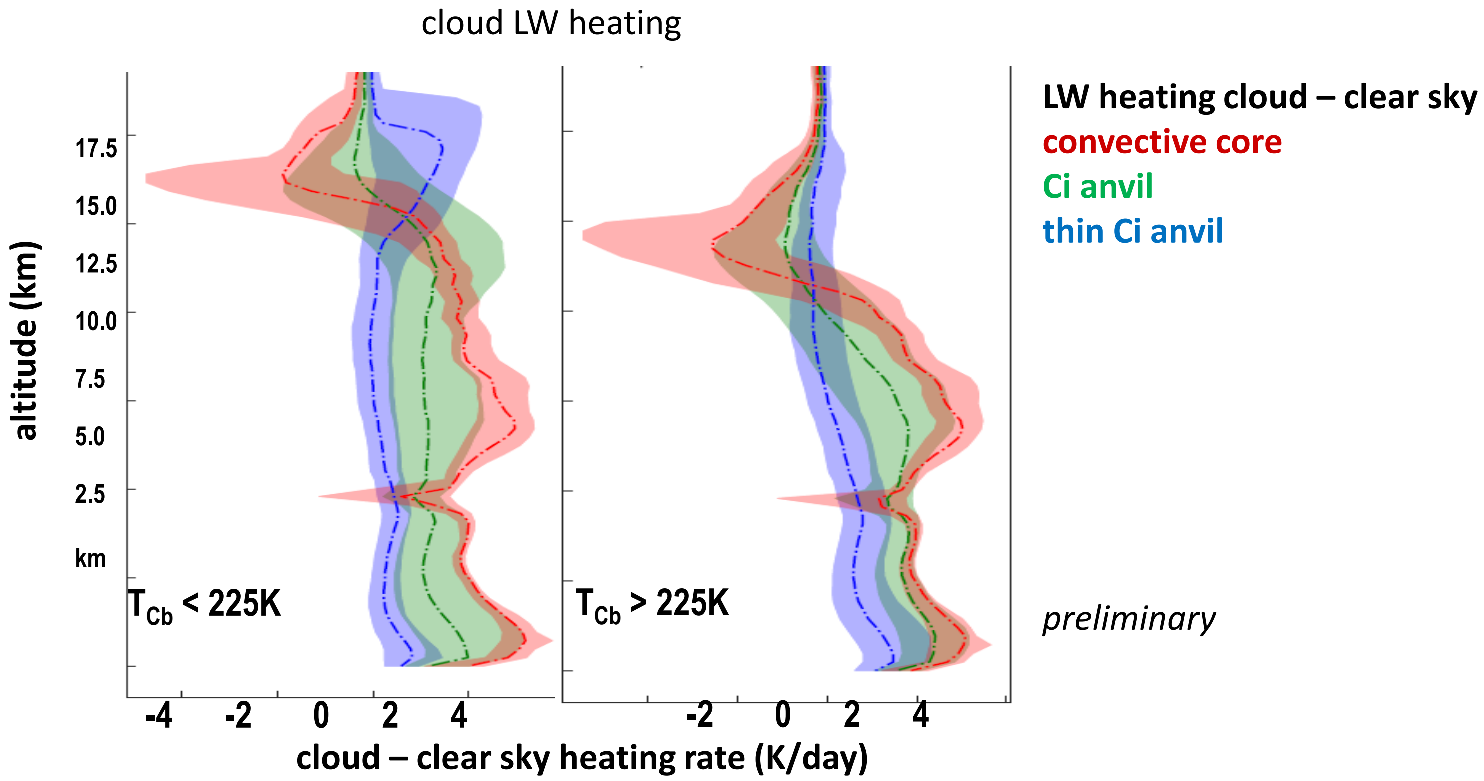
cloud – clear sky heating rate (K/day)

warmer T_{surf} -> UT cloud net heating occuring in thicker layers

slightly larger thin cirrus heating

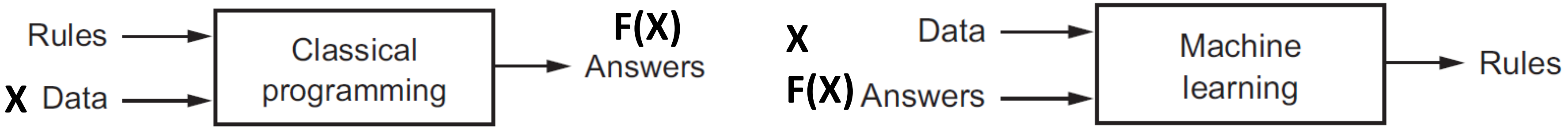
heating rates of UT cloud systems, sampled along track

AIRS UT cloud systems collocated to Lidar-CloudSat FLXHR heating rates wrt to ε_{cld}, p_{cld},



- ➢ clear distinction of heating associated with each category
- ➢ cold convective systems have a larger thin Ci heating

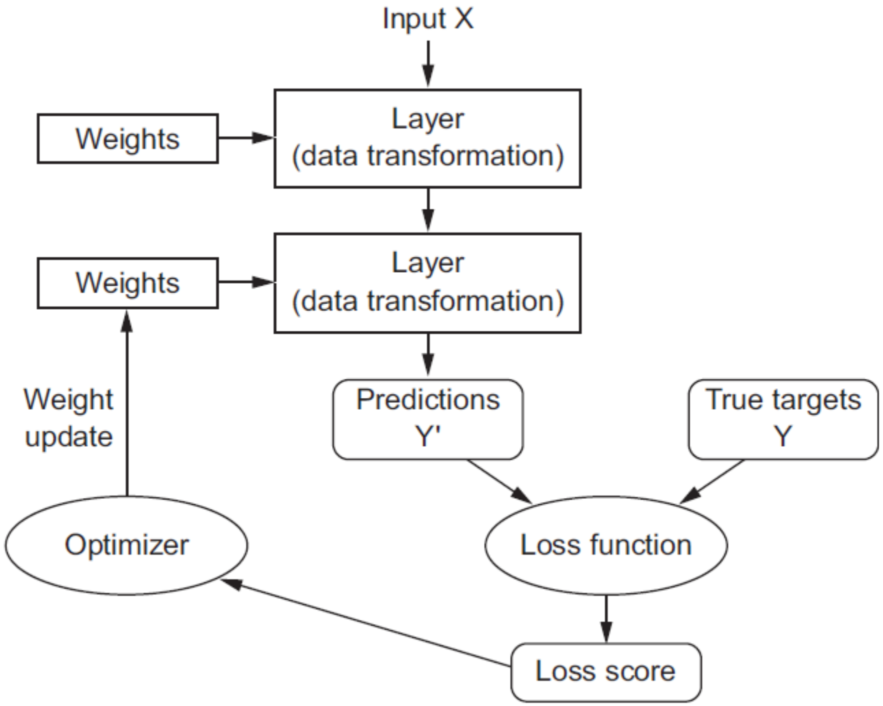
2) expand vertical structure across UT cloud systems via deep machine (ANN) learning



spectacular progress in automation of finding most appropriate weights used in the ANN layers

(weights are modified to reduce difference between actual & desired outputs)

TensorFlow framework to train deep learning models using Keras python library



AIRS –CloudSat-CALIPSO synergy
along the track (2007-2010):
X = cloud properties from AIRS & environmental properties from ERA (including horizontal organization)

F(X) = vertical cloud extent or HR

train, validate & test
non-linear regression models

-> test feasibility

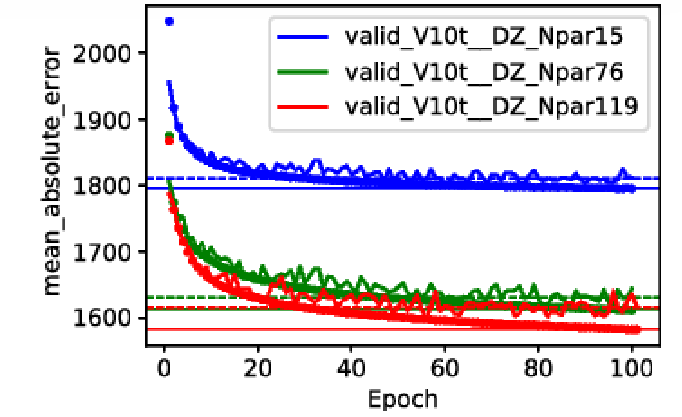
2a) cloud vertical extent via deep learning

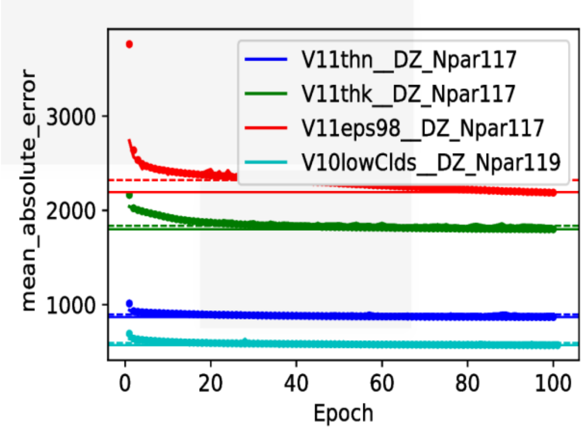
1) ***Explore relevant variables*** : ε_{cld}, p_{cld}, ε_{cld} uncertainty, p_{cld} uncertainty, χ^2_{min}, spat. T_B var., 9 ε_{cld}(8-11μm), OLR, column H_2O, land fraction, p_{surf}, T_{surf}, $p_{tropopause}$, T profiles, H_2O profiles ε_{cld} - p_{cld} PDFs + clear sky frequency over 2° x 2° (43 variables)

2) ***Develop models***: for Cb, Ci, thin Ci, lower clouds

random sampling for training (80%), validation (10%) & testing (10%),

determine nb of iterations & check overfitting





- ➢ Results improve if initial cloud info extended by atmospheric info and/or spatial cloud organization & separate models for cloud types
- ➢ Best results for thin cirrus & low clouds (as their extent is lower)
- ➢ Optically opaque clouds: bimodal Δz distribution; not yet well catched by prediction *-> need to explore other variables (vertical velocity, etc...)*

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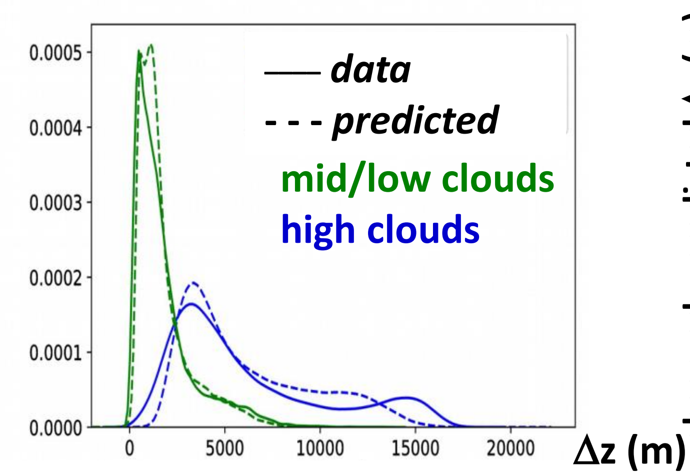

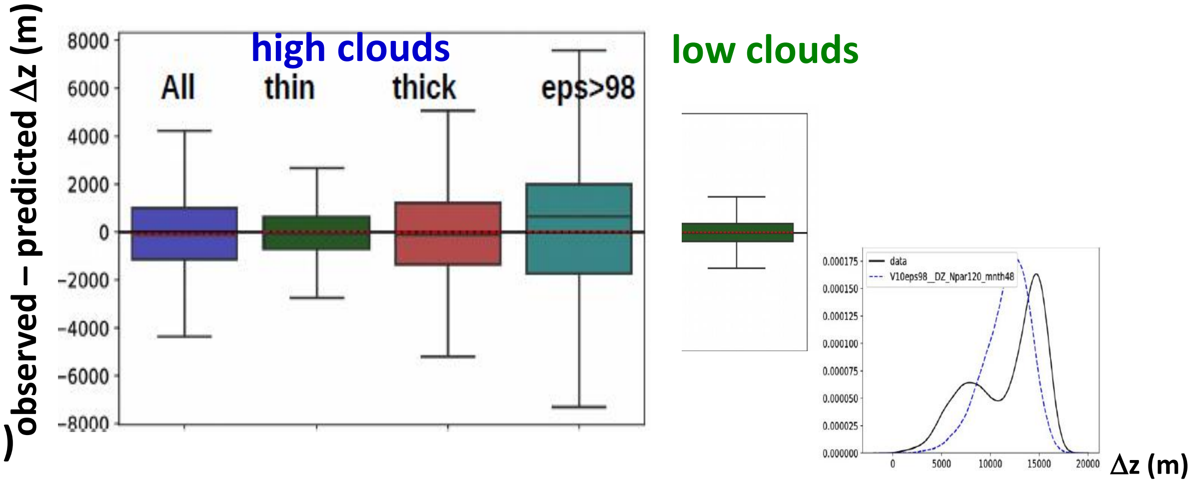

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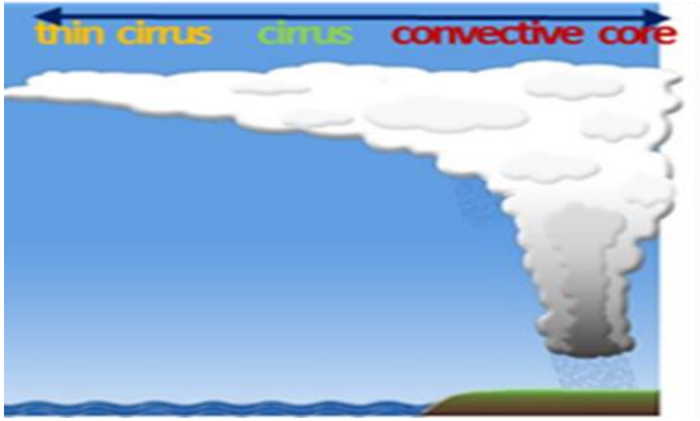
2b) Cloud radiative LW heating rates via deep learning

reduce vertical resolution of NASA heating rates: 100 tropospheric layers -> 20 layers

results improve when initial cloud info extended by atmospheric info

no overfitting, mean absolute error ≤ 0.5 K/day **!**

ε_{cld} critical variable=> models per cloud type

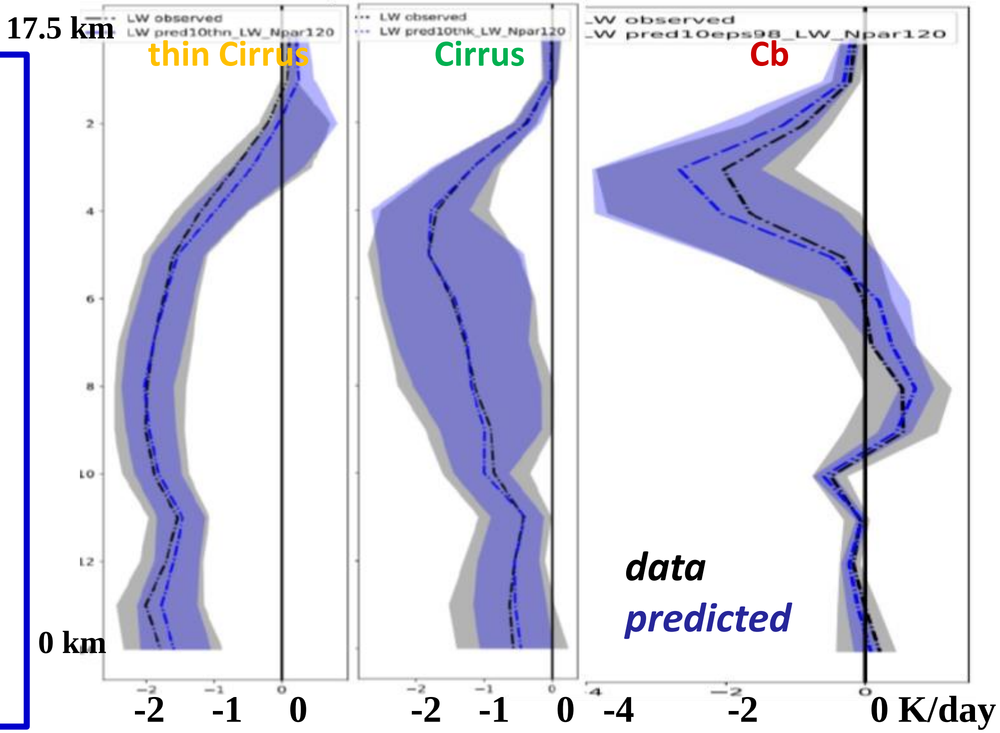


developed models reproduce very well the LW heating rates

will also work out well for low clouds as their Dz can be well predicted

further improvements:

- include ERA 5 for atmospheric thermodynamic & dynamic variables
- revise for best suitable variables
- use new NASA products



preliminary

Summary & Outlook

- synergetic UT cloud system approach based on IR sounder data powerful tool

  1) to study relation between convection & anvil properties:

  emissivity structure of mature systems changes with convective depth:
  more surrounding thin cirrus

  warming might lead to more cold convective systems with relatively more thin cirrus
  this affects then the heating gradients

  2) for process based metrics to evaluate GCM parameterizations linked to
  convection/detrainment/microphysics *(fallspeed – De)*
  -> Marine's talk tomorrow

- categorization of heating rates (A-Train synergy) wrt to ε_{cld}, p_{cld} shows clear distinction between cloud types; *thin Ci heating larger for colder systems*

- Expansion of LW heating rates across UT cloud systems via deep learning:
  first results show a very good reproducibility for separate models of Cb, Ci, thin Ci

- ☐ further exploration of atm. variables, continue with SW heating rates
- ☐ couple observed radiative heating rates with latent heating rates & force GCM to quantify climate system dynamical response to atmospheric heating
- ☐ investigate mechanisms leading to emissivity structure in CRM RCE studies *(large domain)*