Image: https://www.iasi2024.com/

Relationship between latent and radiative heating fields in the tropics from synergistic satellite data

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Key Questions

- Latent heat release and its fluctuations are central to the interactions within Earth's water and energy cycles, with radiative heating (RH) of upper-tropospheric (UT) clouds further enhancing this energy reservoir by at least 20% *[Li et al., 2013, Stubenrauch et al., 2021]*.

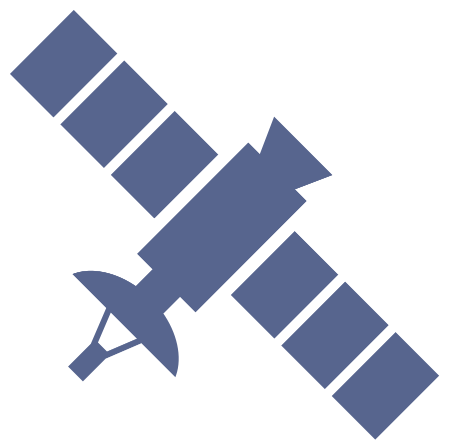
- What is the relationship between latent heating (LH) and radiative heating in mesoscale convective systems (MCS) ?

TRMM radar (2004 - 2018)

AIRS (2004-2018)

IASI (2008-2018)

IR souder



CALIPSO lidar (2006-2010)

CloudSat radar (2006-2010)

Strategy

Complete picture -> multiple datasets

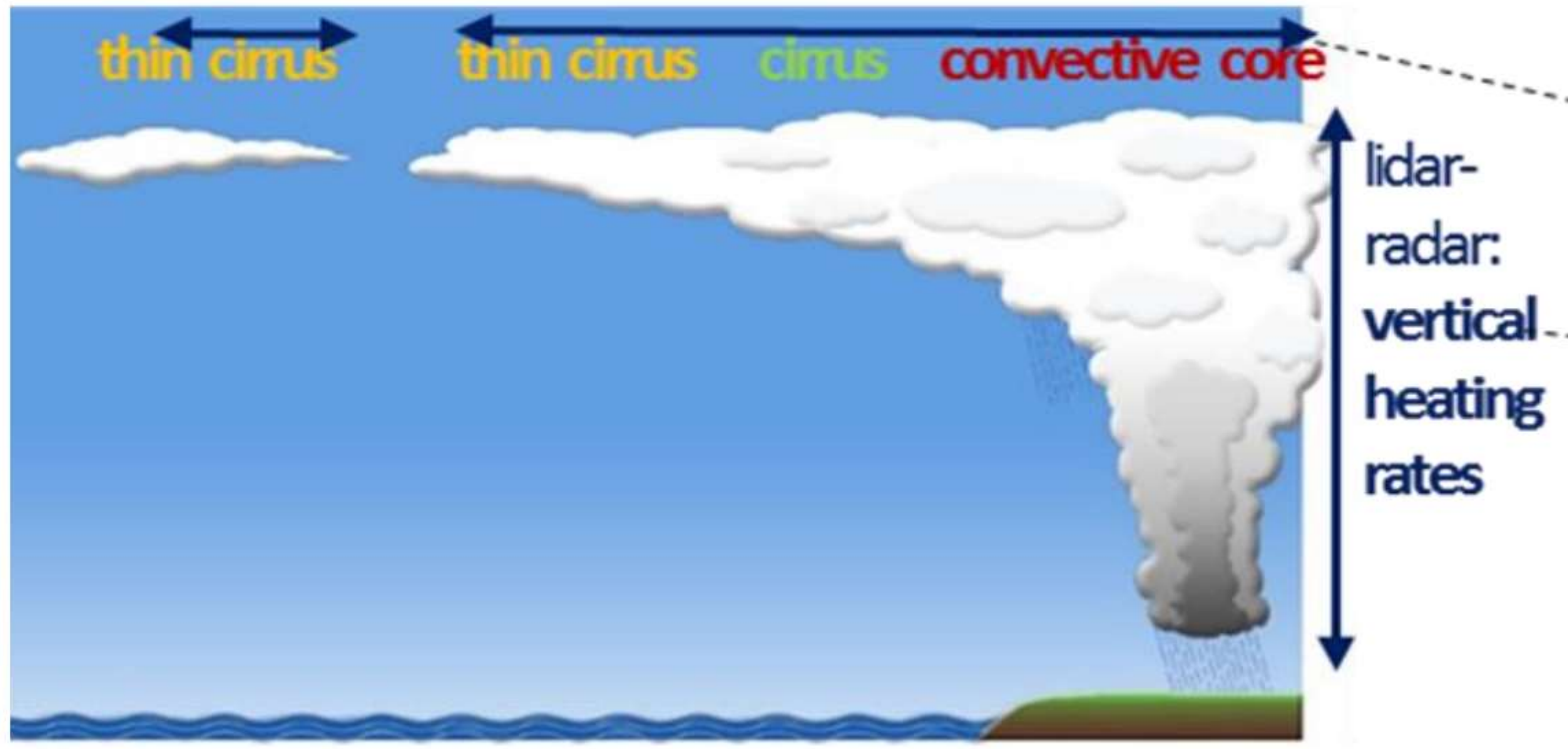
However, sophisticated measurements constrained by limited sampling density.

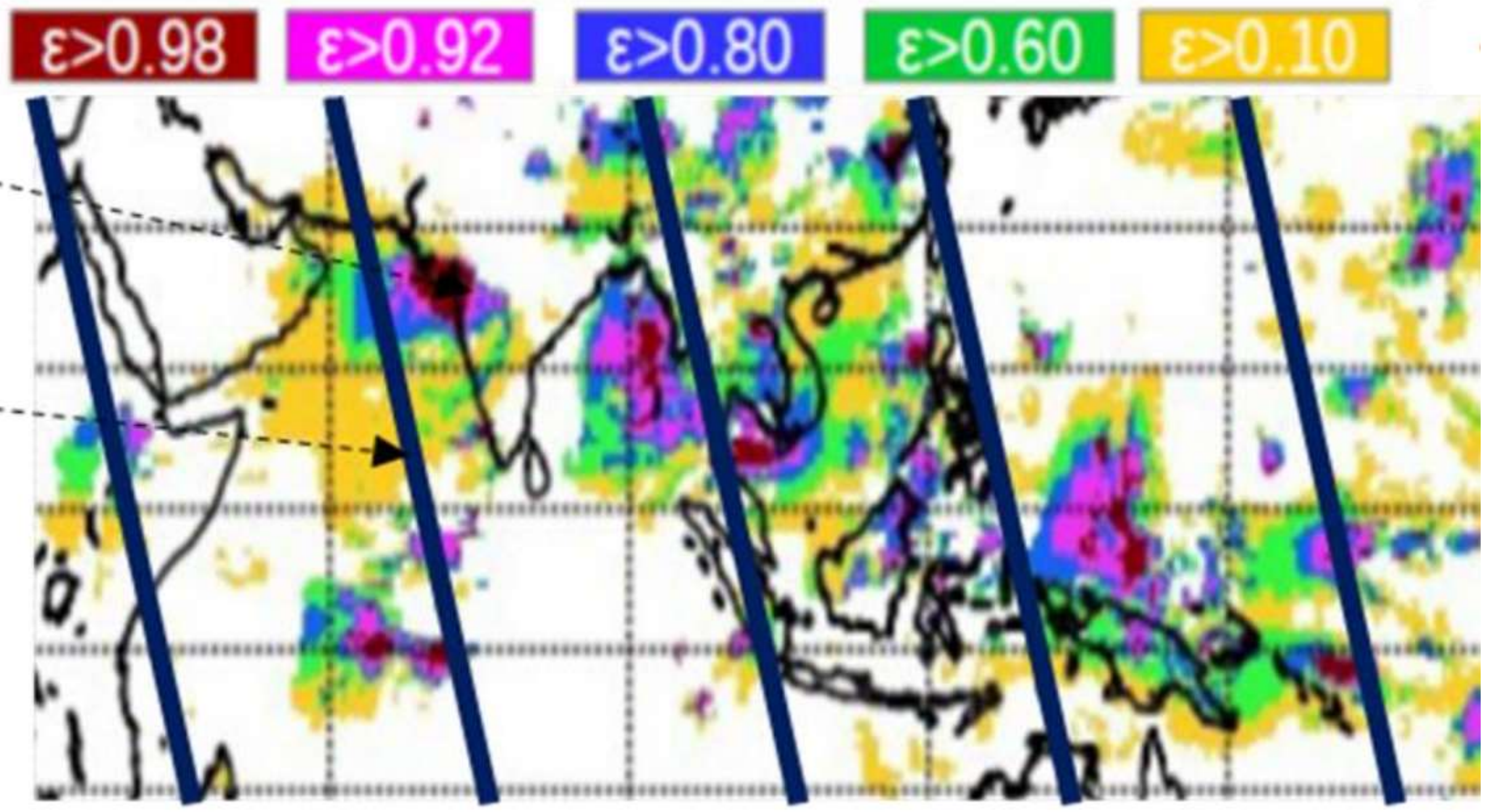
- Constructing a more complete dataset by Artificial Neural Network (ANN) techniques.

  -> 3D Snapshots at 4 specific observation times

  -> Process-oriented analyses

3D snapshot reconstruction using synergistic data & Machine Learning





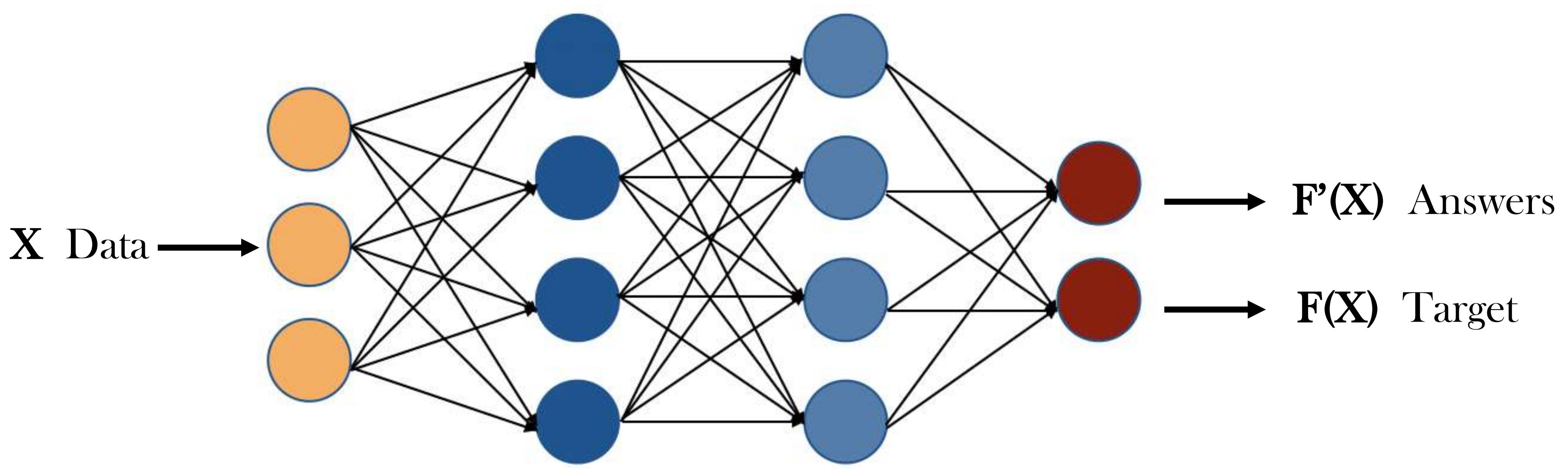
(Stubenrauch et al. 2021)

CIRS (Clouds from IR Sounders) :
only cloud height & emissivity

Vertical structure, radiative heating rate & precipitation:
CloudSat-CALIPSO only on narrow nadir tracks

Expand *radiative heating rate* across AIRS/IASI swath by ANNs

ANN model



Use derived atmospheric properties (similar for AIRS & IASI) :

X : CIRS cloud variables & ERA-Interim atmosphere, surface

F(X) : CloudSat-lidar radiative heating rates, Ztop & Z_{top}-Z_{base}, cloud layering, rain rate *from NASA, FLXHR v4, GEOPROF, PRECIP-column*

Machine learning - Artificial Neural Networks (ANNs)

Expanded radiative heating rates is now available:

https://gewex-utcc-proes.aeris-data/fr

3D snapshot reconstruction using synergistic data & Machine Learning

TRMM radar statistically samples diurnal cycle, but...
at specific local time (1h30 AM), only covers 3%

AIRS swath 70%
IASI swath 77%

Expand *latent heating rate* across AIRS/IASI swath by ANNs

use derived atmospheric properties (similar for AIRS & IASI) :
X : CIRS cloud variables & ERA-Interim atmosphere, surface
F(X) : Latent heating from TRMM SLH profiles L3 day V06 *[Shige et al., 2009]*, fractions of cloud type, clear sky, rainy area and heavy rain area.

Rain rate classification from AIRS ML-CloudSat for scene identification: no rain, light rain, heavy rain

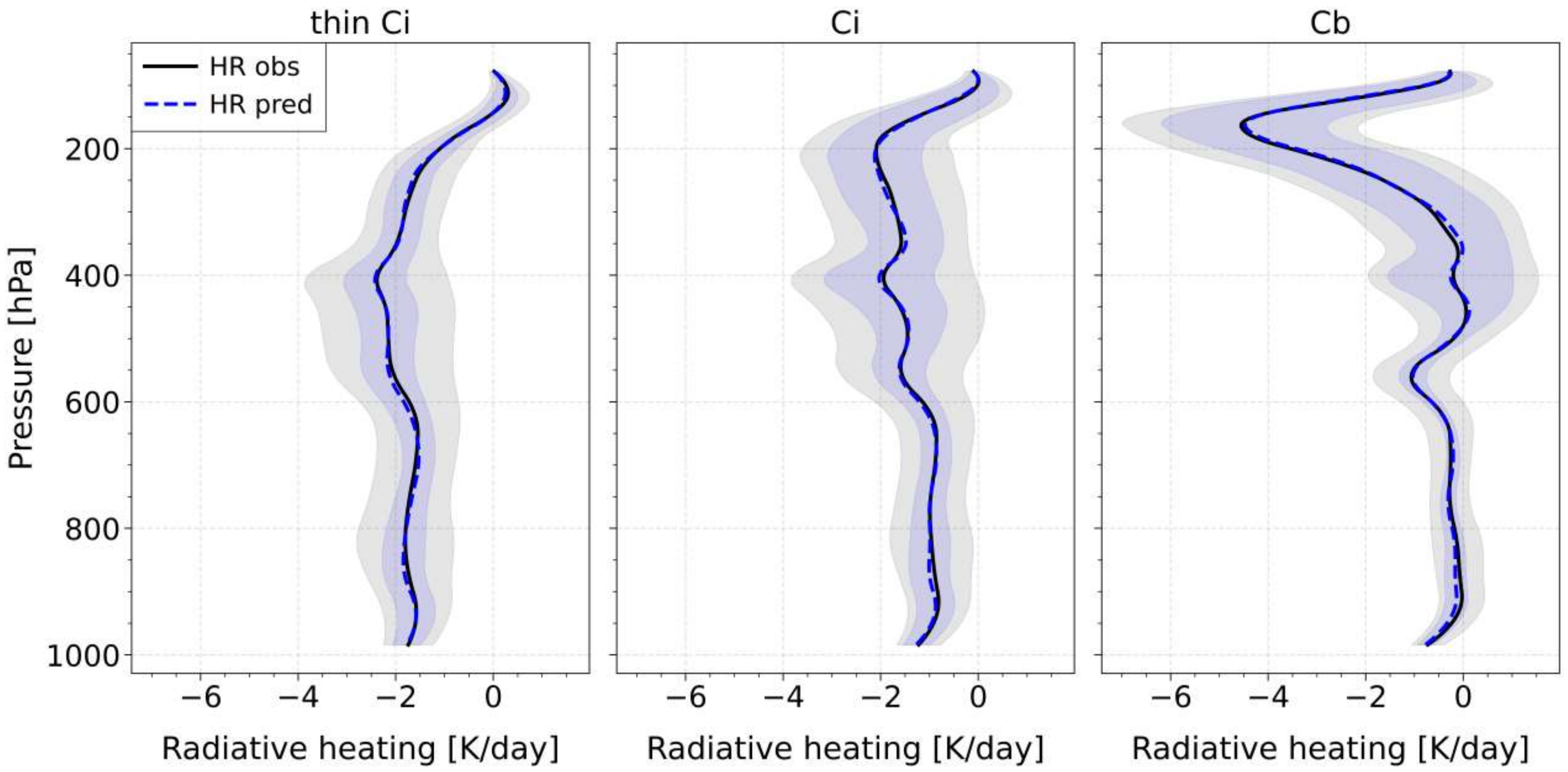
Rain rate intensity is largest for opaque, thickest and highest clouds!

Evaluation of ANN radiative and latent heating

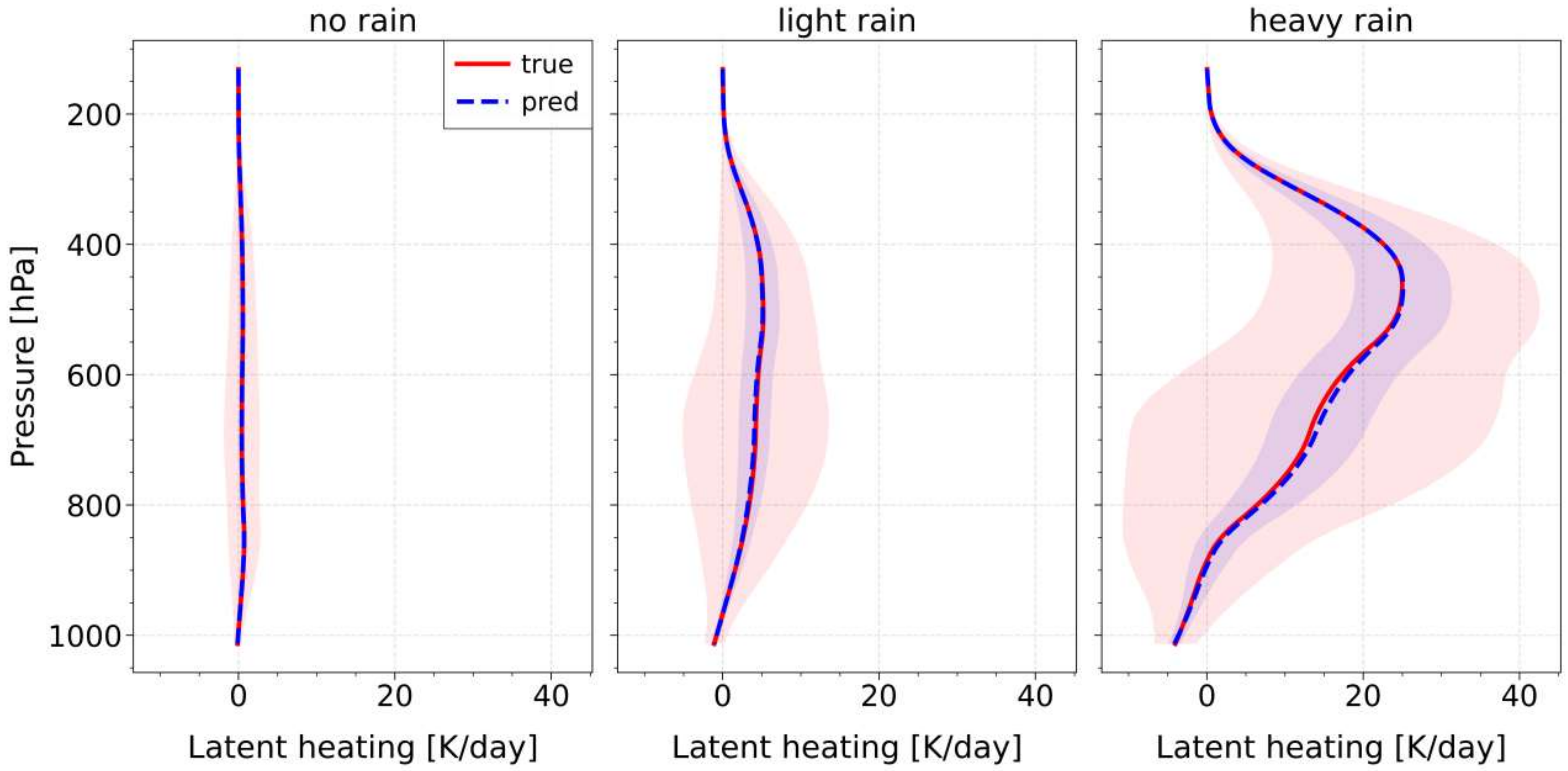
Good predicted mean,
Good predicted variability

Good predicted mean,
Underestimated predicted variability

LW Ocean



LH Ocean



LW radiative heating rates from Calipso-CloudSat

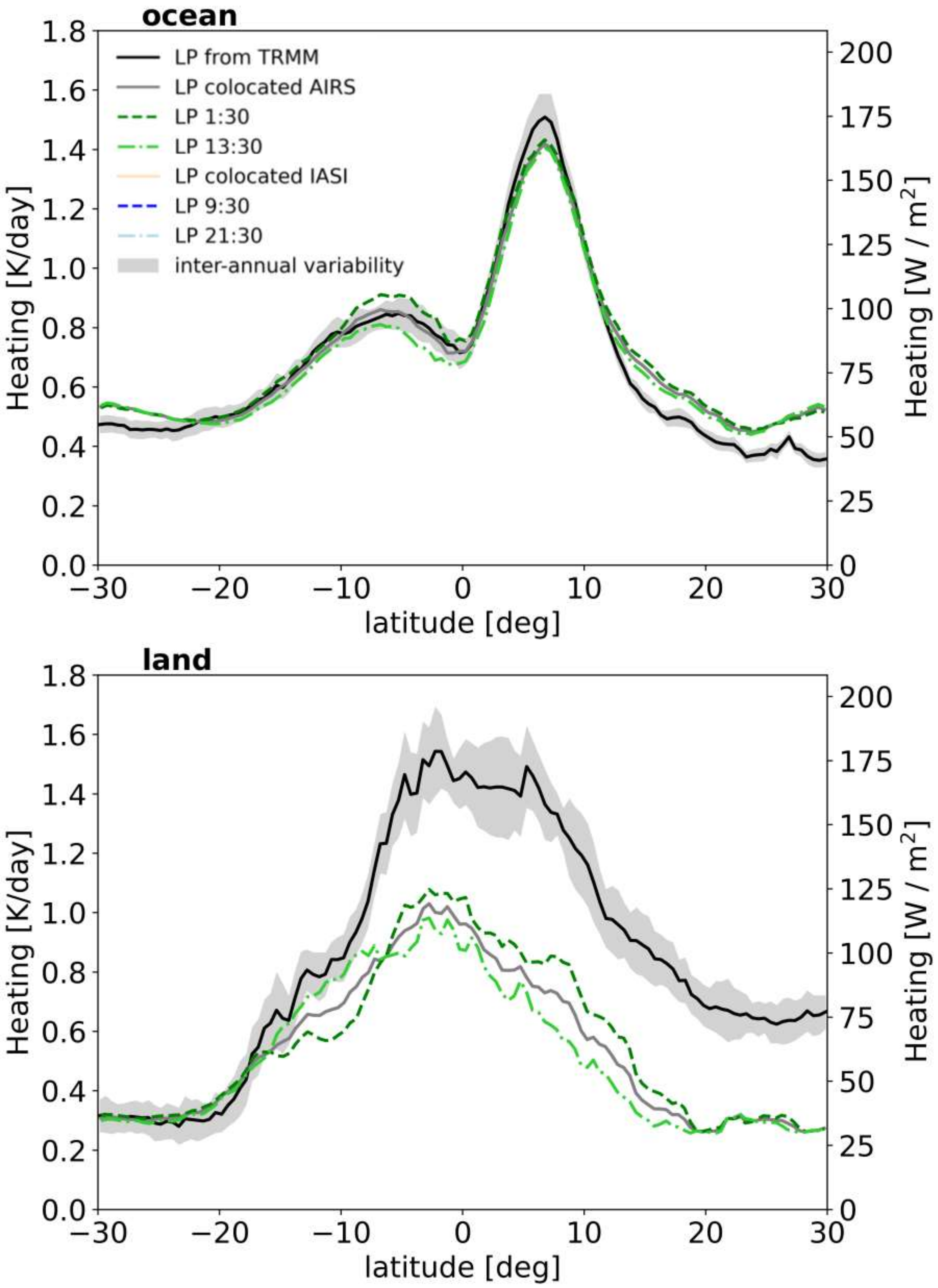
LW radiative heating rates from ANN prediction

Latent heating rates from TRMM

Latent heating rates from ANN prediction

Coherence between TRMM-SLH and ANN predicted LH

Vertically integrated LH over all scenes

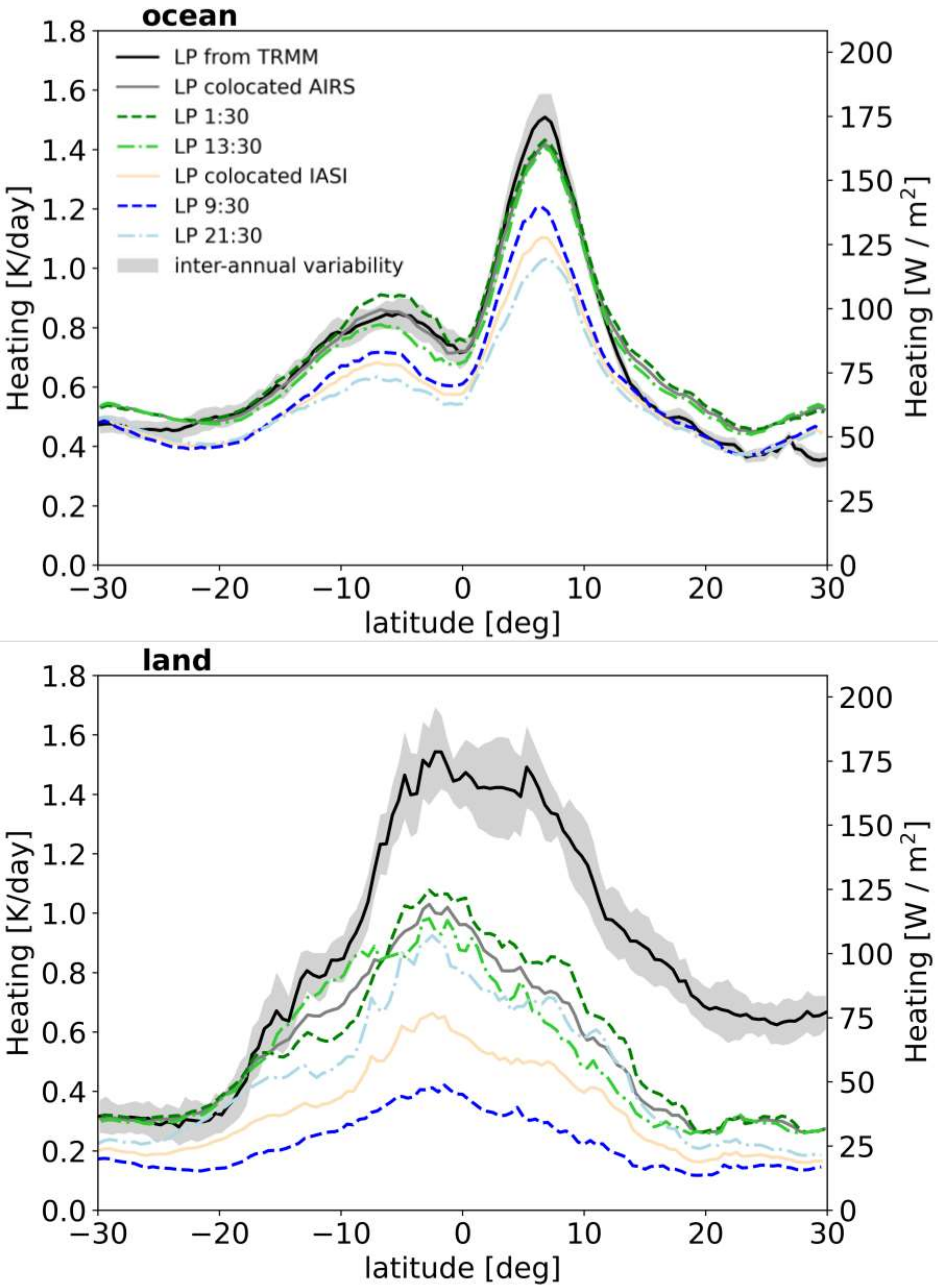


Over ocean, the zonal averages of LH at 1:30 AM&PM agree well with TRMM-SLH complete diurnal sampling.

Over land, we miss strong convection of late afternoon.

Coherence between TRMM-SLH and ANN predicted LH

Vertically integrated LH over all scenes

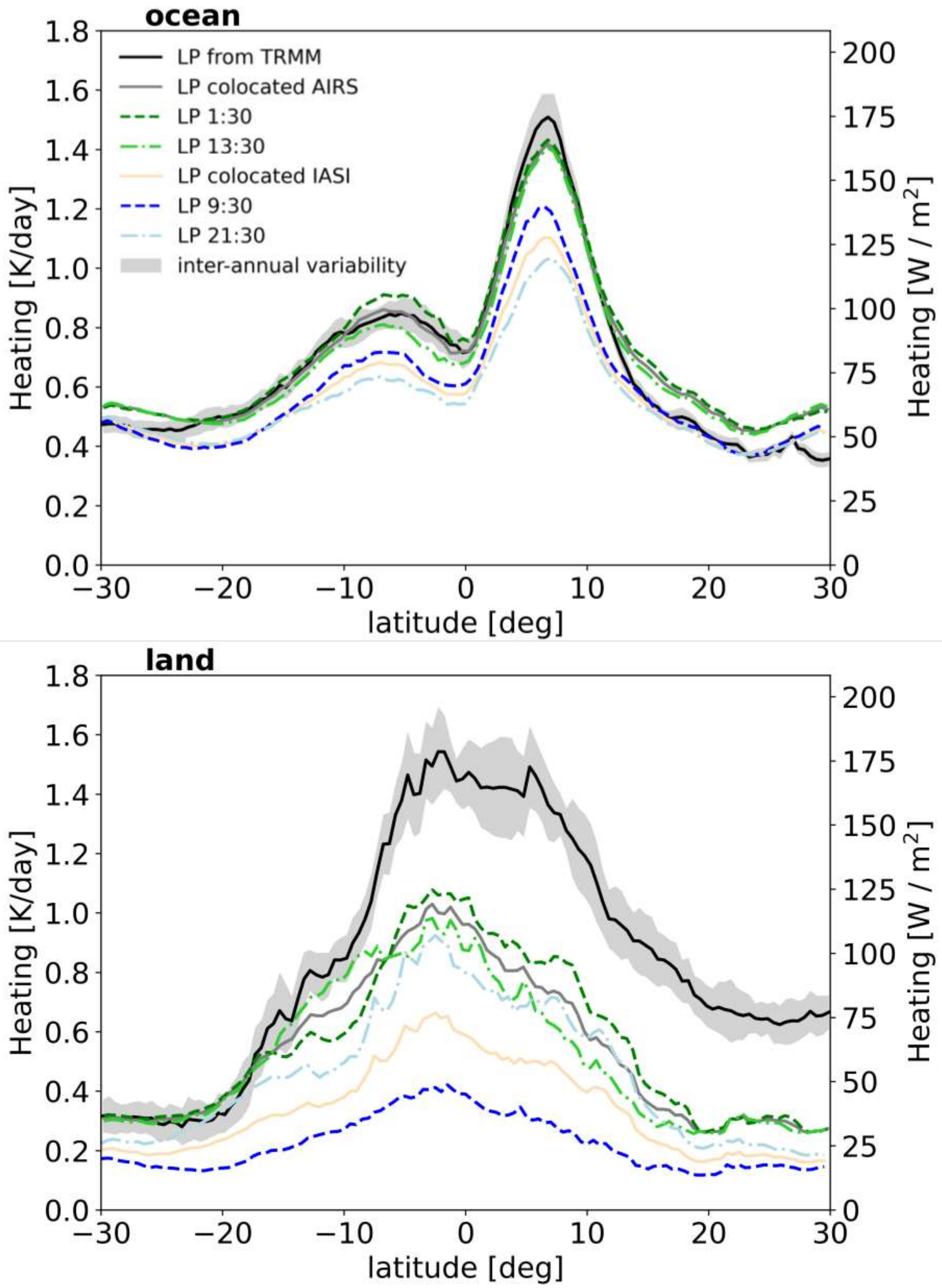


Over ocean, the zonal averages of LH at 1:30 AM&PM agree well with TRMM-SLH complete diurnal sampling.

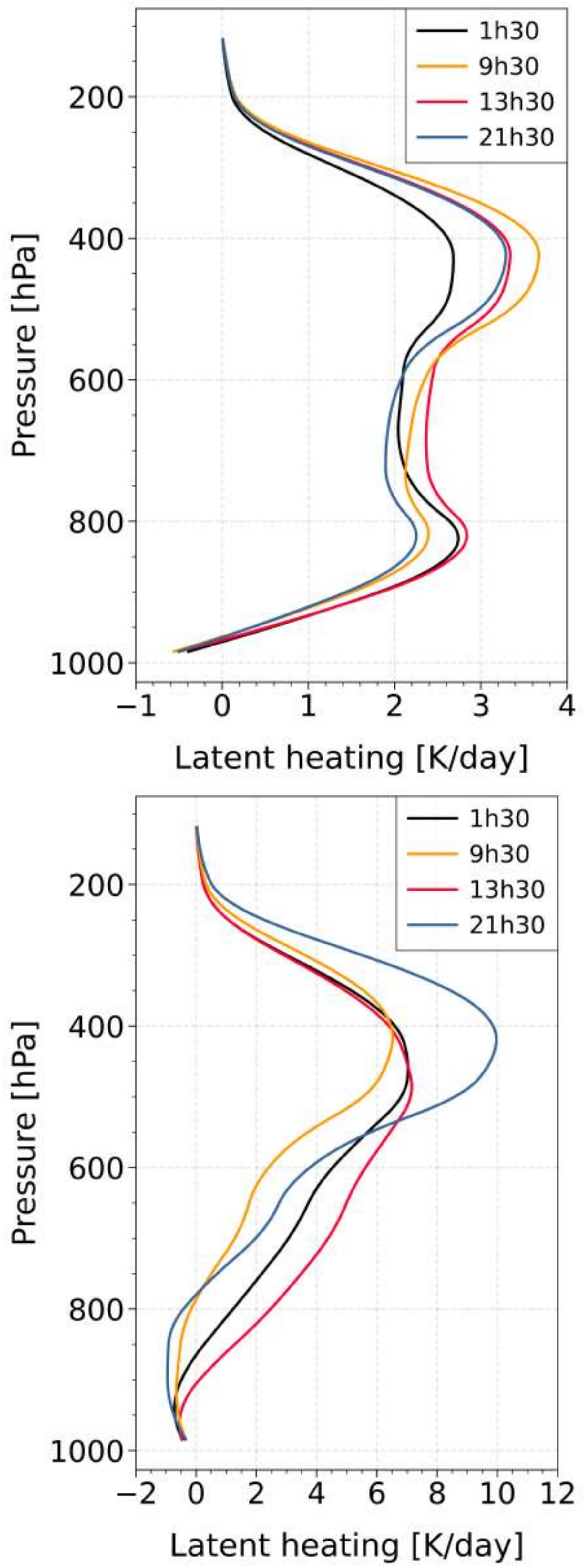
While the sampling at 9:30 slightly underestimates LH

Coherence between TRMM-SLH and ANN predicted LH

Vertically integrated LH over all scenes



LH profiles of rainy scenes



Over ocean, the zonal averages of LH at 1:30 AM&PM agree well with TRMM-SLH complete diurnal sampling.

While the sampling at 9:30 slightly underestimates LH

Shapes of ocean/land profiles are different, as expected with a larger contribution of low level clouds over ocean.

Diurnal cycle as expected:

Over ocean: maximum convection over early morning

Over land: maximum convection in the evening

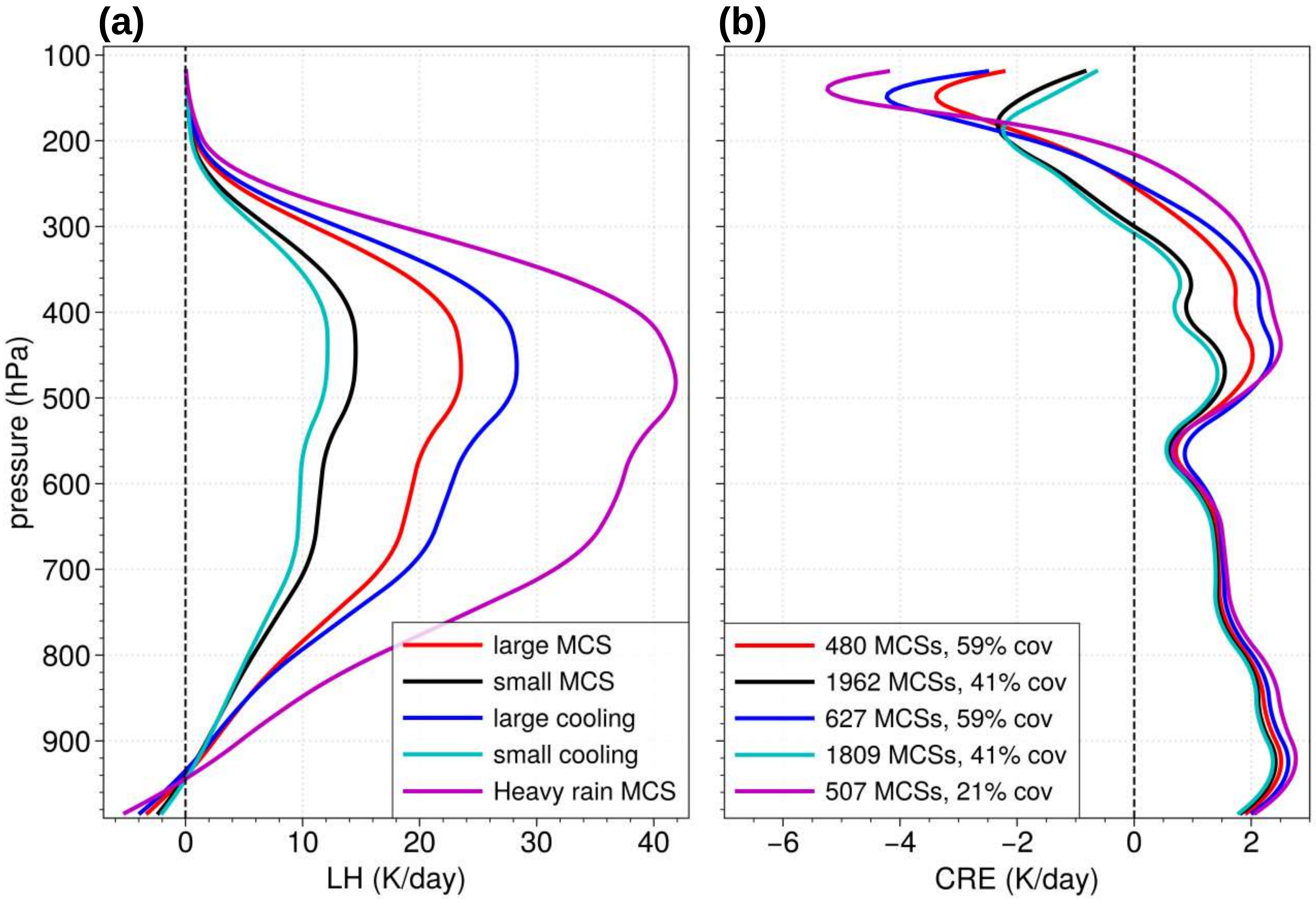
3D structure of diabatic heating

Contrasting La Niña and El Niño events

Atmospheric Cloud Radiative Effect (ACRE): the difference in cloud radiative effects between the TOA and the surface

$$\text{ACRE} = \int \text{HR}\, dp - \int \text{HRclr}\, dp$$

Diabatic heating of mesoscale convective systems of different intensities



MCS reconstruction using CIRS P_{cld} and ε_{cld} (Stubenrauch et al. 2023)

Collocation with ML diabatic heating(only orbits)

Cooling above MCS core increases with opacity

A proxy of deep convection

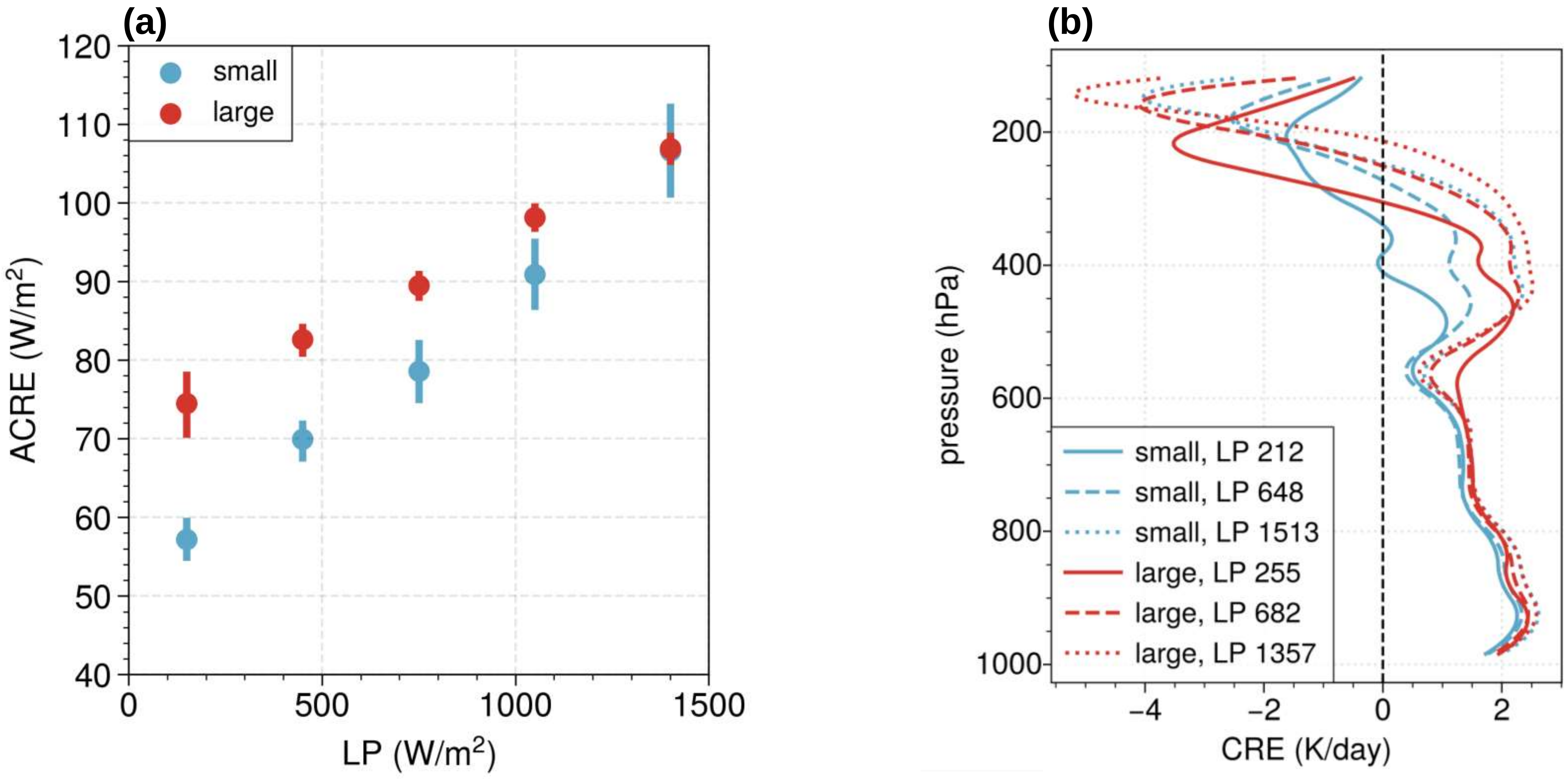
Heavily raining MCS produce largest LH;

Deep convection can also be distinguished by large MCS size or large cooling above MCS cores

ACRE modulation by MCS size

Proxy for convective organisation:
MCS size at the same rain intensity (LP)

Proxy for mature MCS:
Core Fraction: 0.4-0.6



- Convective organization enhances ACRE by up to 20 Wm^{-2}. The effect is decreasing towards larger rain intensities, as ACRE saturates.
- More organized MCSs show larger vertical heating gradients at similar rain intensities.
- This additional ACRE and vertical heating gradients support stronger, sustained convection and impact large-scale environments.

Summary and Outlook

- We reconstructed longterm datasets of 3D radiative and latent heating at 4 observation times using ANN.
- Over ocean, the zonal averages of latent heating at 1:30 AM&PM agree well with TRMM-SLH complete diurnal sampling, while the IASI sampling at 9:30 slightly underestimates latent heating. Over land, we miss about 30% of latent heating due to strong convection of late afternoon.
- This expansion allows us to study horizontal fields of diabatic heating, in particular within MCSs.
- Convective organization enhances ACRE, in particular for MCSs with small rain intensity; more organized MCSs show larger vertical heating gradients, supporting stronger and sustained convection.

Future Plans:

- Future studies should consider the environment surrounding MCSs and incorporate the time dimension.
- The distribution of UT clouds and their environment in the LP–ACRE plane can be used to evaluate climate simulations. (In cooperation with Laurent Li, LMD)
- The CIRS (AIRS & IASI) datasets have been recently reproduced by AERIS, using ERA5 ancillary data: (2004-present). We foresee to retrain all ANNs and reproduce the CIRS-ML dataset (2004-present)

References

- Chen, X., Stubenrauch, C. J., & Mandorli, G. (2024). Relationship between latent and radiative heating fields of tropical cloud systems using synergistic satellite observations. EGUsphere, 2024, 1–35. https://doi.org/10.5194/egusphere-2024-3434

- Stubenrauch, C. J., Mandorli, G., & Lemaitre, E. (2023). Convective organization and 3D structure of tropical cloud systems deduced from synergistic A-Train observations and machine learning. Atmospheric Chemistry and Physics. 23. 5867-5884. 10.5194/acp-23-5867-2023.

- Stubenrauch, C. J., Caria, G., Protopapadaki S.E., and Hemmer F. (2021). 3d radiative heating of tropical upper tropospheric cloud systems derived from synergistic a-train observations and machine learning. Atmospheric Chemistry and Physics, 21(2), 1015-1034.

Heating rates are now available:

https://gewex-utcc-proes.aeris-data/fr