



Relationship between latent and radiative heating fields of tropical cloud systems using synergistic satellite observations

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Abstract. In order to investigate the relationship between latent heating (LH) and radiative heating (Q_{rad}), in particular the heating released by mesoscale convective systems (MCSs), we used synergistic satellite-derived data from active instruments. Given the sparse sampling of these observations, we expanded the spectral LH profiles derived from the Tropical Rain Measurement Mission (TRMM-SLH) by applying artificial neural network regressions to the Clouds from InfraRed Sounders (CIRS) data and meteorological reanalyses, following a similar approach as for the expansion of the Q_{rad} profiles. A direct comparison with the collocated TRMM-SLH data shows excellent agreement of the average profiles, but the prediction range is underestimated, in particular between 550 and 900 hPa. Noise related to discrepancies in rain fraction between TRMM and CIRS-ML (machine learning), as well as an underestimation of extremes, can be reduced by averaging over larger areas. The zonal averages of vertically integrated LH (LP) at 01:30 and 13:30 LT align well with those from the full diurnal sampling of TRMM-SLH over the ocean. For upper-tropospheric (UT) clouds with a large amount of latent heat release, the surface temperature has a larger impact on the atmospheric cloud radiative effect (ACRE) in dry environments than in humid ones, while humidity plays a large role in cool rather than in warm environments. In all situations, the cloud height is mostly responsible for the value of ACRE. The distribution of UT clouds in the LP–ACRE plane shows a very large spread in the ACRE for small values of LP, which is gradually reduced towards larger values of LP. The mean ACRE of mature MCSs increases with LP, up to about 115 W m^{-2} . As expected, the shapes of the LH profiles of mature MCSs show that larger, more organized MCSs have a larger contribution of stratiform rain than the smaller MCSs do. Furthermore, convective organization enhances the mean ACRE of mature MCSs on average by about 10 W m^{-2} over the whole LP range.

1 Introduction

Clouds envelop approximately two-thirds of the Earth's surface, with 40 % originating from upper-tropospheric (UT) clouds (e.g. Stubenrauch et al., 2013, 2017). These cloud formations play a crucial role in modulating the Earth's energy budget and heat transport. They are most abundant in the tropics, constitute around 60 % of the total tropical cloud distribution, and often form as cirrus anvils from convective outflow, building mesoscale convective systems (MCSs), as illustrated by Houze (2004).

Throughout the precipitation process, latent heating (LH) is generated within the convective cores and denser regions of the anvils due to the condensation process, which involves the phase transition of water vapour into tiny liquid or frozen cloud particles. The release of latent heat strongly influences the atmospheric circulation, particularly in the tropics (Tao et al., 2006). Therefore, the interpretation of latent heat release and its fluctuations plays a central role in the complex interactions of the Earth's water and energy cycles (e.g. Gill, 1980; Mapes, 1993; Schumacher et al., 2004; Tao et al., 2016). Radiative heating (Q_{rad}) of UT clouds further aug-

ments this energy reservoir by at least 20 % (Bergman and Hendon, 2000; Li et al., 2013; Stubenrauch et al., 2021). Given the significance of both processes, this article aims to study the relationship between latent and radiative heating, comparing different environments with a focus on MCSs.

In order to study the relationship between latent and radiative heating, we have combined information from multiple satellite instruments. The heating profiles are obtained from active measurements that only overlap a small amount in space and in time with the cloud top properties from passive remote sensing. Previously, we have expanded this vertical information using machine learning (ML) techniques (Stubenrauch et al., 2021), leading to 3D fields of radiative heating at specific local times (LTs). This article describes the expansion of the latent heating and shows to what extent these 3D latent heating fields at specific LTs represent the daily mean of tropical latent heating. In addition, a cloud system approach (Stubenrauch et al., 2023) is used to identify MCSs and to determine their size, which is related to convective organization (e.g. Houze and Hobbs, 1982; Moncrieff, 1992). The data expansion and the following analyses cover the latitudinal band of 30° N–30° S.

Infrared sounders, with their good spectral resolution, are sensitive to cirrus clouds during both day and night (e.g. Wylie et al., 2005; Stubenrauch et al., 2006, 2017, 2024). For this reason, we use cloud top properties retrieved from measurements of the Atmospheric Infrared Sounder (AIRS) on board the National Aeronautics and Space Administration (NASA) Earth Observation Satellite Aqua and from the Infrared Atmospheric Sounding Interferometer (IASI) on board the EUMETSAT Meteorological Operation satellite (MetOp). These instruments are along-track scanners with wide swaths, with a horizontal coverage of about 70 % in the tropics at a specific local time.

Active sensors, i.e. CALIPSO (Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observation) lidar and the CloudSat radar, are part of the A-Train satellite constellation (Stephens et al., 2018) and have worked in synergy with Aqua since 2006. They provide observations of the vertical structure of clouds (e.g. Mace et al., 2009), radiative heating rates (Henderson et al., 2013), and information on precipitation (Haynes et al., 2009). However, these parameters are only available along successive narrow-nadir tracks (~ 2500 km apart).

The satellite orbit of the Tropical Rainfall Measuring Mission (TRMM) allowed it to statistically sample the full diurnal cycle (Negri et al., 2002). Latent heating profiles have been estimated from the precipitation radar (PR) on board TRMM via the spectral latent heating (SLH) algorithm (Shige et al., 2007). However, within a time window of about 1 h, the TRMM data only cover a very small fraction of the tropics: approximately 7 %. For the expansion towards 3D latent heating fields at the specific LTs of AIRS (01:30 and 13:30 LT) and IASI (09:30 and 21:30 LT), we have used a similar approach as in Stubenrauch et al. (2021).

While CALIPSO–CloudSat observations only overlap with those of AIRS, TRMM observations overlap with both AIRS and IASI observations.

Section 2.1 to 2.3 present the data: latent heating profiles from TRMM-PR measurements, cloud properties from AIRS and IASI, and 3D structure and precipitation intensity classification from machine learning trained on CloudSat–CALIPSO. Section 2.4 and 2.5 describe their collocation, as well as the training and evaluation of the artificial neural network (ANN) models developed to expand the TRMM-SLH heating profiles. Section 3 outlines the construction of the 3D LH dataset over the period of 2004–2018 and shows its coherence in comparison to the original TRMM-SLH data. Section 4 describes the reconstruction of the MCSs using the Clouds from InfraRed Sounders (CIRS) data. Finally, Sect. 5 discusses the results regarding the relationship between latent and radiative heating, while Sect. 6 summarizes the key conclusions and suggests future research directions.

In our analyses, we use the following definitions: LH refers to the latent heating profile, LP denotes the vertically integrated latent heating, Q_{rad} represents the radiative heating profile, CRE (cloud radiative effect) refers to the difference between all-sky and clear-sky radiative heating rates, and the ACRE (atmospheric cloud radiative effect) represents the vertically integrated CRE. While the heating rates are expressed in units of K d^{-1} , the vertically integrated heat is given in units of W m^{-2} .

2 Data, methods, and evaluation

2.1 Latent heating data

The primary objective of the TRMM mission (Houze et al., 2015; Kummerow et al., 1998; Liu et al., 2012; Dorian, 2014) was to study the temporal and spatial variability in tropical rainfall. For this purpose, TRMM has an orbital inclination of 35° with 16 orbits per day. TRMM revisits a given area at the same LT every 23 (near the Equator) to 46 d (near 35°). Therefore, according to Negri et al. (2002), TRMM-PR estimates over any 1 h period, even with 3 years of data, are insufficient to accurately describe the diurnal cycle of precipitation for grid sizes smaller than 12° due to inconsistent spatial sampling. The PR is a radar operating at the Ku-band in the microwave range around 13.8 GHz, specifically dedicated to the collection of vertical profiles of precipitation, with a horizontal resolution of about 5 km and a swath width of 247 km. The TRMM mission collected data from 1997 until 2015 and was then continued by the Global Precipitation Measurement Mission (GPM).

The radar measures the echo-top height corresponding to the precipitation top height, identifies the melting layer, determines the rain intensity vertical structure, and distinguishes between convective and stratiform rain. In general, convective LH profiles show heating throughout the vertical layers except near the surface due to evaporation at lower lev-

els. LH profiles of the stratiform rain within the anvils show cooling at low levels below a melting level and heating at levels above (e.g. Chang and L'Ecuyer, 2019, Fig. 3). The peak of LH in isolated convection is also lower in altitude than the one in complex convective systems that include stratiform rain in the anvils (e.g. Hartmann et al., 1984).

Since there is no direct measurement of LH, there are two recognized retrieval algorithms to estimate LH for TRMM (Tao et al., 2022): convective–stratiform heating (CSH; Tao et al., 2018, 2022; Lang and Tao, 2018) and spectral latent heating (SLH; Shige et al., 2007, 2008, 2009; Takayabu and Tao, 2020). Both retrievals use look-up tables (LUT) with LH profiles simulated by cloud-resolving models (CRMs) as a function of precipitation rate and other parameters. However, an important difference between the two approaches is the source of these CRM simulations: for SLH, the LUTs are built from diabatic heating rates using CRM simulations with data from the Tropical Ocean Global Atmosphere – Coupled Ocean–Atmosphere Response Experiment (TOGA COARE) field campaign. Although TOGA COARE itself is an oceanic campaign, the resulting SLH dataset is not restricted to oceanic regions since the TRMM-PR observes reflectivities over both land and the ocean (Dorian, 2014). In contrast, the CSH retrieval uses more diverse data in the CRM simulations to construct its LUTs, including data from six multi-week ocean field campaigns and four multi-week land field campaigns.

In addition to the differences in the data sources for constructing the LUTs of the LH profiles, the SLH and CSH algorithms also differ in their input variables, their convective–stratiform classification methods, and the way that they handle stratiform rain.

In the SLH algorithm, the TRMM-PR input consists of the precipitation top height (PTH), the precipitation rate at the surface (P_{srf}), and the melting (freezing) level (P_0), as well as convective–stratiform classification. The convective–stratiform classification is based on the Goddard cumulus ensemble (GCE) method (Churchill and Houze, 1984), which identifies convective and stratiform regions using surface rain rate thresholds, cloud water content, and vertical velocity profiles from CRM simulations. The stratiform part is further separated into shallow-stratiform and deep-stratiform (anvil) clouds based on the relationship between PTH and the melting level height (4.4 km; Shige et al., 2004). The LUTs used in SLH are constructed differently for different rain types. For convective and shallow-stratiform rain, the LUTs are based on PTH, while for deep-stratiform rain, P_0 is used instead of PTH. In the latest SLH retrieval version (V6; Takayabu and Tao, 2020), deep-stratiform rain is further divided into two subcategories: one where precipitation decreases from the melting level toward the surface and one where precipitation increases. The first case represents typical stratiform rain where evaporation-driven cooling occurs below the melting level, and the cooling magnitude is estimated from the difference between P_0 and P_{srf} . The second

case, more common near convective areas, requires a separate set of LUTs, where the profile magnitude is determined directly by P_{srf} (Tao et al., 2016; Takayabu and Tao, 2020).

In the CSH algorithm, the surface precipitation rate, composite radar reflectivity, freezing level height, and echo-top height (ETH) are used as inputs. The CSH algorithm also applies a convective–stratiform classification, but the method differs from that of SLH. In CSH V6 (Tao et al., 2022), the convective–stratiform separation follows a method more consistent with the GPM classification approach (Steiner et al., 1995). This method identifies convective and stratiform rain based on the radar reflectivity profile, comparing local reflectivity values to background averages and detecting bright bands (sharp reflectivity decreases near the melting level). In CSH, stratiform profiles are further divided based on mean ETH, with deep stratiform defined as $\text{ETH} > 5$ km. To estimate low-level evaporative cooling in stratiform regions, CSH uses the vertical gradient of low-level reflectivity to distinguish between profiles with increasing and decreasing precipitation below the melting level (Lang and Tao, 2018; Tao et al., 2022).

A comparison study by Tao et al. (2022) over five tropical (warm-season) regions shows that both retrievals capture the general structure of convective and stratiform heating, with broad heating in the middle troposphere in convective regions and heating aloft but cooling below in stratiform regions. However, SLH shows stronger heating aloft in the stratiform anvils across all cases. In addition, the peak heating height in SLH profiles tends to be higher than in CSH, which was also reported by Elsaesser et al. (2022). This difference may be related to the fact that SLH is based on cloud-resolving simulations from the TOGA COARE field campaign, which represents oceanic convection with a larger fraction of stratiform rain (Tao et al., 2016). Another notable difference is that SLH-derived LH profiles show more structural details in stratiform regions, with three distinct heating peaks, while CSH-derived profiles generally show only two heating peaks over most regions.

In this investigation, we utilize the latent heating profiles of the GPM TRMM-SLH dataset (V06) gridded at 0.5° latitude $\times$ 0.5° longitude and with a vertical resolution of 250 m (Shige et al., 2007). We used the unconditional LH profiles averaged over all measurements within each grid cell and therefore used the averaging contributions from shallow and deep convection, from deep-stratiform rain, and from the clear sky.

2.2 Cloud and atmospheric data

The AIRS instrument (Chahine et al., 2006) on board the polar-orbiting satellite Aqua offers high-spectral-resolution measurements of the Earth's atmosphere at 01:30 and 13:30 LT since 2002. Its spectral coverage spans 2378 radiance channels within the wavelength range of 3.7–15.4 μm . AIRS footprints are grouped as 3×3 arrays. These arrays

correspond to the size of the Advanced Microwave Sounder Unit (AMSU) footprints, as this instrument is also on board. The spatial resolution of an AIRS footprint is about 13.5 km at nadir, and the swath width is approximately 1650 km. The latter leads to substantial horizontal coverage of approximately 70 % in the tropics at a specific local time.

The IASI instruments (Hilton et al., 2012) are operational on the European MetOp platforms, having started data acquisition in 2007. They provide measurements at 09:30 and 21:30 LT. IASI is a hyperspectral and high-precision Fourier transform spectrometer. The 8461 spectral channels cover the infrared spectral domain from 3.6 to 15.5 μm . IASI footprints are grouped as 2×2 arrays. Again, these arrays correspond to the size of the onboard AMSU footprints (August et al., 2012). The spatial resolution of an IASI footprint is about 12 km at nadir, and the swath width is about 2200 km, leading to 77 % coverage at a specific local time in the tropics.

The Clouds from InfraRed Sounders (CIRS) retrieval reconstructs cloud properties from both AIRS and IASI measurements. It relies on a weighted χ^2 methodology employing eight channels in the vicinity of the 15 μm CO_2 absorption band, as explained by Stubenrauch et al. (2010, 2017). The choice of eight channels was made to establish a consistent long-term cloud climatology by employing the same retrieval method across AIRS, IASI, and High-Resolution Infrared Radiation Sounder (HIRS) data (Stubenrauch et al., 2006). This retrieval simultaneously provides cloud emissivity (ε_{cld}) and pressure (P_{cld}), along with associated uncertainties. CIRS cloud types are defined according to P_{cld} and ε_{cld} : high clouds ($P_{\text{cld}} < 440$ hPa) are further categorized into high opaque clouds (Cb) with $\varepsilon_{\text{cld}} > 0.95$, cirrus clouds (Ci) with $0.95 > \varepsilon_{\text{cld}} > 0.5$, and thin cirrus (thin Ci) clouds with $0.5 > \varepsilon_{\text{cld}} > 0.05$. UT clouds with $P_{\text{cld}} < 350$ hPa are part of the high-cloud category. Mid-level clouds ($440 \text{ hPa} < P_{\text{cld}} < 680 \text{ hPa}$) and low-level clouds ($P_{\text{cld}} > 680 \text{ hPa}$) are further divided into opaque clouds with $\varepsilon_{\text{cld}} > 0.5$ and partly cloudy conditions with $\varepsilon_{\text{cld}} < 0.5$.

For consistent diurnal cloud variability from AIRS and IASI (Feofilov and Stubenrauch, 2019) the CIRS cloud retrieval uses auxiliary data (surface pressure and temperature, atmospheric temperature and humidity profiles, and snow and sea ice information) from an identical source: ERA-Interim, obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) meteorological reanalysis (Dee et al., 2011). These atmospheric profiles are also used to convert cloud pressure to cloud temperature (T_{cld}) and cloud height (Z_{cld}).

The ERA-Interim reanalyses have a spatial resolution of $0.75^\circ \times 0.75^\circ$ and are available at 00:00, 06:00, 12:00, and 18:00 UTC. They have been interpolated to the AIRS and IASI observation times by employing a cubic-spline function. The spatial colocation was done in such a way that each array of footprints was associated with the closest ERA-Interim grid cell.

2.3 Input data for the artificial neural networks

Table 1 summarizes the input variables that are used in the artificial neural network predictions described in Sect. 2.5.1.

Since the target data (TRMM-SLH) are given at a spatial resolution of 0.5° , we adapt the input data by also gridding them to 0.5° . The atmospheric properties (specific humidity and temperature profiles with a reduced vertical resolution containing 10 layers, total precipitable water, and tropopause height) and surface properties (pressure and temperature) from the ERA-Interim ancillary data are averaged over 0.5° , as well as cloud properties such as P_{cld} and ε_{cld} and their uncertainties. In addition, we keep the cloud properties averaged over the most frequent scene (high-level or mid- and low-level clouds) in each grid cell. We also utilize the horizontal sub-grid structure within the grid cells: fractions of Cb, Ci, thin Ci, mid-/low-level clouds, and clear sky. The spectral variability in the effective cloud emissivity between 9 and 12 μm that is computed using the retrieved P_{cld} indicates if the footprint is partly cloudy (Stubenrauch et al., 2017). Additional variables are the atmospheric window infrared (IR) brightness temperature and its spatial variability, brightness temperature differences between the atmospheric window and water vapour absorption channels, and the number of atmospheric layers down to the surface.

Furthermore, we use additional variables from the CIRS-ML dataset (Stubenrauch et al., 2023) for evaluation and for scene identification, but they are not considered input variables. As CIRS only identifies the uppermost cloud layer in the case of multiple-layer clouds, the occurrence of a cloud underneath was deduced by a binary artificial neural network (ANN) classification per footprint, trained using CloudSat–CALIPSO layer information. A rain intensity classification (0 for no rain, 1 for light rain, 2 for heavy rain) was also obtained by ANN classification per footprint but was trained with precipitation rate data from CloudSat (2C-PRECIP-COLUMN; Haynes et al., 2009). The rain intensity classification considers light rain to be $\leq 5 \text{ mm h}^{-1}$ and heavy rain to be $> 5 \text{ mm h}^{-1}$. In combination with a CloudSat 2C-PRECIP-COLUMN quality flag, which indicates certain rain, we also expanded a rain rate indicator via a binary ANN classification and then averaged it per 0.5° grid cell (Stubenrauch et al., 2023). The rain intensity classification used for the scene identification for the ANN training and production is based on this averaged rain indicator, with heavy rain starting around 2.5 mm h^{-1} . We show that this category corresponds to an average certain-rain fraction of at least 0.8 (not shown), while the light-rain category corresponds only to 0.3 over the ocean (0.5 over land). The advantage of using the CIRS-ML rain intensity classification is that the CIRS-ML data are available together with the CIRS–AIRS and CIRS–IASI data records, so we can use it for scene identification for the training as well as for the application of the ANN models developed for the different scenes discussed in Sect. 2.5.1.

Table 1. List of input variables for the prediction of latent heating gridded over a $0.5^\circ \times 0.5^\circ$ grid.

Input variables	Definitions
Clouds	
$\epsilon_{\text{cld}}, P_{\text{cld}}, T_{\text{cld}}, Z_{\text{cld}}, d\epsilon_{\text{cld}}, dP_{\text{cld}}$	CIRS cloud properties and uncertainties
$\epsilon(\text{scene}^*), P(\text{scene}^*), \text{frac_scene}$	CIRS cloud properties and fraction of the most frequent scene
$\sigma(\epsilon(\lambda_i))$	Spectral variability in effective cloud emissivity over six wavelengths (9–12 μm)
Atmosphere	
TB(11.85 μm), σ (TB)	AIRS/IASI brightness temperatures and spatial variability
TB(11.85 μm) – TB(7.18 μm), TB(11.85 μm) – TB(7.23 μm)	Brightness temperature difference between the atmospheric window and water vapour absorption channels
q, T within 10 layers	ERA-Interim specific humidity and temperature profile
Total precipitable water, $P_{\text{tropopause}}$	ERA-Interim column water vapour and tropopause height
Surface	
$P_{\text{surf}}, T_{\text{surf}}$, number of atmosphere layers down to P_{surf}	ERA-Interim surface properties
Horizontal sub-grid structure of CIRS cloud types from footprints	
frac_Cb, frac_Ci, frac_thCi	Fraction of cumulonimbus, cirrus, and thin cirrus clouds
frac_mlow	Fraction of mid- and low-level clouds
frac_clr	Fraction of clear sky

* The scene is 1 for high-level clouds and 2 for mid-/low-level clouds.

2.4 Collocation of input and target data

Due to their different orbit characteristics, the observations from the TRMM, Aqua, and MetOp satellites seldom coincide in both time and geographical location when observing the Earth. Consequently, only a subset of their respective observational databases can be overlaid and employed for the training. We allow a 20 min time differential between the CIRS and TRMM data. AIRS orbits (01:30 and 13:30 LT) and IASI orbits (09:30 and 21:30 LT) are independently collocated with TRMM orbits. Figure 1 illustrates the different swath widths of the Aqua–AIRS and TRMM–PR measurements and their overlaps for a specific day at a specific observation time. Within a time window of ± 20 min, the overlap between the TRMM–PR and the AIRS measurements is only 3 %. Our goal is to expand this coverage to about 70 % and 77 % (swath coverage of AIRS and IASI, respectively) by applying ANN methods to the input data described in Sect. 2.3. This allows us to then relate horizontal fields of clouds, LH, and Q_{rad} at specific local times, as shown in Sect. 3 and in the MCS analysis described in Sect. 5.2.

The collocated AIRS–TRMM data spanning from 2004 to 2013 consist of approximately 2 300 000 cases, and the IASI–TRMM data from 2008 to 2014 contain about 1 600 000 cases for each of the morning/evening measurement times.

2.5 Artificial neural network predictions and evaluation

2.5.1 Development of prediction models

As the distribution of precipitation rates is very skewed, with a large peak at 0 mm h^{-1} and a very long tail towards larger values, we first examine the shapes and statistics of the TRMM–SLH LH profiles within the collocated data.

In general, convective towers that produce strong latent heating can be identified by a heavy rain rate. However, these occur much less frequently (10 %) than scenes of lightly precipitating (25 %) and non-precipitating (65 %) high-level clouds. Over land, the diurnal variation in these convective towers is larger than over the ocean, as expected, with a minimum in the morning (7 %) and a maximum in the evening (12 %), while non-precipitating high-level clouds vary from 65 % at night to 77 % in the afternoon. The distinction between non-precipitating, lightly precipitating, and heavily precipitating clouds is given by the rain intensity classification described in Sect. 2.3. For the training of the artificial neural network regression models, the least frequent scenes, i.e. the ones with heavy precipitation (see above), will be less represented, but these are the scenes that we are most interested in (for the MCS studies in Sect. 5).

Figure 2 presents LH profiles of high-level clouds, which are separately averaged over these three rain intensity scenes and over the ocean and land, at the four CIRS observation times. Although the rain intensity categorization is derived from CloudSat radar and ANN classification using CIRS and

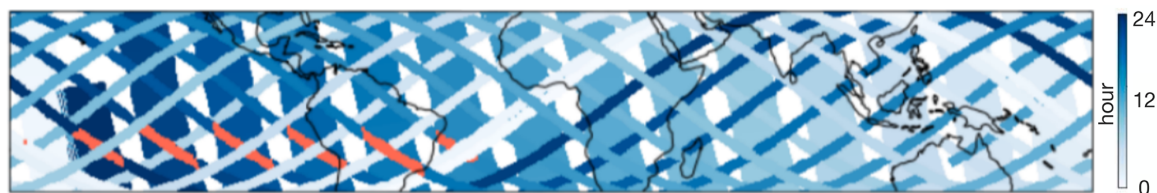


Figure 1. Illustration of the temporal and spatial match between the Aqua–AIRS and TRMM–PR orbits. Orange represents the satellite trace segments that coincide within a time window of ± 20 min, for 1 specific day. The narrow swaths represent TRMM–PR orbits, while the broader swaths represent Aqua–AIRS orbits. Shades of blue indicate variations in the sampling time difference.

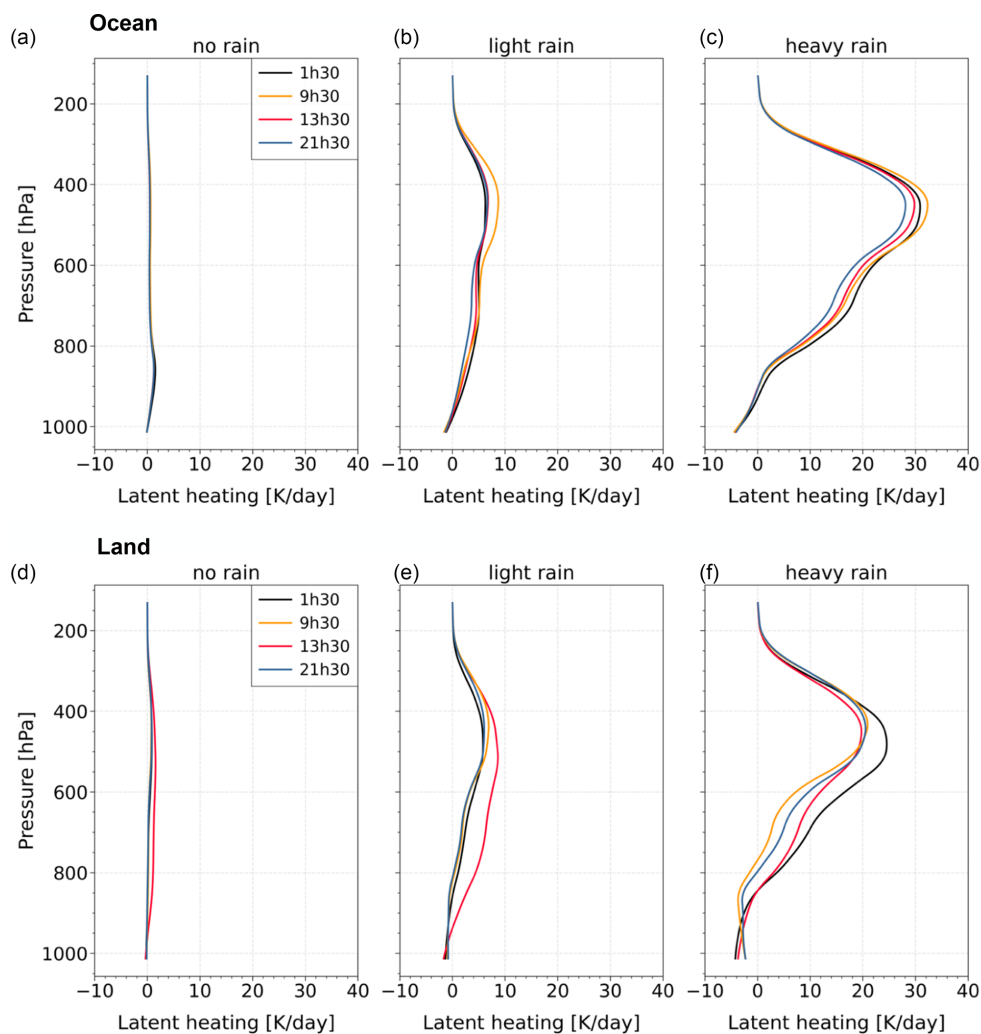


Figure 2. TRMM–SLH LH profiles of high-level clouds categorized by the CIRS–ML rain intensity described in Sect. 2.3 at four observation times (01:30, 09:30, 13:30, and 21:30 LT) over the ocean (**a–c**) and over land (**d–f**). The data are averaged over the TRMM–CIRS collocated data during the period of 2008–2013 within 30° N– 30° S at a spatial resolution of 0.5° .

ERA-Interim data, the shape of the TRMM LH profiles is consistent with this scene classification for both ocean and land cases. As expected, the LH profiles of these three scene types differ considerably, with nearly no LH for the no-rain situation and very large amounts of LH for heavy rain. The latter show large peaks in LH around 450 hPa, with a larger

maximum over the ocean (30 K d^{-1}) than over land (approximately 20 K d^{-1}). This may be linked to smaller systems over land than over the ocean (e.g. Liu, 2007). A larger diurnal variation over land is also observed, as expected.

When considering all precipitating high-level clouds or even all precipitating clouds (Fig. S1), the averages are far

smaller than the averages of heavy precipitation because heavy precipitation occurs only rarely. Since the LH profile shapes and statistics of the different rain intensity categories are very different, we developed ANN models for each of the three classes of rain intensity and separated them over the ocean and over land. If we had trained only one single ANN regression model for all scenes together, the LH of heavy rain would have been underestimated because of the small number of data points (as has been shown for radiative heating rates in the case of all clouds and Cb alone in Stubenrauch et al., 2021). For each of these precipitation classes, we also separated scenes of high-level clouds from those of mid- and low-level clouds. The latter show a peak of only about 5 K d^{-1} at about 900 hPa in the case of heavy rain (Fig. 5b of Stubenrauch et al., 2023; Figs. S6 and S8). This leads us to develop 12 ANN regression models to predict LH profiles from AIRS or from IASI. The predicted LH rates are given at a spatial resolution of 0.5° and at a reduced vertical resolution of 20 layers; they are given within the same pressure layers as the CIRS-ML radiative heating rates (Stubenrauch et al., 2021).

The final ANNs of the regression models consist of two hidden layers that both have 32 neurons and one output layer, as shown in Fig. S2. We applied the rectified linear unit (ReLU) activation function to the hidden layers. In addition, we used the root-mean-square propagation (RMSprop) optimizer with a learning rate of 0.0001 and a batch size of 512. Furthermore, we applied a min–max normalization to the variables. The collocated dataset was randomly divided into three categories: 60 % for training, 20 % for validation, and 20 % for testing. The latter two were not directly used in the training; while the validation data are used in the iteration process of the training, the test data are used for evaluation after the training (Sect. 2.5.2).

We use the mean squared error as a loss function for the regression models, which evaluates the mean squared difference between observed and predicted values. The model parameters are fitted by minimizing this loss function. The mean absolute error (MAE) is the average of absolute differences between observed and predicted values, and it is used to assess the quality of these regression models. In order to avoid overfitting, we stop training when the loss function does not improve for 20 iterations. We compare the behaviour of the loss function of the training data with that of the validation data. Similar results suggest that the model performs consistently well on both datasets, showing a certain level of generalization ability. Figure S4 shows good performance, except for a slight overfitting for heavy precipitation.

The hyperparameter selection of the neural network may influence the training results. Therefore, we tested different deep-learning parameters (e.g. number of neurons per layer, number of layers, learning rate, regression kernel) to optimize these ANN regression models. The results show only slight differences in training/validation loss and MAEs

among these tests, and there was no significant impact on the LH results.

To study the impact of the variable selection on the predictions, we have experimented with various input variables; in particular, we included and excluded information on the rain intensity substructure within the 0.5° grid cells. Using this information, the results were slightly better, in particular, the spread of the predicted LH was slightly larger. However, this approach resulted in a slight positive anomaly in vertically integrated LH for March 2014 and later on, when considering the time series of LH derived from AIRS data (not shown). The LH time series derived from IASI were not affected. In March 2014, the AIRS instrument was impacted by a solar flare event that led to tiny artefacts that show up in the ANN rain rate classification (Stubenrauch et al., 2023). Consequently, we have excluded these grid fractions of different rain intensity classes from our input variables.

We also assessed the effectiveness of the fraction of clouds below CIRS clouds. For the non-precipitating high-level clouds in Fig. 2, the very small LH peak of less than 1 K d^{-1} at about 900 hPa can be explained by the lower clouds underneath that produce rain (Fig. S3). Over land, this lower small peak is vertically more extended and is only observed at 13:30 LT. This may be due to the developing convection, which has its peak in the late afternoon and was missed by the AIRS and IASI observation times (see Sect. 3). While this CIRS-ML variable effectively shows low clouds underneath (Fig. S3), it did not improve the results as an additional input.

Therefore, we kept the configuration that uses the 27 variables given in Table 1 as input variables.

2.5.2 Evaluation using test data

We have evaluated the LH prediction results by comparing them with those of the target TRMM-SLH, using the 20 % test data from the collocated data.

For both AIRS and IASI, the MAE values presented in Table S1 are notably small, varying from 0.02 K d^{-1} for non-precipitating to 0.55 for heavily precipitating high-level clouds. Moreover, the loss function presented in Fig. S4 decreases rapidly with the iterations (epochs), which is followed by stabilization.

As shown in the upper panels of Figs. 3 and S6, as well as in Figs. S5 and S7, the predicted LH profiles capture, on average, the specific patterns of the high-level clouds exactly.

1. For the heavy-rain case, high-level clouds produce noticeable 25 K d^{-1} LH at about 450 hPa.
2. In the light-rain case, the predicted LH exhibits a much flatter distribution with only a very small peak of about 5 K d^{-1} at around 450 hPa.
3. In the no-rain case, LH is close to 0 K d^{-1} , with a tiny peak of approximately 0.7 K d^{-1} in the low-altitude re-

gion ($P > 800$ hPa), corresponding to low-level clouds that are mostly underneath non-precipitating cirrus, as suggested by Fig. S3, which shows a peak twice as large when only selecting cases with clouds below, according to a classification from CIRS-ML (see Sect. 2.5.1).

While the averages of the predicted results of the different scenes agree well with those of the target TRMM-SLH data, the spread of the predicted values is much smaller. The TRMM-SLH data reveal large variability between 550 and 900 hPa, which may be linked to the variability between stratiform and convective rain within the 0.5° , as well as due to additional precipitation from the underlying clouds. This decrease in the prediction of the variability may be due to insufficient input information and a too coarse spatial resolution but may also be because of the skewness of the precipitation distribution itself.

Compared to the LH prediction, the lower panels of Fig. 3 show the average CIRS-ML radiative longwave (LW) heating profiles and the target CloudSat–CALIPSO fluxes and heating rates (FLXHR) profiles (Henderson et al., 2013) as well as their spread, shown separately for thin cirrus, cirrus, and high opaque clouds. Here the spread of the predicted and target data is similar, in particular for the optically thicker clouds. Relatively opaque clouds contribute to the heating of the atmospheric column below by trapping surface emissions, while inducing cooling effects in the column above due to excess emission. In contrast, thin cirrus clouds warm the UT by intercepting LW radiation originating from below (Stubenrauch et al., 2021). Notably, above Cb clouds, the cooling is on average -4.5 K d^{-1} around 170 hPa. The small amount of cooling observed at approximately 550 hPa is attributed to the melting process, which takes place at or just below the freezing level, typically around 5 km above sea level across tropical regions.

Figure S7 shows that the LH profiles predicted from AIRS have slightly larger values in the lower troposphere (below 500 hPa) than the ones predicted from IASI, in particular over land. This may be explained by the diurnal cycle of precipitation coming from clouds at different heights since both AIRS and IASI predictions are on average in excellent agreement with the target TRMM-SLH profiles.

3 Construction of the 3D latent heating dataset by applying the ANN models

During the training process, ANN models are tuned to fit the data through continuous adjustment of hyperparameters by the optimization algorithm to minimize the difference between the predicted output and the target data (loss function). We use these trained models to extend the TRMM-SLH data, which only cover about 3 % of the CIRS observations, to a coverage of 70 % and 77 %, corresponding to the AIRS and IASI swaths over the periods of 2004–2018 and 2008–2018, respectively. We evaluate the effect of using only specific lo-

cal times (given by the ANN-predicted LH at the observation times of AIRS and IASI), and we compare the vertically integrated LH (LP) to the original temporal sampling of TRMM. At the end of this section, we illustrate how the ML-derived data can be used to compare the horizontal and vertical structure of LH and Q_{rad} between La Niña and El Niño.

3.1 Coherence in diurnal variation

Figure 4 shows the vertical LH profiles from the ML production for precipitating clouds. We consider all clouds and specifically high-level clouds, treating the groups separately over the ocean and over land. AIRS and IASI observations allow us to examine these profiles at four distinct observation times. The results are coherent with our expectations on the diurnal variation.

1. The shape of the LH profiles averaged over precipitating clouds strongly differs between ocean and land. Over the ocean, the mean LH profiles have two peaks, at 450 and at 850 hPa, corresponding to the contributions from high-level clouds and low-level clouds (Shige et al., 2004), while over land, the LH is mostly produced by high-level clouds.
2. The diurnal spread is larger over land than over the ocean, as expected. Over land, the precipitation frequency typically peaks in the late afternoon, whereas over the ocean, the diurnal cycle is less pronounced, with a maximum occurring in the early morning (e.g. Nesbitt et al., 2000; Dorian, 2014). The observations at 13:30 LT are before the peak of land precipitation, while those at 01:30 LT are before the early-morning peak of ocean precipitation. LH also involves the intensity of precipitation, and given that MCSs contribute to over half of intense precipitation (e.g. Roca et al., 2014), we observe the largest peaks at 450 hPa (corresponding to stratiform anvil precipitation) at 21:30 LT over land and at 09:30 LT over the ocean, which is a few hours after convection had started and MCSs were able to form.
3. In particular over land, we notice a diurnally changing profile shape, with a stronger contribution from lower atmospheric levels in the early afternoon, corresponding to the development of cumulus congestus. Later in the evening, the peak moves higher into the UT, corresponding to stratiform anvils. During the night there may be a more complex vertical structure with convection from lower clouds underneath the high-level clouds, and LH is at a minimum in the morning.

Small differences from the original TRMM-SLH averages in Fig. S1 may be explained by the different spatial sampling (70/77 % coverage compared to 3 % coverage).

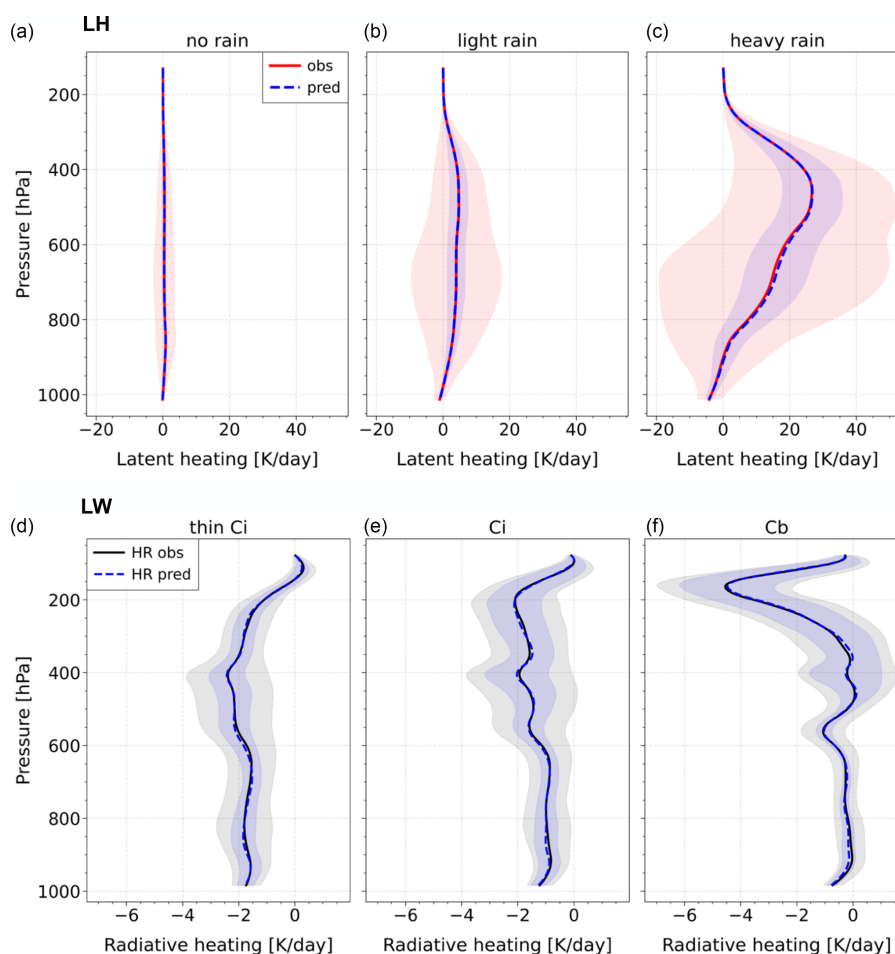


Figure 3. Average and range of predicted (dashed) and target (solid) latent heating (2004–2013) and radiative heating (2007–2010) of high-level clouds within 30°N – 30°S at a spatial resolution of 0.5° . ANN models were trained on collocated AIRS–TRMM and AIRS–CloudSat–CALIPSO data. The upper panels show the latent heating rates for different rain rate intensities (no rain, light rain, and heavy rain); the lower panels are the radiative longwave heating rates for different UT cloud types (thin cirrus, cirrus, and cumulonimbus). Shaded areas indicate $\pm 67.5\%$ of the standard deviation, which approximately correspond to the quartiles.

3.2 Coherence between TRMM-SLH LP and ML-predicted LP

Due to the large diurnal cycle of occurrence and intensity of precipitation over land, the time sampling plays an important role in order to obtain reliable monthly means of LH. Figure 5 presents zonal averages of the vertically integrated LH (LP): ML-derived LP at specific observation times and original TRMM-SLH LP with its specific diurnal sampling, shown separately over the ocean and over land.

We note the following points.

1. Over the ocean, all zonal means of LP show a peak around 5° north of the Equator, with a small, broader peak from the Equator to approximately 10°S that corresponds to the large amount of LP released over the Pacific warm pool. Over land, there is only one broad peak from about 10°N to 10°S .
2. Overall, the latitudinal behaviour of LP given by AIRS-ML and IASI-ML is consistent with the one given by TRMM-SLH with broader diurnal sampling. It is remarkable that over the ocean, the zonal averages of LP at 01:30 and 13:30 LT agree very well with those from TRMM-SLH. However, over land, as expected, considering LP only at these two observation times underestimates the daily mean LP because the strong convection in the afternoon is not captured. The effect is the worst at 09:30 LT.

Furthermore, Fig. S9 compares the LP zonal means of the ML-derived data with the collocated TRMM-SLH data, shown separately over the ocean and over land at the four observation times. One has to keep in mind that the spatial sampling is much smaller than the one in Fig. 5. In general, the LP zonal averages from ML agree quite well with that from the collocated data, with small explainable biases: a

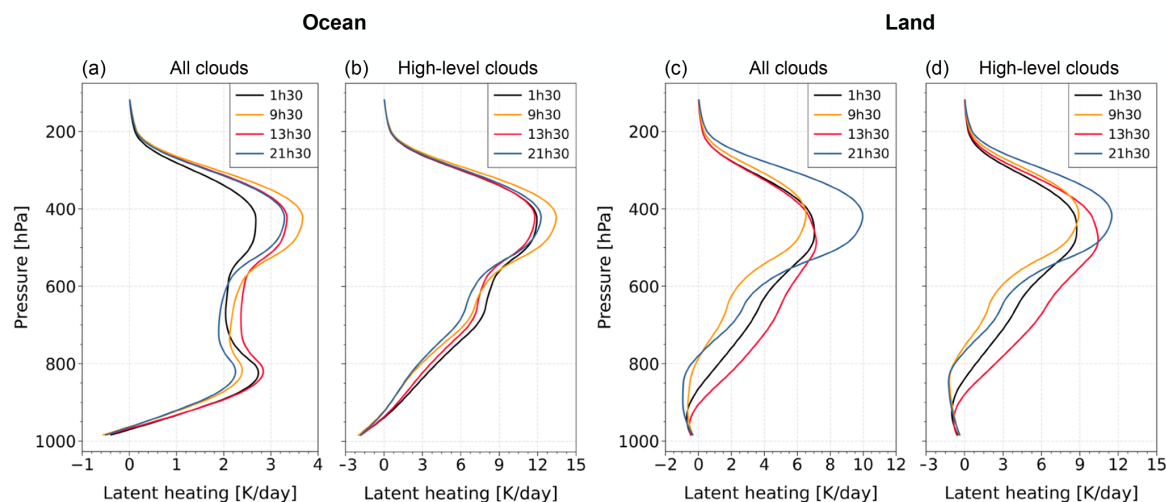


Figure 4. Average CIRS-ML LH profiles of all precipitating cloud scenes (a, c) and precipitating high-level clouds (b, d) at four observation times (01:30, 09:30, 13:30, and 21:30 LT) separated into over the ocean (a, b) and over land (c, d). Data are from the CIRS-ML production during the period of 2008–2013 within 30° N–30° S at a spatial resolution of 0.5°.

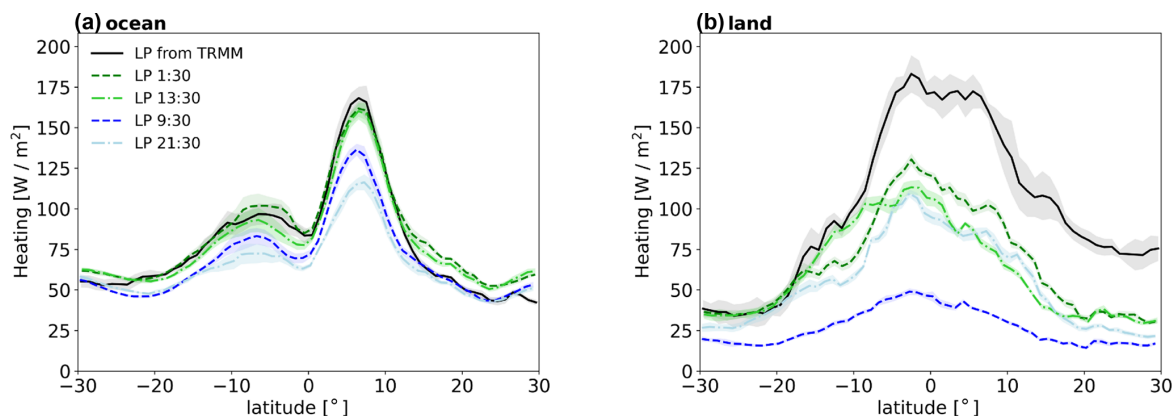


Figure 5. Zonal averages of vertically integrated LH (LP) at four specific observation times (01:30, 09:30, 13:30, and 21:30 LT) from the CIRS-ML production and for the original TRMM, including diurnal sampling (a) over the ocean and (b) over land. Latitude intervals are 1°. The LP from TRMM-SLH data for the period of 2008–2013 is represented by a solid black line. The dashed green line and dash-dotted bright-green line represent LP from the ML regression using TRMM–AIRS (2008–2013) as inputs at 01:30 and 13:30 LT, respectively. The dashed blue line and dash-dotted light-blue line represent LP from ML regression using TRMM–IASI (2008–2013) as inputs at 09:30 and 21:30, respectively. Shaded areas correspond to inter-annual variabilities.

slight underestimation in regions with strong rain (tropical peak region) and a very slight overestimation in regions with not much rain (subtropics).

To investigate the coherence of LP monthly averages over grid cells between TRMM-SLH and CIRS-ML in more detail, we examined their relationship at different scales over the ocean, using averages over 1, 2.5, 5, and 10°. Differences from a 1-to-1 relationship stem from (1) biases in the CIRS-ML LH and (2) differences in the sampling of observation times. Since the diurnal sampling of TRMM is not homogeneous, a larger grid cell has a larger probability of including more observations at 01:30 LT. As the TRMM revisit cycle depends strongly on latitude (Negri et al., 2002), 23 d at

the Equator and up to 46 d at the highest latitudes (the latter should have different observation times sampled in different months), we limited the latitudinal band to 10° N–10° S for this comparison. We computed the slopes and correlation coefficients between monthly mean LP of TRMM-SLH and CIRS-ML averaged over different scales, and Fig. 6 presents the normalized density in the CIRS-ML LP and TRMM-SLH LP plane. While the slopes increase from 0.54 to 0.82 in this latitude band, they vary from 0.44 to 0.77 at higher latitudes (20–30° N and S, not shown), where the TRMM repeat cycle is only half as long as at higher latitudes. The larger slopes in the latitude band nearer to the Equator demonstrate their dependency on the TRMM diurnal sampling variabil-

ity. The increase in the slopes and the increasing linearity of the points with increasing grid cell size in the CIRS-ML LP and TRMM-SLH LP show a strong bias and noise reduction when averaging over more observations within a grid cell. At the spatial averaging over 1° , the small slope is related to the fact that the ANN regression does not capture extreme events well, mainly because of insufficient input information and the skewed distribution of input data, as mentioned in Sect. 2.5, and the relatively noisy relationship is due to the inhomogeneous TRMM sampling at specific times. Therefore, for larger grid cell sizes, the agreement is much better.

In summary, the increasing slopes of the relationship between the LP of CIRS-ML and TRMM-SLH suggest that our ML-expanded LH dataset is suitable at scales larger than about 2.5° (with a slope of 0.68). At a scale of 1° , one still observes a correlation, but the relationship is much noisier, and the CIRS-ML LP is strongly underestimated for large amounts of TRMM-SLH LP. This can be explained by the fact that extreme values are very rare and, as seen in Fig. 3, the ANN regression is capable of producing a reliable mean per scene, but the training dataset of precipitation extremes was most probably too small.

In order to further understand the noise and biases, we analysed the complete statistics of the collocated data in order to link discrepancies in LP with those in rain fraction over the 0.5° grid cells estimated from CIRS-ML (CloudSat) and TRMM. Therefore, we compare the CIRS-ML certain-rain fraction as a function of the TRMM rain fraction and TRMM-SLH LP (Fig. S10). The average certain-rain fraction increases coherently with both, as one would expect. When separating cases with small and large fractions of certain-rain within the grid cells, the CIRS-ML LP is much larger for a large fraction, as one would again expect. Cases with a large certain-rain fraction for very small values of TRMM-SLH LP are rare, but their occurrence leads to a slight overestimation. The distributions of the CIRS-ML certain-rain fraction in the CIRS-ML LP – TRMM-SLH LP space, shown in Fig. S11, explain the noise, in particular for small TRMM LP. Thus, this noise can be mostly explained by a few individual cases that show a mismatch between the certain-rain coverage obtained from ANN classification of certain-rain identified in CloudSat samples ($1.25 \text{ km} \times 2.5 \text{ km}$) and the TRMM radar samples ($5 \text{ km} \times 5 \text{ km}$). Nevertheless, what is important to note is that the CIRS-ML LP seems to be consistent with the certain-rain coverage, even though this variable was not used in the training.

3.3 Structure of diabatic heating: contrasting La Niña and El Niño events

After verifying the ML-derived LH production along the vertical and latitudinal directions, we illustrate that the horizontal patterns produced by this 3D LH dataset for La Niña and El Niño are as expected. Figure 7a, d show geographical maps of LP and ACREs, respectively, for two distinct sce-

narios: La Niña (January 2008) and El Niño (January 2016). LP is marked by contours, while the colours correspond to ACRE values. The LH and CRE profiles averaged over 30°N – 30°S are given as a function of longitude in Fig. 7e and f.

During El Niño (warm phase), sea surface temperatures (SSTs) are higher than normal in the eastern and central equatorial regions of the Pacific Ocean, leading to increased convection and cloudiness in these regions, which cause an increase in latent heat release. Lower SSTs in the western Pacific lead to a decrease in convection and cloudiness in the region, resulting in negative LP anomalies. La Niña shows the opposite behaviour (Fig. 7a and b).

During La Niña, there is a large, structured band of latent heating in the South Pacific Convergence Zone (SPCZ) (Fig. 7c and d), in addition to the large value of LP in the Intertropical Convergence Zone (ITCZ), mostly over the continents. During El Niño, we notice that the maximum distribution of latent heating moves eastward, which happens because the upward branch of the Walker circulation shifts towards the central Pacific (e.g. Bayr et al., 2018). This is even more evident in Fig. 7e and f. Furthermore, there are some regions with negative CRE values at altitudes around 850 hPa, which correspond to the presence of low-level clouds. This effect is more significant during La Niña because convective activity peaks in the western Pacific during La Niña, whereas in the eastern Pacific, with lower SSTs and less convective activity, there is more low-level cloud formation, thereby leading to negative CRE aloft.

We also assessed the geographical coherence between the CIRS-ML-predicted LP and the LP calculated using precipitation data from TRMM (3B42_daily; Huffman et al., 2007) and from the Global Precipitation Climatology Project (GPCP CDR_V2.3; Adler et al., 2016) during the same ENSO events. To facilitate comparison between our ML-derived LP and the precipitation datasets, we estimated $LP = \rho_l L \nu R$ as in L'Ecuyer and Stephens (2007), where ρ_l is the density of liquid water (1000 kg m^{-3}), $L \nu$ is the latent heat of vaporization of water ($2.5 \times 10^6 \text{ J kg}^{-1}$), and R represents the surface rainfall rate (m s^{-1}). Using this formula, the conversion factor to convert precipitation rates from TRMM and GPCP (mm d^{-1}) to latent heat flux LP (W m^{-2}) is $28.9 \text{ W m}^{-2} / (\text{mm d}^{-1})$. Figure 8 shows that the geographical patterns and the absolute values of the monthly mean LP computed from GPCP and from TRMM daily accumulated precipitation agree very well. Moreover, the geographical patterns of our ML-predicted LP align closely with the ones derived from TRMM and GPCP precipitation data during both the La Niña and El Niño phases, although the absolute values in the regions of larger amounts of LP are underestimated, as shown by Fig. S13, which presents the ratio between CIRS-ML LP and TRMM (or GPCP) LP for grid cells with a TRMM (or GPCP) LP larger than 50 W m^{-2} . This was expected from the results presented in Sect. 3.2. Nevertheless, the CIRS-ML LH allows us to study monthly

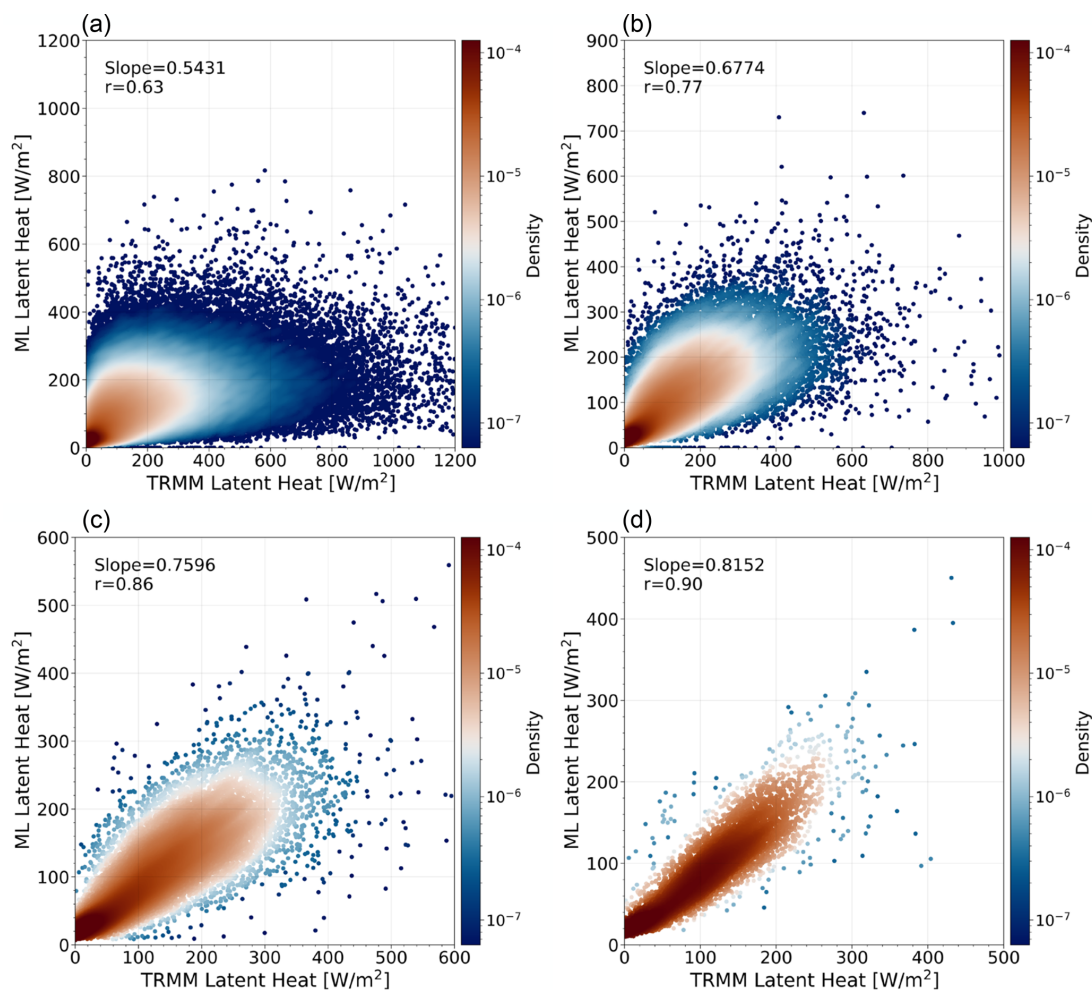


Figure 6. Relationship of LP monthly means per grid cell between TRMM-SLH LP and CIRS-ML at different spatial scales: (a) 1° latitude $\times$ 1° longitude, (b) $2.5^\circ \times 2.5^\circ$, (c) $5^\circ \times 5^\circ$, and (d) $10^\circ \times 10^\circ$. Data points are over the ocean from 10° N to 10° S over the time period of 2004–2013.

mean spatial patterns at four specific times, keeping in mind that the range between the smallest and largest LP values is underestimated. This is not possible with the original TRMM dataset, which does not fully cover the latitudinal band over a whole month at a specific time, as demonstrated in Fig. S12.

All of the above suggests that the monthly means of the CIRS-ML-expanded LP represent the horizontal structures seen in other datasets well and strongly reflect the characteristics of ENSO events. In addition, the ACRE shows a highly matched distribution pattern with LP. In other words, larger ACRE distributions are also seen in the regions of larger LP values, and therefore enhance LP. In Sect. 5, we will explore in more detail the connection between them, in particular at the scale of mesoscale convective systems (MCSs). For this study, we need to average LP and ACREs over the horizontal extent of the MCSs. Therefore, in the next section we describe the reconstruction of these MCSs.

4 Construction of mesoscale convective systems

The study in Sect. 5.2 requires the identification of mesoscale convective systems, including their non-precipitating anvil parts, as these also provide radiative heating. Therefore, we use the CIRS data to reconstruct the first UT cloud systems, using a method developed by Protopapadaki et al. (2017) and refined by Stubenrauch et al. (2023). We consider UT clouds with $P_{\text{cld}} < 350$ hPa. The grid cells of 0.5° latitude $\times$ 0.5° longitude have to be covered by at least 90 % of these clouds. Since ubiquitous thin cirrus in the TTL (tropical tropopause layer) connect with many of the MCSs, we exclude the UT clouds with emissivity smaller than 0.2 for this UT cloud system reconstruction. First, adjacent grid cells with UT clouds of similar heights (within $8 \text{ hPa} \times \ln(P_{\text{cld}} [\text{hPa}])$) are merged together into the same system. Then the size of the convective cores is determined first by counting the number of grid cells with cloud emissivity > 0.98 within regions where the cloud

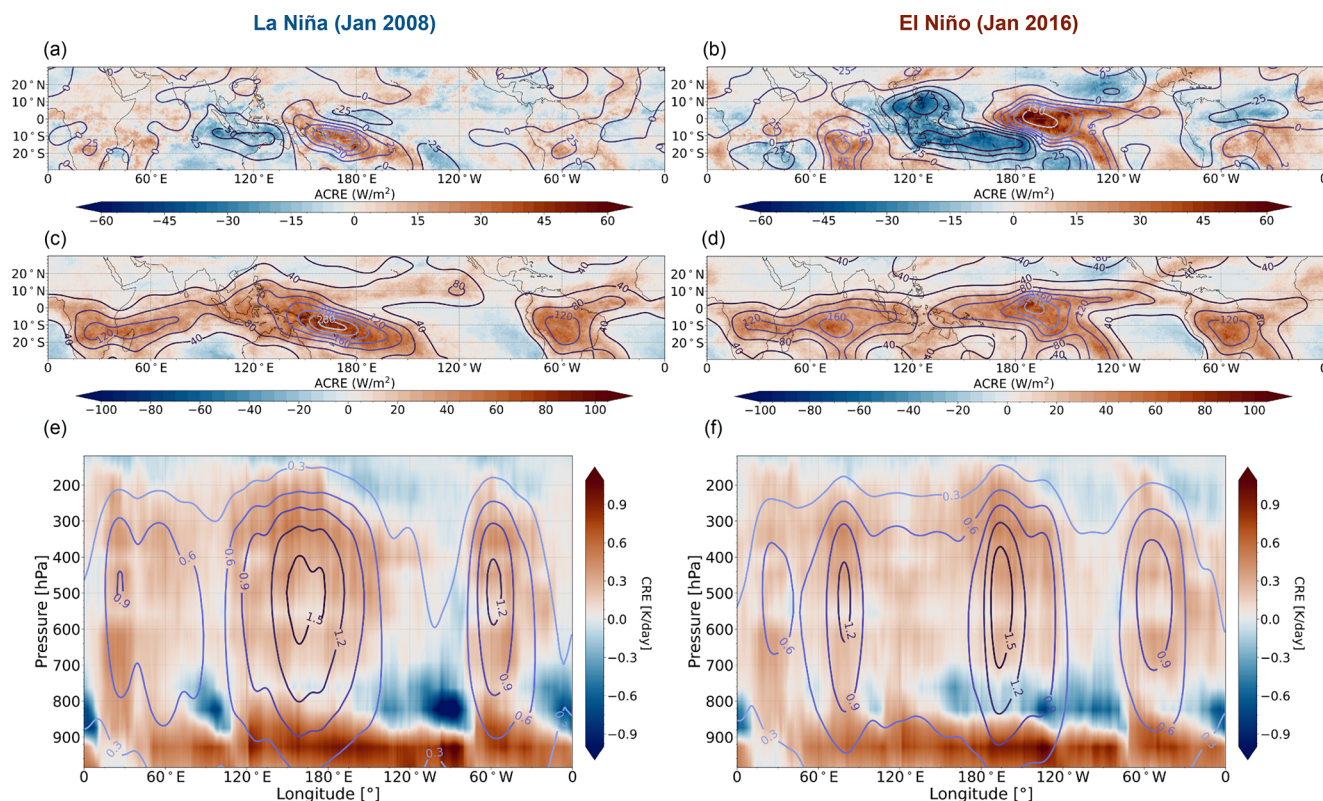


Figure 7. (a, b) Maps of anomalies of vertically integrated LH and the ACRE during La Niña (January 2008) and El Niño (January 2016), which were obtained by subtracting the corresponding 11-year (2008–2018 January) averages. (c, d) Maps of vertically integrated LH and the ACRE during La Niña (January 2008) and El Niño (January 2016), respectively. (e, f) Plots of longitudinal–vertical LH and CRE during La Niña (January 2008) and El Niño (January 2016), respectively. All data are within 30°N–30°S at a spatial resolution of 0.5°. The colour bars represent the El Niño–Southern Oscillation (ENSO) ACRE anomalies (W m^{-2}) and the ACRE (W m^{-2}) and CRE (K d^{-1}) values from CIRS-ML–CloudSat–CALIPSO, while contours correspond to vertically integrated ENSO LH anomalies (W m^{-2}) and vertically integrated LH (W m^{-2}) and LH values (K d^{-1}) from CIRS-ML–TRMM at 01:30 and 13:30 LT (AIRS).

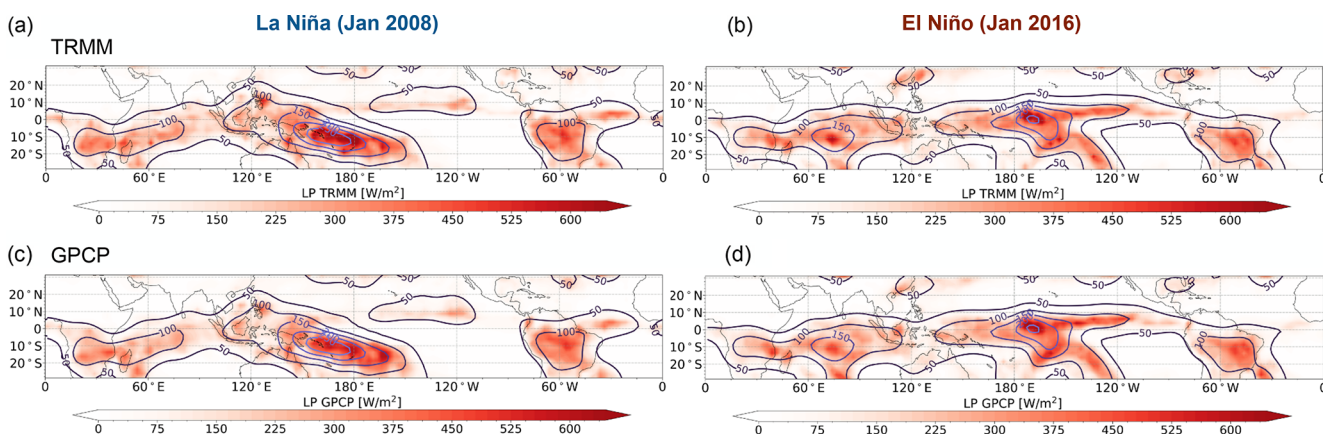


Figure 8. Comparison of horizontal structures between the vertically integrated LH (LP) of CIRS-ML (at 01:30 LT) and those obtained from daily precipitation accumulation of TRMM (a, b) and GPCP (c, d) during La Niña (January 2008) and El Niño (January 2016) within the region of 30°N–30°S at a spatial resolution of $2.5^\circ \times 2.5^\circ$. The LP from CIRS-ML is represented by contours, while the colour bars indicate the LP from TRMM and GPCP.

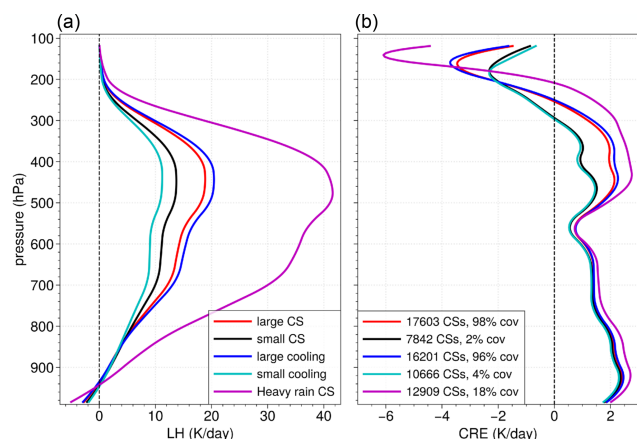


Figure 9. (a) Profiles of latent heating and (b) profiles of CRE. Averages are over CSs with the presence of at least one grid cell with heavy precipitation (magenta), averages over small CSs (black) and MCSs (red), and averages over CSs with small (cyan) and large (blue) LW cooling above the precipitating parts. The classification thresholds are $12\,000\text{ km}^2$ for size and -7.5 K d^{-1} for the minimum of the LW cooling above the precipitating part of the CS. The number and the coverage compared to all CSs are also given according to the category. Data are for oceanic systems over the time period of 2004–2018 within 25° N – 25° S .

emissivity exceeds 0.93 and then by multiplying this number by the grid cell size of 0.5° (approximately 3000 km^2). We define a convective system as a UT cloud system with at least one convective core and the presence of precipitation. Earlier studies (Protopapadaki et al., 2017; Stubenrauch et al., 2019, 2023) have shown that the convective core fraction, given by the ratio of the convective core size over the MCS size, can be used as a proxy for the maturity stage.

Since for the cloud system reconstruction the gaps between the orbits have been filled (Protopapadaki et al., 2017), but the CIRS-ML diabatic heating and precipitation intensity classification have only been extended within the orbits of AIRS and IASI, we select for the following analyses only reconstructed cloud systems that overlap by more than 70 % with the ACRE and LP swaths. Furthermore, we concentrate only on oceanic systems, defined as systems with less than 10 % of their size overlapping land, and we limit the latitude band to 25° N – 25° S because most of these systems are located there according to Fig. 5 of Protopapadaki et al. (2017). These criteria leave us with about 26 358 convective systems (CSs) for the period of 2004–2018.

In order to test the coherence of the data, we compare the diabatic profiles of different categories of convective systems. Therefore, we explore various proxies for convective intensity: (1) the presence of heavy precipitation (e.g. Takahashi et al., 2021), (2) MCS size (e.g. Roca and Fiolleau, 2020; Stubenrauch et al., 2023), and (3) the minimum of the LW cooling above the precipitating part of the MCS. The latter is directly linked to the opacity: the larger the LW cooling

above the cloud, the denser the cloud itself (Stubenrauch et al., 2021).

Figure 9 presents profiles of latent heating and CRE averaged over CSs of different precipitation intensities distinguished by the proxies described in the paragraph above and using the thresholds given in the figure caption. All profiles show a peak in latent heating at around 450 hPa. This is much higher than one would expect from an isolated convective tower and is linked to additional stratiform rain from the thick anvils (i.e. Hartmann et al., 1984; Schumacher et al., 2004; Chang and L'Ecuyer, 2019). The CSs including heavy precipitation, covering about 20 % of the area of all CSs, produce the largest amount of LH, with a maximum of about 40 K d^{-1} around 450 hPa and a broad shoulder downwards to 700 hPa. CSs with a large size (MCSs) or with strong LW cooling above their precipitating parts also show a larger amount of LH than those of smaller size or with smaller LW cooling. Radiative heating adds a small amount of positive heating from 200 hPa downward and cooling above the opaque parts of the CSs. Cooling and heating are much stronger for CSs including heavy precipitation, leading to strong vertical gradients.

The size threshold of $12\,000\text{ km}^2$ corresponds to approximately four grid cells of 0.5° , and it differentiates between CSs and MCSs, the latter with 17 603 data points covering about 98 % of all CSs identified by CIRS.

5 Reinforcement of latent heating by UT cloud radiative heating

Over the deep tropics (15° N – 15° S), UT clouds have a net radiative heating effect of about 0.3 K d^{-1} on the troposphere from 250 hPa downward, and this radiative heating enhances the column-integrated latent heating by about $22 \pm 3\%$ (Li et al., 2013; Stubenrauch et al., 2021). Regionally and temporally, this enhancement varies, however. It was shown that both the ACRE and LP depend on surface temperature (Hartmann and Larson, 2002; Cesana et al., 2019) and column humidity (e.g. Bretherton et al., 2004; Holloway and Neelin, 2009; Masunaga and Bony, 2018; Needham and Randall, 2021; Masunaga and Takahashi, 2024). Therefore, we explore the relationship between latent and radiative heating as a function of these environmental factors (Sect. 5.1) and then, more specifically, for mesoscale convective systems (Sect. 5.2). Since we found the CIRS-ML LP at 01:30 and 13:30 LT to be more similar to the LP of the diurnally sampled TRMM-SLH over the ocean, we consider in the following only precipitating clouds over the ocean.

5.1 Relationship between LP, ACRE, and the environment

On average, the radiative enhancement in ACREs increases with LP, as seen in Fig. 10a and b (black curves) and as already discussed by Stephens et al. (2024). This increase flat-

tens for LP larger than about $250\text{--}500\text{ W m}^{-2}$. Figure 10a and b also show the relationship between ACREs and LP for different environmental conditions: (1) warm and humid, (2) warm and dry, (3) cool and humid, and (4) cool and dry. These environmental conditions are given by SST and by the integrated column water vapour (CWV) obtained from the ERA-Interim meteorological reanalyses.

When stratified by environmental conditions, we still observe the increase in the ACRE with increasing LP, but for each LP interval, the average ACRE is largest for the warm and humid situations and smallest for the cool and dry situations. Figure 10a (all precipitating clouds) and b (only precipitating UT clouds) differ mostly for smaller amounts of LP, as lower clouds do not produce as much LP. The averages of ACREs in dry situations at these smaller amounts of LP show that UT clouds radiatively heat the atmosphere, while low-level clouds cool the atmosphere (aloft). For UT clouds with LP greater than 500 W m^{-2} , ACRE differences between cool-dry and warm-humid conditions increase from 30 to 50 W m^{-2} with increasing LP. It is interesting to note that the ACRE is similar between warm-dry and cool-humid conditions, and both are quite close to the ACRE in warm-humid situations. This means that for UT clouds releasing a large amount of latent heat, the SST has a larger impact on the ACRE in dry than in humid environments.

Now how can UT clouds that release similar amounts of latent heat differ so much in the ACRE? The cloud height in these different environments plays a key role, as shown by the cloud top pressure distributions in Fig. 10c and d for all precipitating clouds with a small value of LP ($< 500\text{ W m}^{-2}$) and only precipitating UT clouds with a large value of LP ($> 500\text{ W m}^{-2}$), respectively. A larger ACRE can be explained by a higher cloud height (lower cloud top pressure): the highest clouds (peak at 170 hPa or about 15 km) are situated in a warm and humid environment and the lowest UT clouds (peak at 240 hPa or about 11 km) are situated in a cool and dry environment; the cloud height distributions in cool-humid and warm-dry environments are situated between those in warm-humid and cool-dry environments, with each being progressively lower than those in the warm-humid environment.

For clouds that only release a small amount of latent heat, humidity seems to be more important than SST for slightly larger ACREs (Fig. 10a), as already pointed out by Needham and Randall (2021). This can be explained by the fact that UT clouds are much more frequent in humid than in dry regions, while lower-level clouds exist mostly in dry regions (Fig. 10c).

Why does cloud height differ under varying SST-CWV conditions? Humid environments increase the buoyancy of convective clouds, which allows clouds to reach higher heights (Holloway and Neelin, 2009). In contrast, in dry environments, the lower water vapour content results in smaller plume buoyancies, limiting convection and preventing clouds from reaching the same height as in humid conditions, a

fact confirmed by Fig. 10c. The impact of lower-tropospheric moisture on buoyancy through entrainment seems to be particularly significant compared to other mechanisms, although additional processes may also contribute (Derbyshire et al., 2004). Under lower-humidity conditions, higher surface temperatures lead to higher convective available potential energy (CAPE; Seeley and Roms, 2015), which provides enough energy to lift air upwards, forming taller clouds. This explains why cloud heights and ACREs in humid and warm-dry conditions are similar, while both cloud heights and ACREs are significantly lower in a cool-dry conditions (Fig. 10b and d). In addition, low-level wind shear can also influence cloud development: moderate low-level wind shear, where cold pool outflow balances environmental shear, can help convective clouds develop to greater heights and persist longer, while too weak or too strong low-level shear tends to suppress deep convection and reduce cloud top height (Rotunno et al., 1988).

When considering the distribution of UT clouds in the LP-ACRE plane, with SST and CWV averaged over each interval in LP and ACREs, as shown in Fig. 11a and b, respectively, we observe a very large spread in the ACRE for a small value of LP, which is gradually reduced towards larger values of LP. As one would expect, UT clouds heat the atmosphere, and the occurrence of negative ACRE values for LP values of less than 500 W m^{-2} should correspond to thin cirrus clouds with lower precipitating clouds underneath. In this case, the CIRS cloud retrieval itself only provides the properties of the uppermost cloud.

The occurrences in the LP-ACRE plane and the associated average environments can be compared to the results of Masunaga and Takahashi (2024, Fig. 6): they have characterized three convective regimes (bottom-heavy, mid-heavy, and top-heavy) based on the net moisture and moist static energy (MSE) transport associated with vertical motion (their Fig. 5), and then they associated different parts of the ACRE-LP space to these convective regimes, again according to the import and export of net moisture and MSE (their Fig. 6). By comparing these convective regimes projected to the LP-ACRE plane with Fig. 11a and b, UT clouds in the more or less warm-humid conditions correspond mostly to a mid-heavy convective regime, while the bottom-heavy convection regime, with a small value of LP and a widely spread ACRE, occurs in a cool-dry environment, with UT clouds on top of lower convection. For larger values of LP, the cases of low ACREs should correspond to the top-heavy convective regime, and these are also associated with a cool-dry environment. The results are robust when averaged over 5° (Fig. S14).

In order to explain the smaller ACRE in the cooler and drier environment, which corresponds to top-heavy convective regimes, Fig. 12 shows the heating profiles of the UT clouds for the environments defined above in two LP intervals, with $\text{LP} > 500\text{ W m}^{-2}$ and $\text{LP} < 500\text{ W m}^{-2}$. Indeed, for the small LP interval and the cool environments, the LH

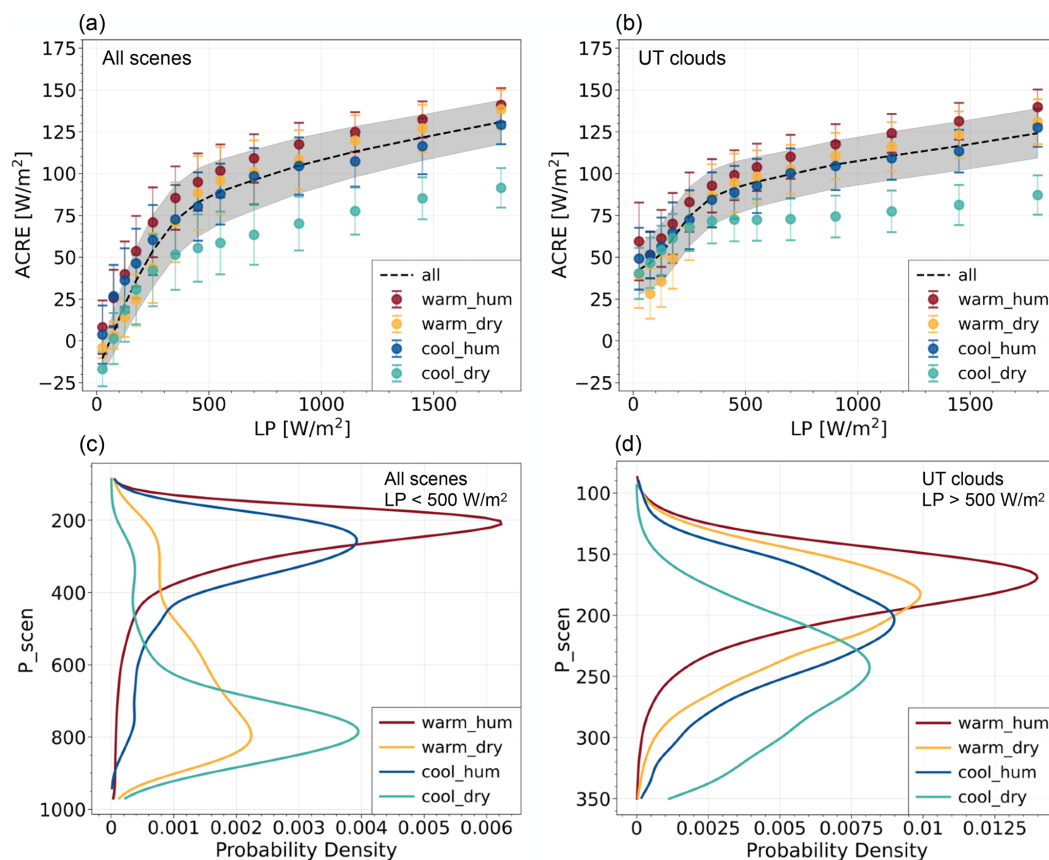


Figure 10. ACRE as a function of LP of precipitating cases (a) for all cloud scenes and (b) for UT clouds only for four specific environments (cool to warm and humid to dry). Shaded areas and error bars indicate $\pm 67.5\%$ of the standard deviation. The probability density of cloud pressure for these different environments (c) for all cloud scenes and (d) for UT clouds is shown. The environments are defined as follows: warm–humid is SST > 302 K and CWV > 60 mm, warm–dry is SST > 302 K and CWV > 45 mm, cool–humid is SST > 298 K and CWV > 60 mm, and cool–dry is SST > 298 K and CWV > 45 mm. All data are from the period of 2004–2013 within 30° N–30° S at a spatial resolution of $2.5^\circ \times 2.5^\circ$ over the ocean.

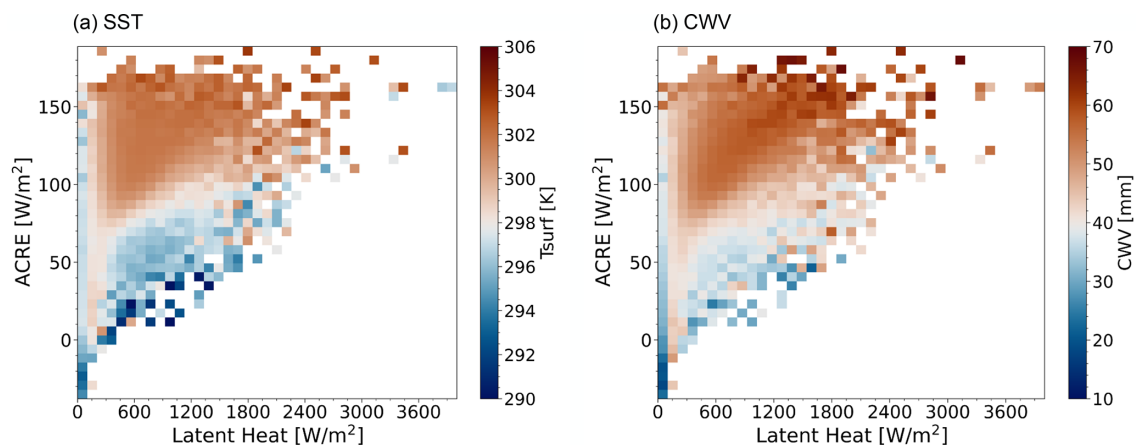


Figure 11. Averages of (a) SST and (b) CWV as function of LP and the ACRE released by precipitating UT clouds over the ocean for the period of 2004–2013, spanning 30° N to 30° S at a spatial resolution of 2.5° . LP and ACREs are from CIRS-ML, while SST and CWV are from ERA-Interim at 01:30 and 13:30 LT. Each square corresponds to an interval of 100 W m^{-2} in ML LP and 5.75 W m^{-2} in the ACRE.

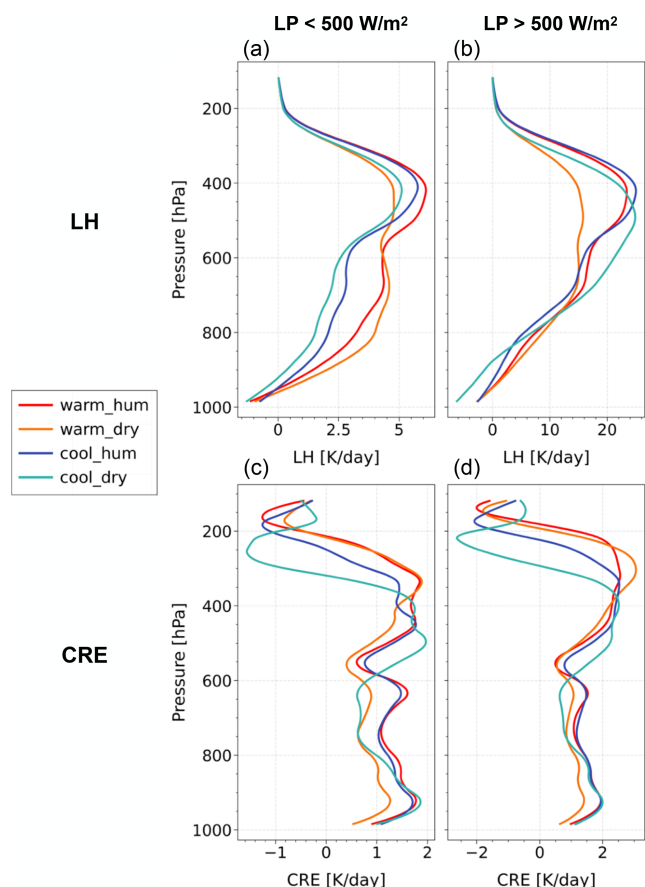


Figure 12. LH (a, b) and CRE (c, d) profiles of precipitating UT clouds, segmented by an LP threshold of 500 W m^{-2} and averaged across the environments of Fig. 10. All data are from the period of 2004–2013 within 30° N – 30° S at a spatial resolution of $2.5^\circ \times 2.5^\circ$ over the ocean.

profiles seem to be dominated by stratiform rain, with a relatively narrow LH peak around 410 hPa, while the LH profiles for the warmer environments also show heating in the middle and lower part of the troposphere. For larger values of LP, the LH profiles are more similar between these different environments, with increasing and broadening of the peak towards the middle and lower troposphere. This indicates either an increase in the latent heating produced by the convective cores (mid-heavy) or additional heating by the bottom-heavy lower convection underneath the anvils (as suggested by Masunaga and Takahashi, 2024). Note that the scales of LH in Fig. 12a (-2 to 6 K d^{-1}) and Fig. 12b (-5 to 25 K d^{-1}) are different, reflecting the large difference in the LH peak values between the two LP intervals. The relatively small ACRE in the cool–dry environment in Fig. 11 corresponds to radiative heating below a height of 450 hPa and relatively large and broad cooling above this height. The reason why the ACRE is smaller under these environmental conditions is that the UT clouds are lower in height (as shown above) and that the cooling above them is more pronounced. The larger cooling can

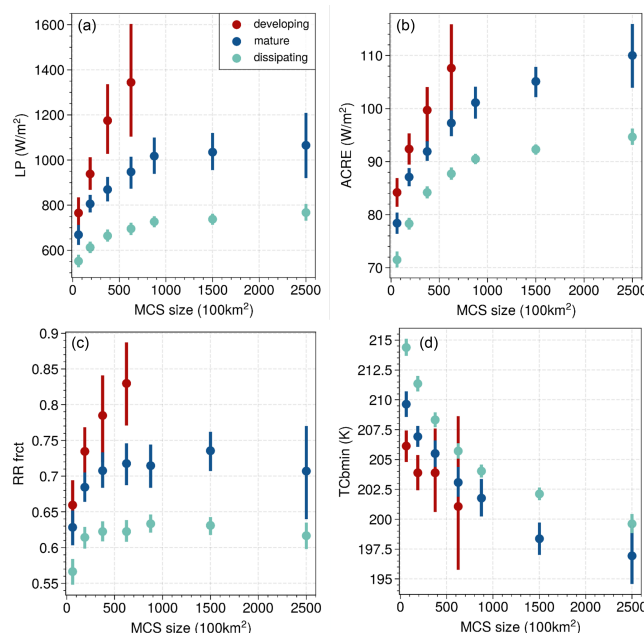


Figure 13. LP (a), ACRE (b), rainy area fraction (c), and minimum cloud top temperature within the convective core (d) as a function of the CS size, shown separately for developing, mature, and dissipating CSs (distinguished by convective core fractions of 0.6–0.9, 0.4–0.6, and 0.2–0.4, respectively). All size intervals except the first two include MCSs exclusively. Choosing the coldest part of the core avoids the inclusion of parts of the thicker anvil. This figure shows CSs over the ocean at 01:30 and 13:30 LT in 2004–2018 in the range of 25° N – 25° S .

be explained by the fact that lower clouds may be optically denser in addition to their warmer temperature; thus, they emit more LW radiation, and the atmosphere above cools more. The larger cooling also leads to a slightly larger vertical gradient in radiative heating. The smaller height may be interpreted as anvils of convective systems having descended at a later stage in their life cycle (Strandgren, 2018) or as relatively thick clouds with diffusive tops, for which the retrieved (radiative) height may be deeper within the cloud because of very low ice water content in the upper part of the cloud (e.g. Liao et al., 1995; Stubenrauch et al., 2010, 2017).

5.2 Diabatic heating of the MCS

Deep convection in the tropics leads to a large outflow of anvil clouds. The radiative heating of these UT clouds originating from convection enhances the latent heating associated with precipitation and thereby strengthens the circulation (Stephens et al., 2024). In the following, we explore the relationship between LH and Q_{rad} within the CSs and MCSs.

First, we study how LP and the ACRE change with the size of the MCS. It has been shown that the horizontal extent of the CS depends on the intensity and organization of convection, but it also changes during its life cycle (e.g. Machado

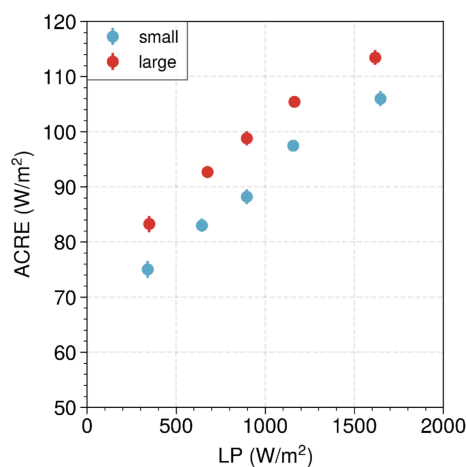


Figure 14. The relationship between the radiative enhancement ACRE and precipitation intensity LP-averaged per MCS, shown separately for small MCSs (below the 40th percentile) and large MCSs (above the 60th percentile) when considering MCSs larger than four grid cells ($1^\circ \times 1^\circ$). Only mature MCSs (convective core fraction of 0.4–0.6) are included. MCSs are over the ocean at 01:30 and 13:30 LT from 2004 to 2018 in the region of 25°N – 25°S .

et al., 1998; Takahashi and Luo, 2014; Protopapadaki et al., 2017). Therefore, we analyse the CS/MCS properties separately at different life stages: developing, mature, and dissipating, which are defined by convective core fractions of 0.6–0.9, 0.4–0.6, and 0.2–0.4, respectively. Figure 13 shows that both LP and the ACRE increase with MCS size, as expected from Fig. 9. The increase flattens for larger MCS sizes. Furthermore, for a similar size, LP and the ACRE decrease from the developing towards the dissipating stage, as expected (e.g. Bouniol et al., 2021; Takahashi et al., 2021; Elsaesser et al., 2022). These behaviours are in line with those of the fraction of precipitation area within the MCS and the minimum cloud top temperature within the convective core: the fraction of precipitating area increases similarly to LP with CS size, and the core top temperature decreases with CS size, which explains the increasing ACRE. On the other hand, the slightly decreasing anvil emissivity (not shown) should dampen the ACRE increase.

As deduced from Fig. 6, the reliability of the values of the LP average over the CS should increase with increasing CS size. This means that LP should be slightly more underestimated in the first size intervals than in the later ones. Nevertheless, the results of Fig. 13a seem, at least qualitatively, to agree with the expectations.

In order to isolate the effect of convective organization, we only select mature MCSs and compare the ACRE between smaller, less organized and larger, more organized MCSs at similar average rain intensities in Fig. 14 (using LP as a proxy). On average, the ACRE increases with LP, when averaged over mature MCSs for both small and large MCSs. Most importantly, we observe for each rain intensity interval

given by LP that the mean ACRE of larger, more organized MCSs is larger by about 10 W m^{-2} than the one for smaller MCSs. Considering Fig. 6, we expect LP to be underestimated by a certain factor, and this factor should be smaller for large MCSs than for small MCSs. Such an underestimation means a stretching of the LP axis, but this stretching should be slightly larger for the small MCSs than for the large MCSs, while their ACREs would not change. So, indeed, the result in Fig. 14 is robust, and the enhancement effect of convective organization may be even slightly underestimated.

The LP intervals shown in the legend of Fig. 15 correspond to the first, third, and fifth pairs of dots in Fig. 14. As expected (e.g. Houze, 2004), the shape differences in the averaged LH profiles of the mature MCSs between the larger, more organized MCSs and the smaller MCSs can be explained by a larger contribution of stratiform rain in organized MCSs, with a larger peak in the upper troposphere and a larger vertical gradient down towards the surface from the anvil heating and cooling below, except for the most precipitating ones that show a large amount of heating through the whole atmosphere. More detailed studies at a better spatial resolution are required to understand if the heating in the middle troposphere comes from more productive cores or from an anvil with precipitating systems underneath, as was already suggested by Masunaga and Takahashi (2024).

In general the core top temperature decreases slightly with increasing LP, slightly more for the larger MCSs (not shown), which is also reflected in the shapes of the radiative heating profiles of the mature MCSs in Fig. 15b. Figure 15b reveals that the vertical gradients increase with increasing LP for both small and large MCSs, with increasing cooling above and increasing heating within the MCSs. Furthermore, in each of the three chosen LP categories, the vertical gradient of the larger, more organized systems is larger compared to that of the smaller MCSs. This additional ACRE and larger vertical heating gradient then may further support stronger and more sustained convective intensity by enhancing updraughts, maintaining the system, and modifying the larger-scale environment.

6 Conclusions and outlook

In this article we explored the relationship between latent and radiative heating in the tropics. The diabatic heating rate profiles have been obtained from active instruments, which have sparse sampling. In order to expand these heating rates in space and time, we used techniques based on artificial neural networks (ANNs). While the radiative heating and a precipitation classification were already expanded earlier (CIRS-ML dataset; Stubenrauch et al., 2021, 2023) using ANNs trained separately for different CIRS cloud scenes with CloudSat–CALIPSO FLXHR and CloudSat PRECIP-COLUMN data, we presented here the extension of the latent heating rates. After assessing the consistency of the extended

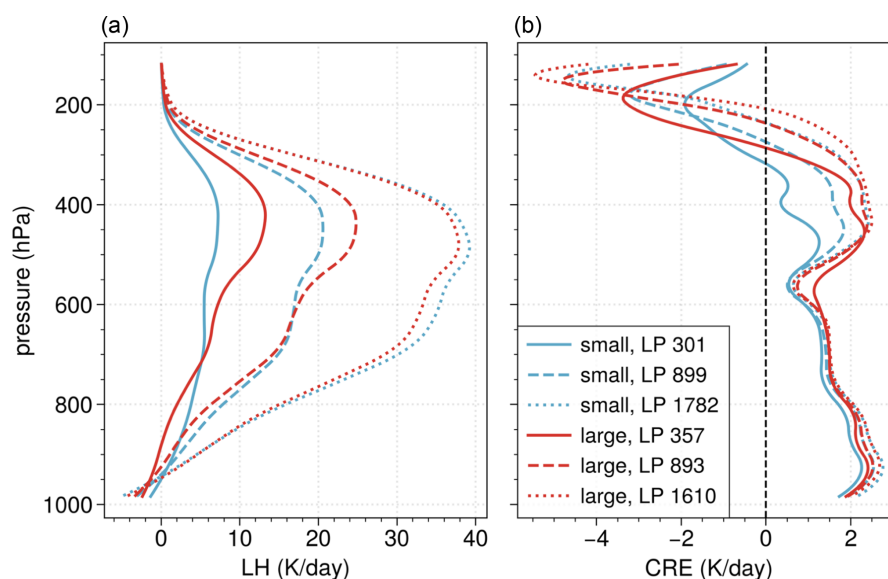


Figure 15. Profiles of latent heating (a) and of cloud radiative effect (b) averaged per mature MCS (core fraction of 0.4–0.6), shown separately for the three LP intervals used in Fig. 14 (lowest, middle, and highest), with mean values of approximately 320, 900, and 1700 W m⁻² (LP in the legend is in W m⁻²). Data are also shown separately for small MCSs (below the 40th percentile) and large MCSs (above the 60th percentile), considering MCSs larger than four grid cells (1° × 1°). MCSs are over the ocean at 01:30 and 13:30 LT from 2004 to 2018 in the region of 25° N–25° S.

LH and Q_{rad} fields, we examined the relationship between latent and radiative heating for different atmospheric environments and within MCSs.

For the expansion of the TRMM-SLH latent heating rates (Shige et al., 2009), we used similar ANN regression methods and inputs as were used for the radiative heating expansion. However, the ANNs were separately trained for different CIRS-ML precipitation scenes with gridded data at a spatial resolution of 0.5°. While for the radiative heating rates the predicted averages as well as their variability match those of the CloudSat–CALIPSO FLXHR target data well, the predicted LH profile means agree very well with the TRMM-SLH target data. However, the range of the predicted values is much narrower than the one of the target data, likely due to insufficient input information and its coarse spatial scale. We were further able to demonstrate that some of the noise in the prediction comes from discrepancies in the rain fraction between TRMM and CIRS-ML (originally CloudSat), with different instrument sensitivities and spatial sampling. When comparing vertically integrated LH (LP), this noise may lead to an overestimation of LP for small TRMM-SLH values and an underestimation of LP for large TRMM-SLH values.

We reconstructed the 3D latent heating fields at four observation times: at 01:30 and 13:30 LT (AIRS) over the period of 2004–2018 and at 09:30 and 21:30 LT (IASI) over the period of 2008–2018.

The zonal averages of LP at 01:30 and 13:30 LT align well with those from the full diurnal sampling of TRMM-SLH over the ocean. However, over land, the daily mean LP is

underestimated because the strong convection in the late afternoon is not captured at these observation times. The observation times of IASI (09:30 and 21:30 LT) underestimate the daily mean LP over both ocean and land. Therefore, we have performed all relationship analyses of the diabatic heating fields using CIRS-ML–AIRS over the ocean. The slopes between the monthly averages of TRMM-SLH LP and CIRS-ML LP over the ocean increase from 0.54 to 0.82 for scales between 1 and 10°, with slopes of 0.68 and 0.76 for 2.5 and 5°, respectively. Although the complete collocated TRMM-CIRS datasets have less than 5 % of the data points of the expanded dataset, which may lead to inhomogeneous sampling, the comparison of the zonal LP averages between TRMM-SLH and CIRS-ML shows a slight underestimation in bands of strong precipitation, like the ITCZ, and a very slight overestimation in bands including deserts.

Geographical maps show a close association between LP and the vertically integrated atmospheric cloud radiative effect (ACRE) and reflect the characteristics of ENSO events well. Furthermore, the horizontal structure of LP closely matches the one from the precipitation obtained from TRMM and GPCP, although the range of the CIRS-ML LP values is underestimated. Nevertheless, when taking these systematic biases into account, this dataset can be used to study the horizontal structure of LP at four specific observation times. This is not possible with TRMM monthly averages at a specific time because they do not fill the tropical band at all.

The main purpose of this article was to study the relationship between latent and radiative heating for UT clouds,

first under different atmospheric environments characterized by sea surface temperature (SST) and column water vapour (CWV) and then within MCSs. For similar rain intensities as given by LP, the ACRE is generally largest in warm–humid conditions and smallest in cool–dry conditions, which is essentially linked to higher and lower cloud heights, respectively. For UT clouds releasing a large amount of latent heat, SST has a larger impact on the ACRE in dry environments than in humid ones. On the other hand, humidity plays a larger role in cool environments.

The distribution of UT clouds in the LP–ACRE plane shows a large spread in the ACRE for the small value of LP, which is gradually reduced towards larger amounts of LP. Compared to the association of convective regimes with the LP–ACRE plane by Masunaga and Takahashi (2024), the UT clouds in the more or less warm–humid conditions correspond mostly to mid-heavy convective regimes. The cool–dry environments are linked, on the one hand, to the bottom-heavy convection regimes with small LP values and a widely spread ACRE, and, on the other hand, for larger LP values and a smaller ACRE, to the top-heavy convective regimes. The smaller ACRE can be explained by slightly larger cooling above the clouds and the smaller (radiative) height of these clouds.

Comparing MCSs of similar size, both mean LP and the ACRE decrease from the developing stage towards the dissipating stage of the MCSs. Furthermore, both mean LP and the ACRE slightly increase with MCS size. In order to study the effect of convective organization, we selected MCSs in the mature state and compared the relationship between the ACRE and LP separately for small and large MCSs; we found an ACRE enhanced by about 10 W m^{-2} for larger, more organized MCSs than for smaller, less organized MCSs at similar average rain intensities. Convective organization also increases the vertical gradient of the mean radiative heating of these systems at similar rain intensity (LP). This enhanced ACRE and the larger vertical heating gradient may then further support stronger and more sustained convective intensity by enhancing updraughts, maintaining the MCS, and modifying the larger-scale environment. As expected, the shapes of the LH profiles of mature MCSs show that larger, more organized MCSs have a larger contribution of stratiform rain than the smaller MCSs do.

Future studies should also consider the environment around the MCSs and in particular the time dimension. The latter can be achieved by combining the CIRS-ML heating rates with deep-convective cloud systems; using a better spatial and temporal resolution (Fioleau and Roca, 2013; Takahashi et al., 2021); and providing additional parameters such as their life stage, lifetime, and maximum size during their lifetime. The distribution of the UT clouds and their associated environment in the LP–ACRE plane can also be used to evaluate climate simulations, at least qualitatively.

The ML method for the expansion of TRMM LH rates may be further improved by undertaking an ANN training

using collocations at the scale of the AIRS/IASI footprint and integrating a substructure of measurements at an even smaller scale, such as that from the Moderate Resolution Imaging Spectroradiometer (MODIS) together with an auto encoder method, as was done in Shamekh et al. (2023).

Data availability. The TRMM latent heating rates used in this study are from the Tropical Rainfall Measuring Mission (TRMM) dataset: GPM PR on TRMM Spectral Latent Heating Profiles L3 1 Day $0.5^\circ \times 0.5^\circ$, V06, provided by the Goddard Earth Sciences Data and Information Services Center (GES DISC) at <https://doi.org/10.5067/GPM/PR/TRMM/SLH/3A-DAY/06> (TRMM, 2021) and from Shige et al. (2009). The CIRS-ML radiative heating rates, vertical cloud structure, and rain rate classification data are distributed by the French Data Center AERIS (Data and Services for the Atmosphere) via the website for the Process Evaluation Study of Upper tropospheric Clouds and Convection of the Global Energy and Water Exchanges Program (GEWEX UTCC PROES) at <https://gewex-utcc-proes.aeris-data.fr/> (CIRS-ML; Stubenrauch et al., 2021; last access: 25 June 2025). The target data for the ANN-derived rain rate classification are the CloudSat 2C-PRECIP-COLUMN data, provided by the Cooperative Institute for Research in the Atmosphere (CIRA) at Colorado State University at <https://www.cloudsat.cira.colostate.edu/data-products/2c-precip-column> (CloudSat 2C-PRECIP-COLUMN; Haynes et al., 2009). The TRMM (TMPA) Precipitation L3 1 Day $0.25^\circ \times 0.25^\circ$ V7 dataset, used for the comparison of LH horizontal structure with ML-expanded LH, is provided by NASA's Goddard Earth Sciences Data and Information Services Center (GES DISC) at <https://doi.org/10.5067/TRMM/TMPA/DAY/7> (Huffman et al., 2016). The Global Precipitation Climatology Project (GPCP) Monthly Precipitation Climate Data Record (CDR) is provided by the NOAA's National Centers for Environmental Information (<https://doi.org/10.7289/V56971M6>; Adler et al., 2016).

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Author contributions. XC developed and evaluated the ANN models for the expansion of LH, performed the analysis of the expanded LH and Q_{rad} data, wrote the main sections of the paper, and produced the figures. CJS conducted the cloud-system-related analysis, wrote Sect. 5.2, generated the corresponding figures, and made substantial contributions to optimizing and revising the paper. GM analysed the zonal averages of vertically integrated diabatic heating, produced Fig. 5 in Sect. 3, and contributed to the overall improvements of the paper.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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