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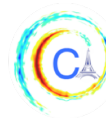
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PREDICTING 3D RADIATIVE HEATING RATE FIELDS FROM SYNERGISTIC A-TRAIN OBSERVATIONS COMBINED WITH DEEP LEARNING TECHNIQUES

Friederike Hemmer¹, Claudia J. Stubenrauch¹, Sofia E. Protopapadaki²

Abstract—Upper tropospheric clouds strongly influence the energy budget of the Earth, but the structure of their vertical heating rate profiles is still poorly known. This is due to the fact that global observations of these heating rates are sparse. The active lidar and radar measurements from CALIPSO and CloudSat as part of the A-Train satellite constellation provide such heating rate profiles, but only on narrow nadir tracks separated by about 2500 km between successive orbits. The Atmospheric Infrared Sounder (AIRS) on the other hand provides cloud properties with a large instantaneous horizontal coverage, but not their vertical structure. In this study, we train deep learning neural networks with four years of collocated data, including meteorological reanalyses, to develop optimized non-linear regression models which predict these heating rates as a function of the most suitable cloud and atmospheric properties. These models are then applied to the full statistics of more than 15 years of AIRS observations in order to construct complete 3D radiative heating rate fields which can be related to the different parts of tropical convective systems for process and climate studies.

I. MOTIVATION

Clouds play an important role in the global climate system by altering the net surface radiation and influencing the diabatic heat budget of the atmosphere through radiative heating/cooling as well as latent heat release (e.g. [1], [2]). In particular, Upper Tropospheric (UT) clouds, which are most frequently observed in the tropics and represent about 40% of the Earth's total cloud cover [3], often form as cirrus anvils from convective outflow, building mesoscale systems. In a warming climate, tropical convection will intensify,

leading to colder convective systems which may include a larger fraction of thin cirrus within and around the anvils. The radiative heating of these thinner cirrus may be critical to cloud climate feedback. However, the horizontal and vertical structure of the radiative heating rates is still poorly known which is partly due to a lack of observation. This study aims to fill some of these gaps by constructing complete 3D radiative heating rate fields obtained from combining several satellite observations and meteorological reanalyses with deep learning which is an extremely active research area [4] with a constantly increasing number of applications in climate science.

The satellite observations used here originate from the A-Train constellation [5] composed of several satellites equipped with different instruments in a sun-synchronous polar orbit with local overpass times around 1:30 AM and 1:30 PM. We will focus on AIRS aboard the Aqua satellite as well as the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) aboard CALIPSO and the Cloud Profiling Radar (CPR) aboard CloudSat. The good spectral resolution of AIRS leads to reliable cloud properties, even for thin cirrus. As a passive cross-tracking instrument it provides a large horizontal coverage but does not give information on the vertical structure of the clouds. The latter can be obtained from the active CloudSat radar and CALIPSO lidar measurements which are performed only on a narrow nadir path, so the coincidence with the passive measurements is limited to narrow nadir tracks separated by about 2500 km (see upper panel of Fig. 1 for illustration). To fill the gaps between the orbits and expand the vertical information over complete cloudy scenes, we use supervised deep learning based on artificial neural networks (ANN) to relate the cloud properties retrieved from AIRS, together with coincident atmospheric and surface properties from the meteorological reanalyses

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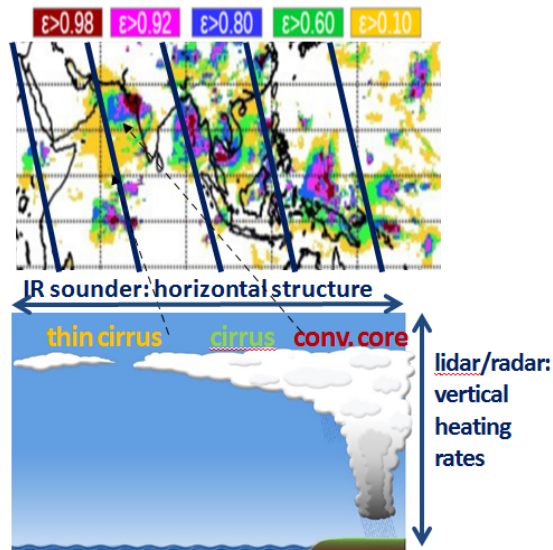


Fig. 1. Upper panel: emissivity distribution of UT cloud systems from AIRS, overlaid with the nadir tracks of the CALIPSO lidar/CloudSat radar. Lower panel: illustration of the cloud system approach.

ERA-Interim [6], to the vertical radiative heating rate profiles obtained from CloudSat/CALIPSO.

II. METHOD

A. Cloud System Concept

As mentioned above, we are particularly interested in UT clouds which occur most frequently in the tropics. Thus, we will focus on the tropical latitude band (30°N to 30°S) in this paper. UT clouds often form as cirrus anvils from convective outflow and build mesoscale systems. To study their properties in dependence of the convective strength, a cloud system concept has been developed which is based on two independent variables retrieved from AIRS measurements: emissivity and height [7]. As a first step, cloud systems are built from adjacent elements of similar cloud height represented by a cloud pressure $p_{\text{cloud}} < 440$ hPa. Secondly, the horizontal emissivity structure allows to distinguish between convective cores (Cb defined by an emissivity $\epsilon > 0.98$), thick cirrus ($0.5 < \epsilon < 0.98$) and thin cirrus anvil ($\epsilon < 0.5$). The lower panel of Fig. 1 illustrates such a cloud system with its three different cloud types where the convective core only represents a small portion of the system. The upper panel presents an example of the horizontal emissivity structure of these cloud systems.

B. Data

The Aqua satellite carrying the AIRS instrument has been launched in 2003, hence a 15-year time

series of cloud properties is available (2003-2018)[3]. The retrieved cloud properties are cloud emissivity, pressure, temperature and height, together with their uncertainties, derived from eight radiances along the wings of the CO₂ absorption band around $15\ \mu\text{m}$. The retrieval is based on a weighted χ^2 -method [8]. To relate adjacent pixels within $2^\circ \times 2^\circ$ grid boxes, 16 weather states have been determined based on a k-means method applied to histograms of cloud emissivity and pressure as described by [9]. ERA-Interim meteorological reanalyses [6] are used to obtain surface and atmospheric properties, including temperature and water vapor profiles from which the relative humidity (RH) for ten atmospheric layers is calculated in a similar way as in [10]. All variables are summarized in Table I.

The shortwave (SW) and longwave (LW) radiative heating rate profiles retrieved from the active instruments originate from the CloudSat 2B-FLXHR-LIDAR product which is provided by the National Aeronautics and Space Administration (NASA) and has been described by [11] and [12]. CloudSat and CALIPSO have been launched in 2006. The collocated AIRS-CloudSat-CALIPSO-ERA-Interim dataset used in this study comprises four years of data from 2007 to 2010.

C. Algorithm and Experiments

To extend the vertical heating rate structure throughout entire cloud systems, we develop optimized non-linear regression models by using supervised deep learning. The models are trained and tested along the nadir tracks of the active instruments using the four years of collocated AIRS-CloudSat-CALIPSO-ERA-Interim data. We apply the TensorFlow framework and the Keras program library for python. Our ANN consists of three fully connected layers with relu activation. The training data set is randomly separated in three portions as follows: 80% are used for training, 10% for validation and 10% for testing, stratified by cloud type and by a day/night flag. We use the mean absolute error (MAE) between the prediction and the true value along the track as loss function. The training is performed by the Adam optimizer.

Two different kinds of sensitivity studies are conducted. On one hand, the effect of varying input variables is tested. On the other hand, we investigate how many models have to be developed to optimally extend the radiative heating rate profiles. This second set of sensitivity studies is performed to examine if it is advantageous to separate the training for land and ocean as well as for different cloud types, since the

TABLE I
 LIST OF VARIABLES.

Clouds	
CIRS-AIRS cloud properties	$\epsilon_{\text{cloud}}, p_{\text{cloud}}, T_{\text{cloud}}$
Cloud retrieval uncertainties	$d\epsilon_{\text{cloud}}, dp_{\text{cloud}}, dT_{\text{cloud}}, \chi_{\text{min}}^2$
Cloud spectral emissivity diff.	$(\epsilon_{\text{cloud}}(12 \mu\text{m}) - \epsilon_{\text{cloud}}(9 \mu\text{m}))$
CIRS weather state at $2^\circ \times 2^\circ$	WS (1-16), kernel distance
Atmosphere	
Brightness temperatures	$T_{b11.85}, \sigma(T_{b11.85}), T_{b7.18}$
ERA-Interim atmos. properties	total precip. water, $p_{\text{tropopause}}$
Atmospheric classification	TIGR atmosphere [13]
Relative humidity profile	RH profile over 10 layers
Temperature profile	T profile over 10 layers
Surface	
ERA-Interim surface properties	$T_{\text{surf}}, p_{\text{surf}}, \text{nb of atm. layers}$

cloud properties vary strongly between the cloud types and over land/ocean.

III. RESULTS

To analyse the influence of the different input variables, ANN models have been developed without cloud type separation including data of all cloud types over ocean. Table II presents the MAE of the predicted cloud LW heating rates, depending on the set of input parameters. As a first step, the basic cloud properties (emissivity, spectral emissivity difference, pressure and temperature, together with their according uncertainties and the minimum from the χ^2 -method as quality index), atmospheric properties (total precipitable water, tropopause pressure, classification of the atmospheric profile from TIGR [13] and brightness temperatures at $11.85 \mu\text{m}$ and $7.18 \mu\text{m}$ as well as the brightness temperature variance at $11.85 \mu\text{m}$ over 3×3 AIRS footprints) and surface properties (surface pressure, temperature and the number of layers of the profile) have been used. For this basic experiment, a MAE of 0.84 is obtained. Adding firstly the weather states, secondly the RH profile and finally the temperature profile, leads to slight improvements. However, using all available parameters the maximum improvement is only about 6% compared to the basic experiment.

As a next step, we investigated if the training should be performed separately over land and ocean and for different cloud types. Figure 2 shows the predicted LW heating rate profiles for Cb, cirrus and thin cirrus over ocean compared to the observations (black line). The dark blue line represents the prediction from the model that has been trained with only high clouds only over ocean, the light blue line represents the prediction from the model trained with all clouds only over ocean and the red line represents the prediction

 TABLE II
 MEAN ABSOLUTE ERROR OF THE DIFFERENT EXPERIMENTS.

Basic	+ weather states	+ RH profile	+ T profile
0.84	0.84	0.80	0.79

from the model trained with all clouds over ocean and land together. The predicted profiles are very similar for all cases and agree well with the observations from CALIPSO-CloudSat. The cloud type Cb may be represented slightly better when applying the model developed for only high clouds because the frequency of Cb is small compared to the other cloud types (only 5% of all clouds). Figure 2 also illustrates the strong cooling above Cb (200 hPa) and a slight heating of thin cirrus (100 hPa) in the upper troposphere.

Finally, the models developed for all clouds over ocean and land together as well as over ocean and land separately have been applied to one month of data, January 2008, corresponding to a La Niña situation. During La Niña, the tropical convection is shifted towards the West Pacific as illustrated by the observed emissivity structure of the UT cloud systems for this month presented in Fig. 3. Figure 4 shows the corresponding LW radiative heating rates at the four pressure levels of 106, 200, 525 and 850 hPa from the predictions with the two different models compared to the nadir track statistics from the CALIPSO/CloudSat observations. The horizontal structure of both predictions agrees quite well with the one from CALIPSO/CloudSat. However, the structure of the laterally extended fields appears much clearer. Compared to Fig. 3, the warming in the upper troposphere (106 hPa) corresponds to thin cirrus while the cooling at 200 hPa is found above optically thick cirrus which heat the middle troposphere (525 hPa) at the same time. In the lowest layer (850 hPa), a cooling above low clouds and a heating by thick high clouds can be observed. The LW radiative heating rate fields

ϵ structure of UT cloud systems

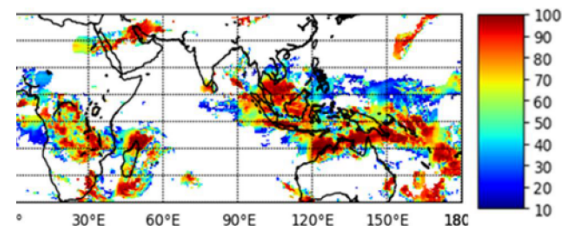


Fig. 3. Emissivity structure of UT cloud systems from AIRS for January 2008 (La Niña).

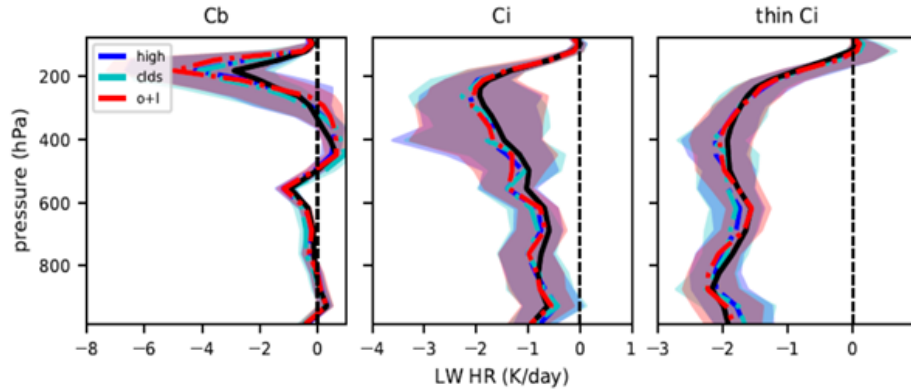


Fig. 2. Observed (black line) and predicted (dark blue line: model trained with only high clouds over ocean, light blue line: model trained with all cloud types over ocean, red line: model trained with all cloud types over ocean and land together) LW radiative heating rate profiles for Cb, cirrus and thin cirrus (from left to right).

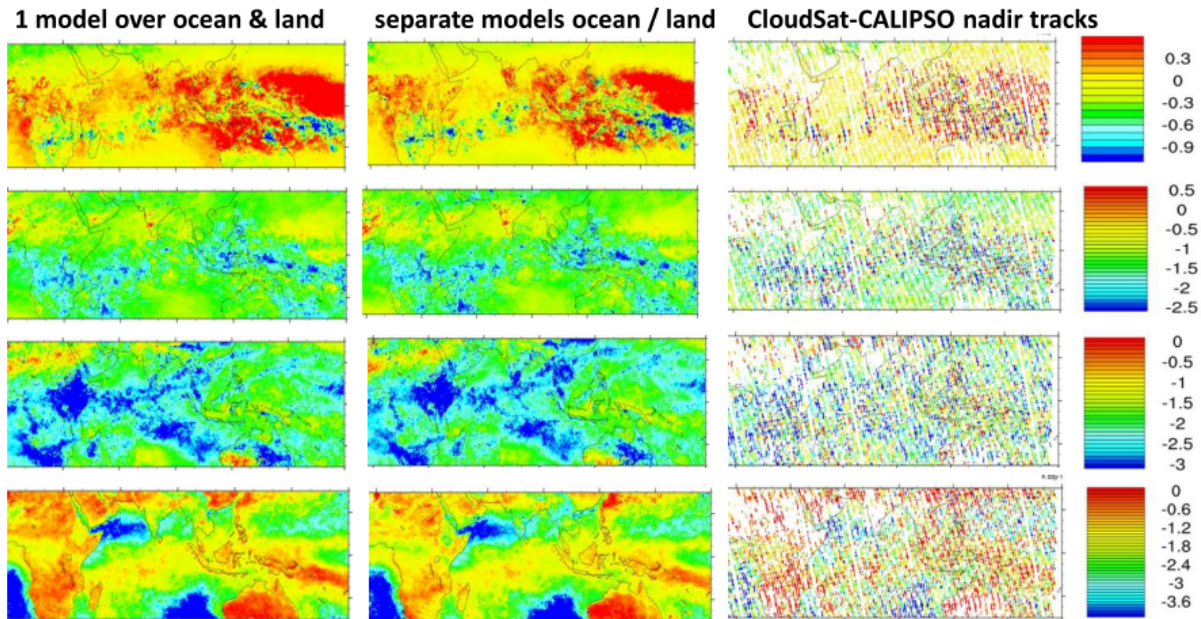


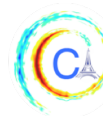
Fig. 4. Tropical map (30°N to 30°S) of the LW radiative heating rates at pressure levels of 106 hPa (first row), 200 hPa (second row), 525 hPa (third row) and 850 hPa (fourth row) for January 2008 (La Niña) at local time 1:30 PM. The first column shows the predictions of the model trained with all clouds over ocean and land together, the second column the predictions of the models trained with all clouds over ocean and land separately and the third column the monthly statistics obtained from the observations.

predicted by the two different models are very similar although slight differences occur, especially concerning the intensity of the heating. These differences are currently under investigation.

IV. CONCLUSIONS AND PERSPECTIVES

We have shown for the first time that deep learning permits to relate the appropriate cloud and atmospheric properties from AIRS and ERA-Interim to the LW (and SW) radiative heating rate profiles, which are only given along the CALIPSO/CloudSat nadir

tracks, to laterally extend these heating rates. To improve our ANN models, the most suitable variable configuration has been investigated by conducting sensitivity studies on the parameters that govern the heating rates. The complete 3D radiative heating rate fields obtained for the AIRS 15-year time series together with the cloud system approach will allow detailed process and climate feedback studies. It is planned to use these fields to force a global climate model which will permit to investigate their influence on global circulation patterns.



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