On the possibility of retrieving near-surface rain rate from the microwave sounder SAPHIR of the Megha-Tropiques mission

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In this study, *ab initio* atmospheric profiles generated through high-resolution calculations from the community weather model WRF, suitably matched up with both TRMM Microwave Imager (TMI) and Precipitation Radar (PR) instruments of the TRMM satellite were used to compute simulated brightness temperatures (BTs) corresponding to SAPHIR frequencies, through an in-house polarized radiative transfer code. An artificial neural network was then constructed and trained to return the near-surface rain (NSR) rate given the six BTs corresponding to SAPHIR. For accomplishing the retrievals, measured BTs of SAPHIR (level 1 data) were used. NSR rates were calculated for two precipitating systems, namely (i) cyclone *Neelam* and (ii) cyclone *Phailin*. Rain rates thus estimated were then validated with the TMI–PR combined rain product of TRMM (2A12). The results showed that there is good agreement between the two. An inter-comparison between rain rates derived from MADRAS and SAPHIR was also done. This unexpected ability of the SAPHIR radiances provide us with the rainfall signature opens up new vistas in achieving the mission objectives of Megha-Tropiques.

Keywords: Brightness temperatures, Megha-Tropiques, *Neelam*, *Phailin*, SAPHIR.

MODERN satellite remote sensing techniques are capable of providing a substantial amount of information about the atmosphere vertical structure and surface properties. The hallmark in satellite meteorology is the ability to estimate geophysical parameters over the open ocean, which is invariably impossible with conventional techniques. During the last few decades, availability of high temporal and spatial resolution satellite data together with the associated physics-based models has helped improve our understanding of weather systems and climate variability of the Earth system. In general, retrieval techniques are inverse problems, wherein satellite measured brightness temperatures (BTs) are inverted to estimate geophysical parameters. Such retrievals are always ill-posed as one invariably wants to estimate a large number of parameters from limited satellite radiance measurements. For the development of a physics-based retrieval scheme, a radiative transfer model that is capable of simulating BTs for an emitting, absorbing and scattering atmosphere is inevitable. A microwave retrieval algorithm can be either emission or scattering type. The former is usually developed for low frequency, whereas the latter is used for high frequency channels. To combine the effect of scattering (due to ice) and emission (due to rain drops), a new class of profiling algorithms was developed[1–3]. These algorithms minimize the error between the simulated and measured quantities, typically satellite radiances or BTs by an iterative procedure, making the whole process computationally expensive. This spurred the development of fast retrieval techniques. Kummerow *et al.*[4] developed a simple profiling algorithm based on Bayesian approach for inverting BT to hydrometeor profiles and thereby avoided explicit radiative transfer calculations. Gerard and Eymard[5] retrieved the liquid water path (LWP) and the total precipitable water (TPW) by creating a database of profiles and their respective BTs. A multivariate regression was used to correlate LWP and TPW with the upwelling radiances. Owing to the high dimensionality and computational cost associated with the retrieval problem, artificial neural networks (ANNs) could be used as a surrogate for inversion. A substantial amount of literature on the use of ANNs for retrieval problems is available. One such is the work of Hsu *et al.*[6] who reported the use of ANN for rainfall estimation from remotely sensed data. Their approach was based on modified counter propagation neural networks (MCPNs). Studies on short-term precipitation using ANN were done by Kuligowski and Barros[7]. Facilitating the retrieval of vertical temperature and dew point profiles in a cloudy atmosphere, Kuligowski and Barros[8] used both IR and microwave radiometers with ANN. Kumar *et al.*[9] demonstrated the use of multi-layer feed-forward ANN for rainfall retrieval from TRMM Microwave Imager (TMI) radiometric observations over different land and oceanic regions. Ramanujam and Balaji[10] developed an algorithm for the retrieval of the vertical structure of cloud and rainfall from Microwave Analysis and Detection of Rain and Atmospheric Systems (MADRAS) imager. They used hydrometeor profiles from the WRF–ARW community model collocated with the TRMM–TMI and Precipitation Radar (PR) pixels to develop an a priori database. This was followed by the development of a Bayesian approach for the retrievals. In the present study, an attempt has been made to use ANN directly for the retrieval of rain rates from radiances of the microwave sounder Sondeur Atmosphrique du Profil d'Humidit Intertropicale par Radiomtrie (SAPHIR). It needs to be emphasized that SAPHIR is designed primarily to obtain humidity profiles in the atmosphere. If SAPHIR can pick up the rain signature with reasonable accuracies, it will benefit the Megha-Tropiques mission in which the primary rain-measuring microwave imager MADRAS has been facing difficulties, due to which MADRAS data are currently not available.

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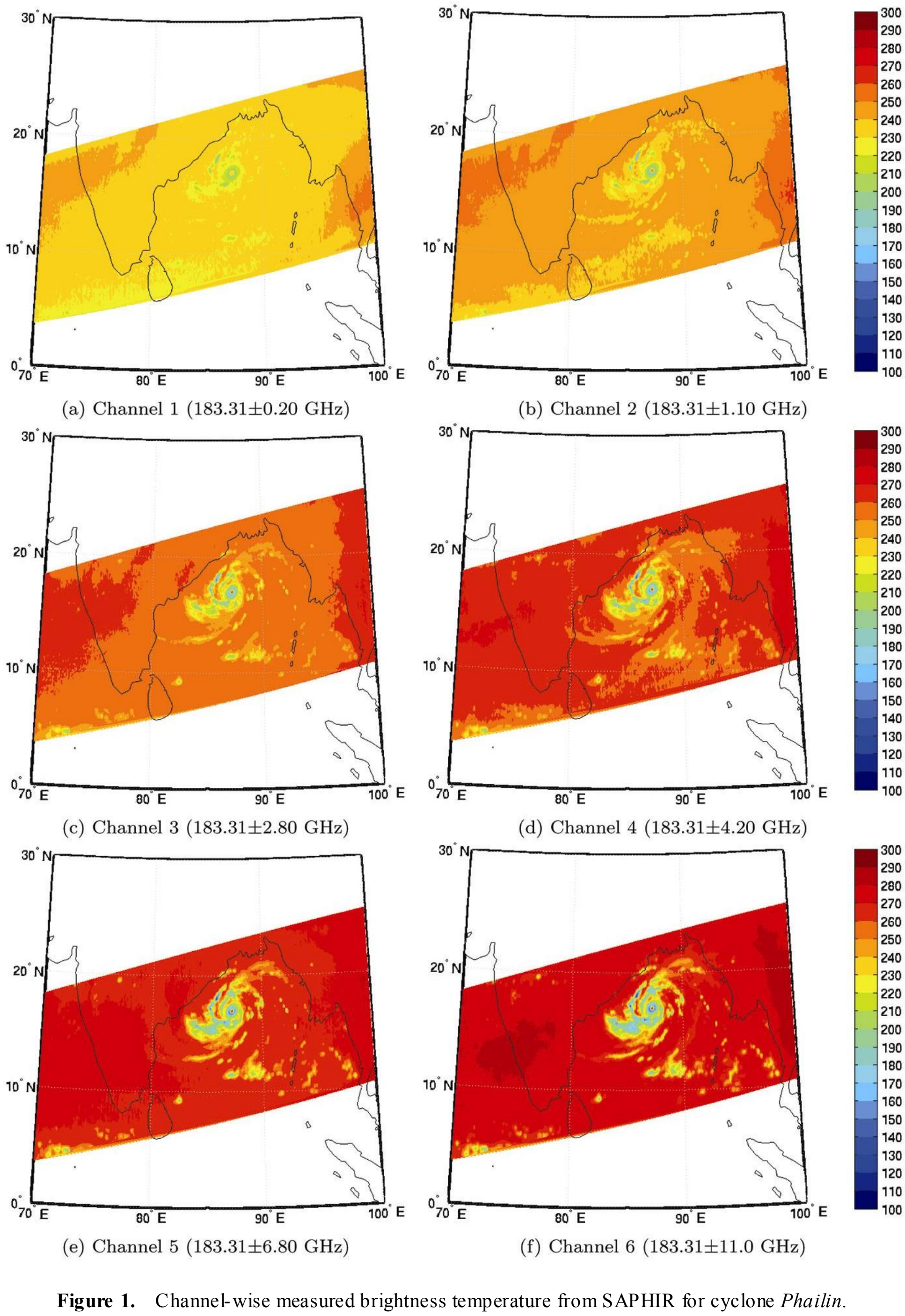

Figure 1. Channel-wise measured brightness temperature from SAPHIR for cyclone *Phailin*.

Megha-Tropiques is an Indo-French joint satellite mission launched on 12 October 2011. The main objectives of this mission are to study the effect of water cycle on tropical weather and their influence on the energy as well as moisture budget. In line with its mission, it carries three payloads, viz. MADRAS, SAPHIR and SCARAB (Scanner for Radiation Budget). MADRAS is a conical scanning microwave imaging instrument which scans the atmosphere at five different frequencies. The presence of low and high frequency channels facilitates sensitivity to a wide range of precipitation phenomena. SCARAB is an optical scanning instrument which measures radiative fluxes at the top of atmosphere (TOA). It consists of four independent telescopes which measure the reflected solar and emitted thermal radiation from the Earth's atmosphere. SAPHIR is a multi-channel humidity sounder with cross-track scanning with an incident angle up to 50°. It has a resolution of 10 km at nadir. The SAPHIR instrument has six channels centred around 183.31 GHz, which is a water vapour absorption line. Details of these six channels are given in Table 1. The range of the radiometer present in SAPHIR varies from 4 to 313 K. In every scan line, it collects a fixed number of 182 samples. (For a full discussion on instruments aboard the Megha-Tropiques, refer to Srinivasan and Narayanan[11].)

A forward model is needed to calculate the radiant energy emerging from TOA, which has a direct functional dependence on the geophysical and hydrometeor profile. The conspicuous presence of ice particles demands a polarized model for radiative transfer through clouds. The first step in radiative transfer simulations is to generate interaction parameters for the atmosphere as well as for the ocean surface. In this study, a modified gamma distribution is used for the drop size of suspended particles. Following Evans and Stephens[12], the radiative transfer equation is solved using the

$$\mu \frac{\mathrm{d}I}{\mathrm{d}\tau} = -I(\tau, \mu, \phi) + \frac{\varpi}{4\pi} \int_0^{2\pi} \int_{-1}^{1} P(\mu, \phi, \bar{\mu}, \bar{\phi})\, \mathrm{d}\bar{\mu}\, \mathrm{d}\bar{\phi} + (1-\varpi) B(T) \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad (1)$$

where μ, ϕ are angles in the spherical coordinate system, ϖ denotes the single scattering albedo and τ denotes the optical depth. Radiant intensity I is denoted by the Stokes vector (I, Q, U, V). B is the Planck's distribution function for a black body. Equation (1) implies that radiant intensity I emanating from TOA results from emission, absorption and scattering due to the hydrometeors present in the atmosphere. The Lorentz–Mie theory is used for single scattering computations. The radiative transfer equation is solved using adding and doubling method. Deiveegan *et al.*[13] elaborate the generation of interaction parameters and the solution of polarized radiative transfer through the atmosphere.

The satellite-measured radiances from SAPHIR are available in the form of segmented level-1 data from ICARE Data and Services Center, France (http://www.icare.univlille1.fr). The channel-wise BT values have been obtained from the level-1 data for the SAPHIR overpass over the Bay of Bengal (BOB) region for the cyclonic storms *Neelam* and *Phailin*.

Cyclone *Neelam*, formed as depression on 28 October 2012. Later, it strengthened as a cyclonic storm with a maximum sustainable wind speed of 70–80 knots. It made landfall near Chennai between 16 : 00 and 17 : 00 IST on 31 October 2012. The maximum rainfall recorded during this cyclone was 7 cm. *Phailin*, a recent cyclone, had its cyclogenesis on 9 October 2013. This was recorded as a category 5 cyclone with a maximum wind speed of about 140 knots. *Phailin* made its landfall near Gopalpur in Odisha between 20 : 30 and 21 : 30 IST on 12 October 2013.

A cyclonic system is an excellent test bed to critically evaluate the performance of a retrieval algorithm as several types of clouds and rain structures are present in the system. Figure 1 shows channel-wise BT measurement for one such overpass for the cyclone *Phailin*. From Figure 1, it can be seen that the SAPHIR BTs reproduce the general features of the cyclone well, with channels 5 and 6 showing remarkable resolution. Figure 1 indicates that retrieval of near surface rain (NSR) rate is eminently possible from the SAPHIR BTs.

Table 1. SAPHIR frequencies and polarization

Channel	Central frequency (frequency used for simulation[14])	Polarization
S1	183.31 ± 0.20 GHz (183.11 GHz)	*H*
S2	183.31 ± 1.10 GHz (182.11 GHz)	*H*
S3	183.31 ± 2.80 GHz (180.51 GHz)	*H*
S4	183.31 ± 4.20 GHz (179.11 GHz)	*H*
S5	183.31 ± 6.80 GHz (176.51 GHz)	*H*
S6	183.31 ± 11.0 GHz (172.31 GHz)	*H*

Table 2. Specifications of the WRF–ARW numerical weather prediction model used in the present study

Equation type	Non-hydrostatic
Time integration scheme	Third-order RK3
Integration time-step	15 s
Grid type	Arakawa-C grid
Projection type	Mercator

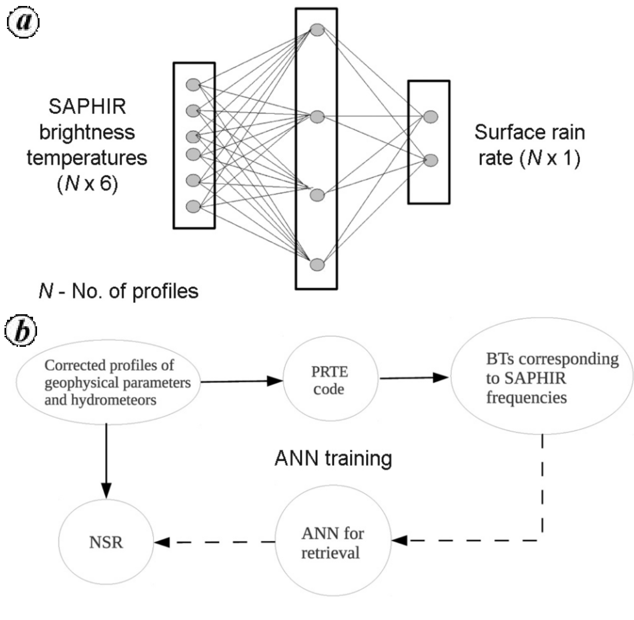

Figure 2. ***a***, Architecture of the neural network employed in the present study. ***b***, Flow chart detailing the retrieval methodology.

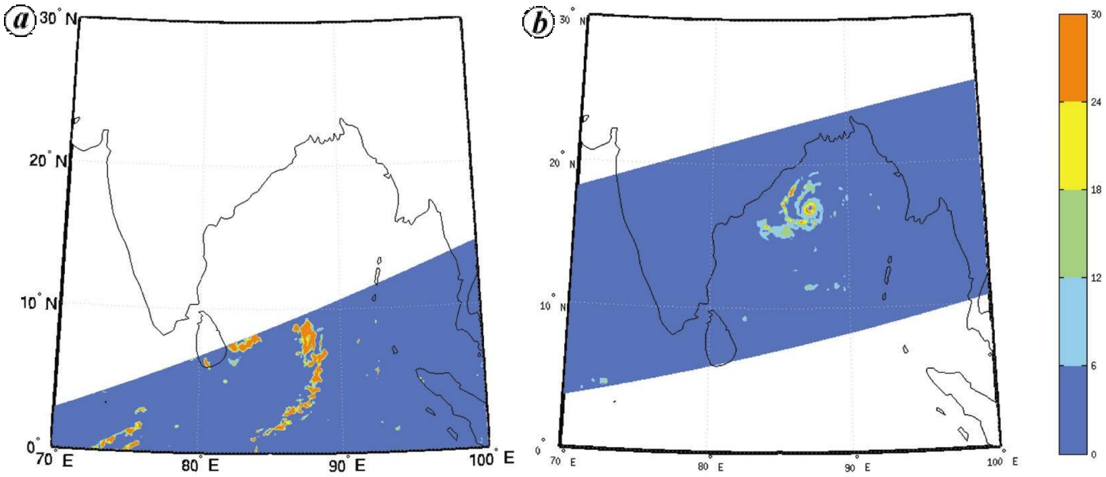

Figure 3. Near-surface rain rate contours retrieved from SAPHIR during cyclones: *Neelam* (***a***) and *Phailin* (***b***).

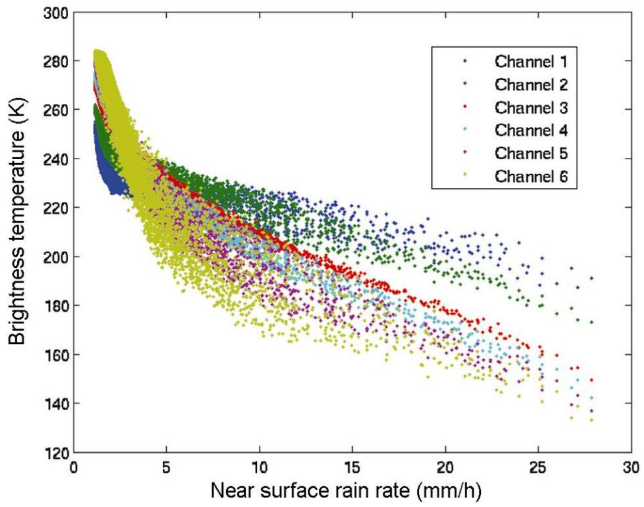

Figure 4. Variation of SAPHIR brightness temperature with the retrieved rain rate.

Table 3. Results of the neuron independence study

Number of neurons	R^2 for one hidden layer	R^2 for two hidden layers
5	0.835	0.887
10	0.929	0.922
15	0.921	0.921
20	0.854	0.866
25	0.906	0.919
30	0.835	0.961
35	0.887	0.884

In the present study an ANN-based retrieval scheme has been attempted, as the number of outputs is only 1 (NSR) with 6 inputs corresponding to SAPHIR BTs, at frequencies corresponding to those indicated in Table 1. It is well established that an ANN performs exceedingly well when the architecture represents a 'compression' type of situation, wherein several inputs characterize a much lesser number of outputs. To retrieve the rain rate from SAPHIR channels, a database covering a wide spectrum of rain events has to be developed.

As mentioned earlier, the database required for training the ANN must accommodate the whole range of rain phenomenon, viz. low to high rain. During the period 2003–2010, 14 cyclones originated in the north Indian Ocean region. With the initial and boundary conditions from final analysis data (FNL), Advanced Research WRF (ARW), a community-based numerical weather prediction model (http://www.wrf-model.org/index.php) was used to generate vertical profiles of the geophysical quantities like temperature, humidity and hydrometeor profiles for all the 14 events. The ARW model solves the flux form of Euler equations numerically using a third order Runge–Kutta scheme. The ARW solver defines the prognostic variables in the form $\Phi = (U, V, W, \Theta, \phi', \mu', Q_{\mathrm{m}})$ and the model equation as $\Phi_t = R(\Phi)$, where U, V and W denote the coupled components of velocity along x, y and z directions respectively. Θ denotes the coupled potential temperature, ϕ' denotes perturbed geo-potential, whereas μ' denotes perturbed pressure. Q_m is the generic coupled moisture variable.

As mentioned earlier, initial and boundary conditions were taken from FNL data at the same times as those of the SAPHIR overpasses. The model was allowed to stabilize for 3 h (spin-up) before the overpass. A resolution of 5 km × 5 km was chosen for the WRF domain. Table 2 shows some of the specifications of WRF used in this study. The resulting profiles from the WRF model in general are prone to errors, e.g. error in the initial and boundary conditions, round-off error, limitations in the physics parameterization schemes and so on. To overcome this, an elaborate match-up exercise was carried out to ensure that the profiles are qualitatively fit. The WRF profiles are matched up with two rain-measuring

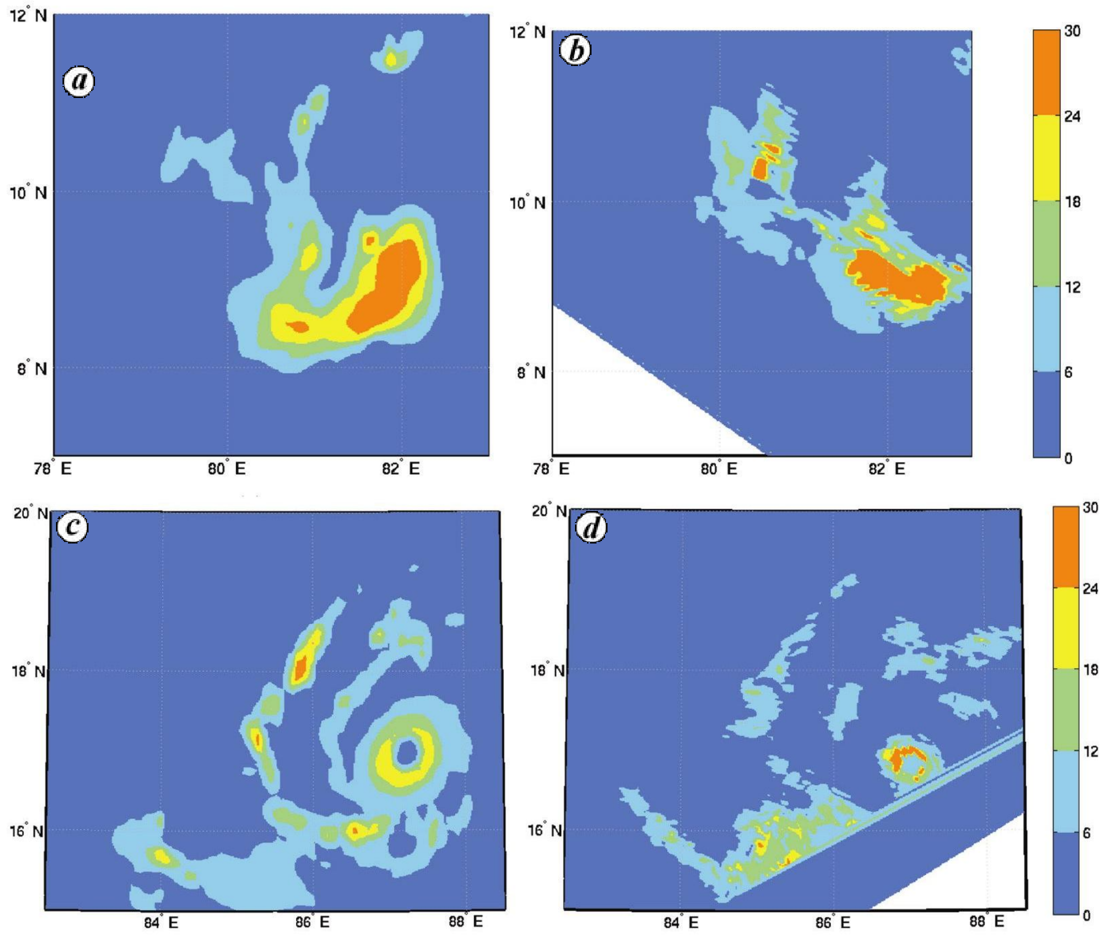

Figure 5. Comparison of retrieved NSR rates from SAPHIR and TMI-derived NSR rates for cyclones *Neelam* and *Phailin*. ***a*** and ***c***, Retrieved rain rates from SAPHIR; ***b*** and ***d***, TMI-derived NSR rates.

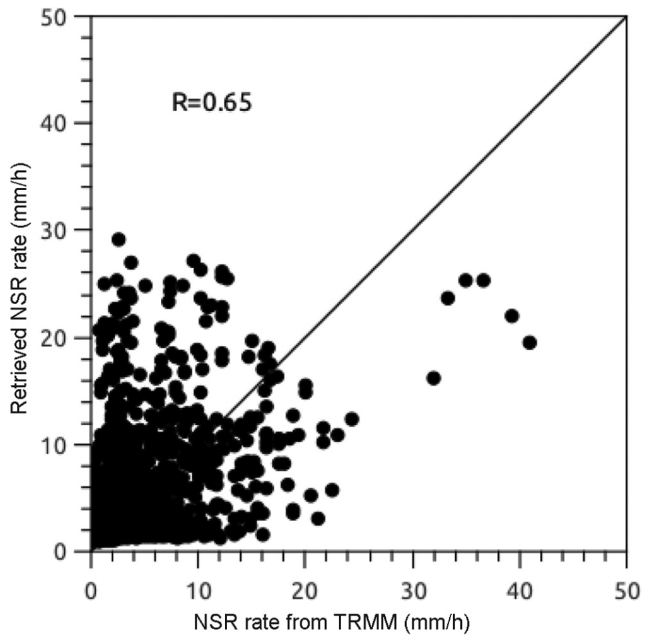

Figure 6. Parity plot showing agreement of SAPHIR-retrieved NSR rates with TMI-derived rain rates.

instruments available in TRMM, namely TMI and PR. At the end of the exercise, a database of 400 high-quality raining vertical atmospheric profiles in the north Indian Ocean was obtained. A complete discussion on this match-up procedure can be found in ref. 10.

In order to train the ANN, BTs were simulated for the matched-up high-quality raining vertical atmospheric profiles, about 400 in number, using the polarized radiative transfer equation (PRTE). Simulated BTs were used primarily to expose the ANN to diverse situations so that the entire spectrum of rainfall events starting from low to high rainfall rate is covered. Furthermore, the two-way collocation between the WRF and SAPHIR, and the limited amount of data available from SAPHIR as it has been functioning only from October 2011, necessitate a different strategy for training the neural network.

Considering this, in order to populate the ANN with diverse profiles, simulated BTs corresponding to the high-quality database previously generated were used. The inputs for the ANN are the six-channel BT and the output was surface rain rate. Figure 2 *a* shows the neuron architecture used for the present study. The neuron

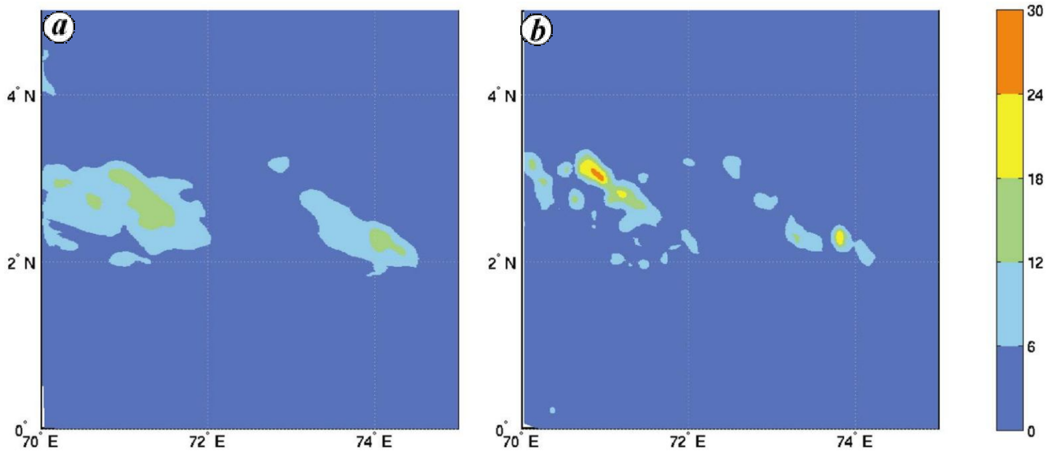

Figure 7. Comparison of retrieved NSR rate from SAPHIR and MADRAS-derived NSR rate for 9 December 2011.

architecture for real-time testing was selected based on the root mean square (RMS) and mean relative error (MRE) errors. Figure 2 *b* gives an overview of the retrieval methodology. Table 3 shows the results of the neuron independence study conducted by changing the number of neurons and also the number of hidden layers. From the table, it is clear that a neural network architecture with 6 inputs, 1 output, 2 hidden layers and 30 neurons in the first hidden layer and 30 neurons in the second layer is adequate.

For the purposes of validation, first the identification of common pixels between two satellite swaths of TRMM and SAPHIR is required. To achieve this, a collocation based on minimum distance strategy was adapted. The distance between a TRMM and SAPHIR pixel is given as

$$d_j = \sqrt{(\mathrm{lat}_{\mathrm{TRMM}} - \mathrm{lat}_{\mathrm{SAP}})^2 + (\mathrm{lon}_{\mathrm{TRMM}} - \mathrm{lon}_{\mathrm{SAP}})^2}, \qquad (2)$$

where *j* refers to the *j*th SAPHIR pixel. The minimum criterion for *d* was chosen to be ~ 1 km.

To check the capability of the developed ANN-based retrieval, experiments were performed for two cyclones, namely *Neelam* and *Phailin* as already mentioned. During these cyclone events Megha-Tropiques and the TRMM satellites made sufficient number of overpasses. With the ANN trained using the database as mentioned earlier, measured values of BT corresponding to the six channels of SAPHIR were given as input and the output was the NSR rate. The SAPHIR pixels were then collocated with the TRMM pixels using the above-mentioned technique. Figure 3 shows snapshots of rain contours of the retrieved NSR rates for the cyclones *Neelam* and *Phailin*. It can be seen that the isohyets of both the cyclones are able to capture the general features of the cyclones quite well; for the cyclone *Phailin*, the eye is captured very well. Figure 4 shows the variation of six channel BTs with the retrieved NSR rate for cyclone *Phailin*. It can be seen that the response of channels 3–6 to rainfall is good. This ensures that SAPHIR can pick up rainfall signature.

To validate the present retrieval methodology, TRMM-derived rain rates have been considered at the same time as the SAPHIR overpasses. After successful collocation based on the procedure described above, pixel-wise rain rates were compared. For the raining cases considered, Figure 5 shows a comparison of the NSR rates obtained from SAPHIR radiances and TRMM-derived (2A12) counterparts. Due to the difference in overpass time between SAPHIR and TRMM, only a few snapshots were available for comparison. Even so, the broad agreement between the two rain rates, more clearly seen for *Phailin* establishes the possibility of exploiting SAPHIR radiances to estimate NSR rates reasonably well.

Figure 6 shows a parity plot between retrieved NSR and TRMM-derived NSR rates for cyclone *Phailin*. From the figure, it is seen that a correlation coefficient (R) of 0.65 has been achieved from ANN-based retrieval. As can be seen from the parity plot, for values of rain rates between 30 and 40 mm/h, a maximum error of under 10 mm/h was recorded. This again is an encouraging result, because even though the correlation coefficient is moderate at 0.65, the ability of SAPHIR to pick up moderate to high rain signature is quite impressive. Furthermore, as SAPHIR data continue to be available, retrieval algorithms can be improved and fine-tuned and the correlation coefficient can be further increased. If eventually this happens, SAPHIR itself can be used as a proxy for rain.

A qualitative comparison between retrieved rain rates from SAPHIR with MADRAS-derived rain rates (level 2) has been made. The rain rates derived from MADRAS radiances on 9 December 2011 are available from an ftp website (http://14.139.159.206/mtdata/). Figure 7 shows the rain rates derived from MADRAS and SAPHIR and this indicates that SAPHIR can pick up moderate to high rain signature. Figure 8 shows a parity plot between

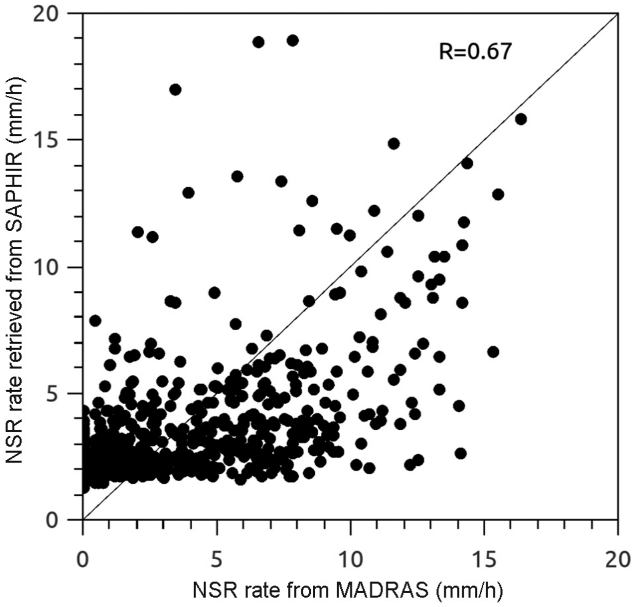

Figure 8. Parity plot showing agreement of SAPHIR-retrieved NSR rates with MADRAS-derived rain rates.

MADRAS and retrieved SAPHIR rain rates. A correlation coefficient (R) of about 0.67 has been observed between the two. The agreement between the two is encouraging.

The present study has explored the possibility of retrieving NSR rates from microwave radiances of the SAPHIR instrument aboard the Megha-Tropiques satellite. The upwelling radiances for SAPHIR frequency were simulated by an in-house polarized radiative transfer code, with hydrometeor profiles from WRF–ARW suitably matched up with TMI and PR instruments with an elaborate procedure involving a large number of rain events. An ANN was trained to regress NSR rates directly from the measured BTs at six frequencies corresponding to SAPHIR, namely 183.31 ± 0.20, 183.31 ± 1.10, 183.31 ± 2.80, 183.31 ± 4.20, 183.31 ± 6.80 and 183.31 ± 11.0 GHz. To populate the database adequately and extensively, simulated BTs were used in the training. However, for retrievals satellite-measured BTs (level-1 products) were used. Retrievals were performed for two cyclones, *Neelam* and *Phailin* with SAPHIR. Even though the SAPHIR channels are centred around the water vapour absorption line, the retrieved rain rates are in good agreement with the TRMM-derived rain rates. A correlation coefficient of 0.65 has been achieved by the current retrieval scheme. It is seen that moderate to high rainfall is retrieved very well with a maximum error around 25%. This unexpected performance of retrievals with SAPHIR radiances will benefit the Megha-Tropiques mission, due to the non-availability of MADRAS imager data. Furthermore, an inter-comparison of MADRAS and SAPHIR rain rates on 9 December 2011 shows good agreement between the two with a correlation coefficient of 0.67. From these findings it is clear that SAPHIR has opened up new vistas for rainfall retrieval. Targetted improvement of algorithms for ground rain rate retrieval with SAPHIR radiances can go a long way in accomplishing the objectives of the Megha-Tropiques mission. Efforts in this direction are currently underway. The next logical step would be to directly assimilate the radiances (level 1) in a numerical weather model to improve forecast skill of cyclones and other precipitating systems in the north Indian Ocean.

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