A new technique for estimating outgoing longwave radiation using infrared window and water vapor radiances from Kalpana very high resolution radiometer

Randhir Singh,[1] P. K. Thapliyal,[1] C. M. Kishtawal,[1] P. K. Pal,[1] and P. C. Joshi[1]

Received 21 August 2007; revised 19 October 2007; accepted 6 November 2007; published 15 December 2007.

[1] A new technique for estimating the outgoing longwave radiation (OLR) from the radiances observations in the infrared window (WIN; 10.5–12.5 μm) and water vapor (WV; 5.7–7.1 μm) channels onboard the geostationary operational Indian National Satellite (INSAT) Kalpana has been developed. The OLR is estimated from the WIN and WV radiances via genetic algorithm (GA). The transfer functions that relate OLR and narrowband radiances (WIN and WV) were developed using radiative transfer model. It is shown that inclusion of the WV information in the development of transfer function significantly reduces the OLR retrieval error as compared to the single WIN channel approach. The analysis shows that the model OLR may be retrieved within 2.5 Wm^{-2} rmse using WIN and WV channels, which is smaller than the rmse by earlier methods used for OLR estimation using two channels (WIN and WV). GA technique shows the clear advantage over multichannel regression in the OLR retrieval from WIN and WV radiances. **Citation:** Singh, R., P. K. Thapliyal, C. M. Kishtawal, P. K. Pal, and P. C. Joshi (2007), A new technique for estimating outgoing longwave radiation using infrared window and water vapor radiances from Kalpana very high resolution radiometer, *Geophys. Res. Lett.*, *34*, L23815, doi:10.1029/2007GL031715.

1. Introduction

[2] The Earth and its atmosphere absorb the shortwave (SW) radiation coming from the sun and emit the thermal longwave (LW) radiation to space. These two radiation streams can be represented approximately by blackbody radiation of 6000 K for the solar (SW) and 288 K for the terrestrial (LW). The total amount of the radiation that is emitted from the earth-atmosphere system to the outer space in 3–100 μm wavelength bands is called outgoing longwave radiation (OLR). The OLR originates partly from the surface and partly from the atmosphere. The balance between the incoming SW radiation and the OLR at the top of the atmosphere determines the temperature of the atmosphere and of the Earth's surface [*Harries*, 1997].

[3] The outgoing longwave radiation is a crucial parameter for studying many areas in the field of atmospheric sciences [*Ohring et al.*, 1984; *Ardanuy and Kyle*, 1986]. The OLR has been used traditionally for radiation budget studies of the Earth atmospheric system. The OLR also has been used for the atmospheric circulation studies over tropical region. This is mainly due to the fact that in the tropics, the OLR is largely modulated by cloudiness. In particular it varies with the cloud top temperature, and consequently, low values of OLR indicate major convective system [*Schmetz and Liu*, 1988].

[4] The observations of OLR by earth orbiting satellites have been made from the beginning of the environmental satellite program. Besides the broadband instruments that are dedicated for observing the OLR, for example, Earth Radiation Budget Experiment (ERBE), Scanner Radiometer for Radiation Budget (ScaRab), and Cloud and Earth's Radiant Energy System (CERES), there are many algorithms that estimate OLR by converting the narrowband radiance observations into broadband flux (3–100 μm). The OLR was routinely obtained from the 10–12 μm window on operational National Oceanic and Atmospheric Administration (NOAA) polar-orbiting satellite beginning in 1974 [*Gruber and Winston*, 1978]. Early operational estimation of OLR employed a simple parameterization using the window channel brightness temperature of the advanced very high resolution radiometer (AVHRR) on NOAA 6–7 [*Ellingson and Ferraro*, 1983; *Gruber and Krueger*, 1984].

[5] New algorithms were developed in subsequent years to improve the accuracy of the OLR. *Ellingson et al.* [1989] have shown that the linear combination of only four (6.6–6.9 μm; 7.9–8.5 μm; 13.1–13.6 μm; 14.3–14.7 μm) HIRS (High Resolution Infrared Sounder) channels could account for more than 99% of the OLR total variance. Comparison with the ERBE [*Ellingson et al.*, 1994] instrument flown in NOAA 9–11 satellites suggested that estimates made with HIRS data exhibited errors of the same order as the estimates from ERBE (5 Wm^{-2}), and the use of AVHRR data exhibits monthly bias of -1 to +2 W.m^{-2} and rms differences of about 14 Wm^{-2} [*Gruber et al.*, 1994].

[6] Geostationary satellite imagery has also been used for OLR estimation. *Schmetz and Liu* [1988] and *Cheruy et al.* [1991] developed OLR retrieval technique using two channels infrared window (WIN) and water vapor (WV) of Meteosat. *Minnis et al.* [1991] developed an algorithm to estimate OLR using Geostationary Operational Environmental Satellite (GOES) Imager window channels with additional water vapor information from analysis. *Ba and Ellingson* [2001] estimated OLR using several channels of the GOES sounder and presented comparisons with the CERES measurements. *Ba et al.* [2003] adapted the HIRS technique to GOES sounder and validated the derived OLR with collocated Tropical Rainfall Measurement Mission (TRMM) and Terra CERES OLR. Their results show

[1] Atmospheric Sciences Division, Meteorology and Oceanography Group, Space Applications Centre (ISRO), Ahmedabad, India.

0094-8276/07/2007GL031715

instantaneous agreement within about 7 Wm^{-2} for $1° \times 1°$ homogeneous scenes.

[7] INSAT series of operational satellites (INSAT-3A and Kalpana) carry the very high resolution radiometer (VHRR) with WIN (10.5–12.5 μm) and WV (5.7–7.1 μm) channels, thereby offering the opportunity for OLR estimation. Due to the different characteristics (spectral width and response function) of the channels, the OLR estimation algorithm from narrowband radiance measurements has to be different for different satellites. The algorithm developed for the GOES or Meteosat cannot be applied to Kalpana or INSAT-3A. The purpose of this paper is to develop the OLR estimation algorithm for Kalpana satellite.

2. Methodology and Data Used

[8] Ideally, the OLR is obtained by integrating the radiances over the long-wave spectral range and over hemispheric solid angles. However, if the observations at entire spectral range are not available, a mapping function of the following form should be determined to retrieve OLR from the available, narrow spectral band radiances:

$$OLR = F(\theta, N_i(\theta)) \qquad (1)$$

Where θ satellite zenith angle and N is is the observed narrow-band radiance. Subscript i is the index for channel.

[9] To find the transfer function relating the input (WIN and WV radiances) and output (OLR) parameters, a large database of the narrowband radiances and OLR was built using the Santa Barbara DISORT Atmospheric Radiative Transfer (SBDART) model [*Ricchiazzi et al.*, 1998, 2000]. The model calculations were performed for 12208 realistic atmospheric profiles. The data used for this study is extracted from SeeBor v3 [*Borbas et al.*, 2005] and consists of temperature, pressure, water vapor, ozone profiles and surface temperatures. In SeeBor data the profiles are taken from NOAA-88 (44 % of total profiles), ECMWF training set (34%), TIGR-3 (9 %), ozonesondes from 8 NOAA Climate Monitoring and Diagnostics Laboratory (CMDL) sites (8%), and radiosondes for 2004 in the Sahara desert (5%). In the data set, the surface temperature ranges from 210 to 320 K with mean 284 K and standard deviation 19 K. The near surface moisture varies from 0 to 29 gkg^{-1} with mean 8 gkg^{-1} and standard deviation 6 gkg^{-1}.

[10] The radiation calculations were performed for 12208 clear and 12208 cloudy conditions. Cloud layers were added at different levels in the vertical. The cloud cover contains up to three overlapping layers, each characterized by random optical thickness, drop size distribution and phase (water and ice). For each profile in the database, the narrow band radiances at 9 zenith angles (0°, 20°, 30°, 40°, 50°, 55°, 60°, 65°, 70°) were obtained using the response functions for two Kalpana-VHRR channels. Genetic algorithm (GA) is used to find the optimum transfer function relating OLR to WIN and WV radiances.

3. Algorithm Development

3.1. Genetic Algorithm

[11] Genetic algorithm (GA) is one of the best techniques [*Szpiro*, 1997; *Alvarez et al.*, 2000; *Singh et al.*, 2006] to determine most optimum relationship between the independent and dependent parameters. Genetic algorithm is programmed to approximate the equation, in symbolic form, that best describes the relationship between independent and dependent parameters. The GA considers an initial population of potential solutions that is subjected to an evolutionary process, by selecting those equations (individuals) that best fit the data. The strongest strings (made up from a combination of variables, real numbers, and arithmetic operators) choose a mate for reproduction whereas the weaker strings become extinct. The newly generated population is subjected to mutations that change fractions of information. The evolutionary steps are repeated with the new generation. The process ends after a number of generations, determined a priori by the user.

3.2. Training

[12] SBDART provided narrowband (WIN and WV) radiances, convolved over VHRR response function, as well as OLR for each profile at 9 satellite zenith angles. The development of the OLR retrieval algorithm involves a number of steps. In the first step, the SBDART simulated data (24416) of narrowband radiances and OLR were divided into two unequal random samples. Sample I (2000 points) is used to train the GA and Sample II (22416 points) is used for evaluation of the algorithm. The GA has the capability to learn the process from relatively smaller datasets [*Szpiro*, 1997]. In Sample-I, the OLR value ranges from 80 to 390 Wm^{-2}, with mean value of 205 Wm^{-2} and standard deviation of 75 Wm^{-2}. Genetic algorithm (GA) was then applied to find optimal relationship between simulated narrowband radiances and OLR for training data (Sample 1). A separate relationship was developed for different zenith angle bins (seven bins between 0°–70°; Table 1). Initially nine equations were developed for 9 zenith angles (0°, 20°, 30°, 40°, 50°, 55°, 60°, 65°, 70°) using Sample-I data (training data set). In order to compute the OLR for Sample-II data, the developed equation for a particular angle (e.g., 30°) was applied to model simulated WIN and WV radiances over a wide range of angles, around the angle (e.g., 30°) for which the equation was developed. The computed OLR were compared with model simulated OLR for Sample-II data and the root mean square error (rmse) was computed. The variation of the rmse with zenith angles were used to optimize the number and range of the angle bins. In this way we arrived at the conclusion that only seven equations (Table 1) out of 9 are enough for the angle ranges (0–70°).

[13] In this paper the results are discussed in detail for θ = 0°. The GA training provides empirical equation relating OLR to narrowband radiances. Figure 1 shows the evolution of the GA processes for one (WIN) and two (WIN and WV) channels radiances as predictors. The root mean square error (rmse) on the training data (Figure 1) is 4.4 Wm^{-2}, when single WIN channel (GA-C1) is used as predictor. The rmse gets halved (2.2 Wm^{-2}) when water vapor radiances (WV) are used with WIN radiances (GA-CII). The equations for θ = 0° using single channel (equation 2) and two channels (equation 3) as predictors are as follow:

$$OLR = 13.94\ WIN - \frac{96.15}{WIN} + 114.11 \qquad (2)$$

Table 1. Developed Equations for GA-CII Training Process

Angle	Empirical Equation
$0° < \Theta < 15°$	$OLR = 11.44\ WIN + 9.04\ WV + \frac{9.11WV}{WIN} - \frac{86.36}{WIN} - 0.14WV^2 + 111.12$
$15° \leq \Theta < 25°$	$OLR = 11.86\ WIN + 14.53\ WV - \frac{28.93}{WIN} + 94.92$
$25° \leq \Theta < 35°$	$OLR = 12.34\ WIN + 16.02\ WV + \frac{0.13WIN}{WV} + 82.59$
$35° \leq \Theta < 45°$	$OLR = 14.34\ WIN + 0.72\ WV + 0.10\ WINWV - \frac{72.27}{WIN} - \frac{14.34}{WV} + \frac{35.99}{WINWV} + \frac{130.06WV}{WIN} + 80.77$
$45° \leq \Theta < 60°$	$OLR = 12.94\ WIN + 16.50\ WV + \frac{10.09WV}{WIN} + \frac{12.94WV}{WIN+0.39} + 77.47$
$60° \leq \Theta < 65°$	$OLR = 13.31\ WIN + 13.73\ WV + \frac{13.31WIN}{\frac{11.37}{WV+0.289\ WIN} + WIN - 5.17} + 71.07$
$65° \leq \Theta < 70°$	$OLR = 13.74\ WIN + 8.37\ WV + \frac{11.01WV^2}{WIN} - \frac{14.60}{8.31WV + 1.71} + 94.49$

$$OLR = 11.44\ WIN + 9.04\ WV + \frac{9.11\ WV}{WIN} - \frac{86.36}{WIN} - 0.14\ WV^2 + 111.12 \qquad (3)$$

Where, WIN and WV represent channel radiances ($Wm^{-2}str^{-1}$). OLR retrieval error varies with zenith angle with maximum (3.1 Wm^{-2}) at 70° and minimum (1.9 Wm^{-2}) at 50°. The empirical equations developed for other angles in case of GA-CII are given in Table 1. In order to assess the magnitude of additional error that would result from the noise in the Kalpana radiances (WIN, WV), we carried out a simulation for two different noise scenarios in the radiances. The noise of the order of 1% and 2 % of the mean radiances in each channel were considered to perform the error analysis. This resulted in an additional error of 0.3 Wm^{-2} (0.9 Wm^{-2}) for 1% (2%) error of mean radiances in the estimation of OLR using equation (3).

[14] The addition of the WV radiances in the GA evolutionary processes significantly improved the accuracy of the OLR retrievals (Figure 1). This is also reported by the earlier studies [*Schmetz and Liu*, 1988]. Because of non linear dependence of OLR on temperature and moisture, the single channel (WIN) techniques lead to error when atmospheric conditions are unusual, for example, over regions like trade wind inversion and deserts. These regions are mostly cloud free or have fewer clouds. In clear-sky situations, the single channel (WIN) algorithms show higher sensitivity to surface temperature and negligible sensitivity to the atmospheric contribution [*Gruber et al.*, 1994] and hence the derived OLR can be much different from the actual when the water vapor distribution is not consistent with the surface temperature [*Ellingson et al.*, 1989].

[15] Using 1, 2, and 4 channels of HIRS, *Ellingson et al.* [1989] could retrieve OLR with rmse ~5.5, 4.5, and 2 Wm^{-2} respectively. In this study the accuracy achieved for OLR retrievals from two channels is better than *Ellingson et al.* [1989] two channels accuracy (4.5 Wm^{-2}). Moreover, *Ellingson et al.* [1989] used only 1600 Atmospheric profiles for the development and validation of their algorithm, while we used 12208 profiles, providing higher confidence to our algorithm.

[16] The improved performance of our 2-channel algorithm can be attributed to the use of GA. A major difference between other optimization techniques and GA is that the later is almost completely objective and data adaptive. A unique advantage of GA is that complex (often nonlinear) relationships between different variables can be obtained in the form of simple and usable equations. Thus, one may ask how non-linear the derivation of OLR from WIN and WV radiances is. We compared the performance of the GA-CII approach in deriving OLR with Multiple Linear Regression (MLR-CII). Sample I data is used to find the MLR equation relating OLR with WIN and WV radiances. The best MLR equation (rmse = 3.8 Wm^{-2}; for $\theta = 0°$) obtained is as follows:

$$OLR = 13.22\ WIN + 23.72\ WV + 70.86 \qquad (4)$$

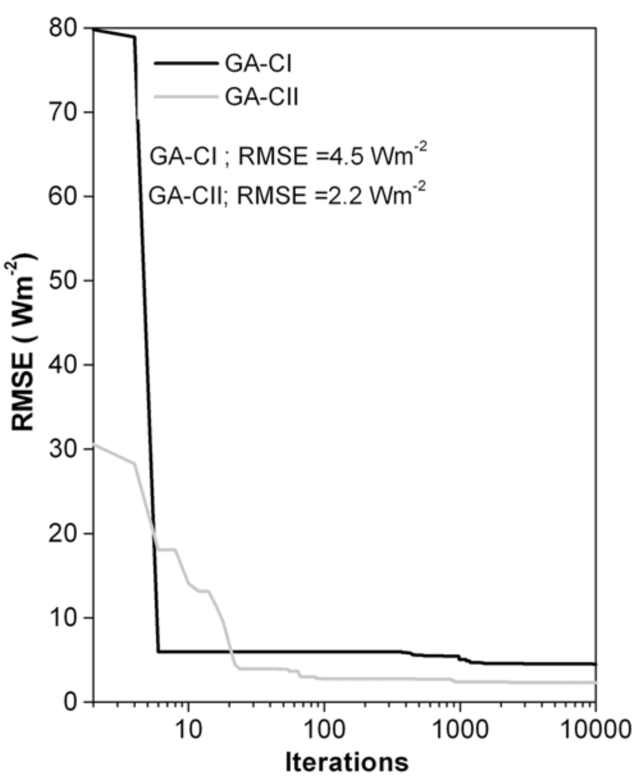

Figure 1. Reduction of RMS error (Wm^{-2}) during GA training phase for single (GA-CI) and two channels (GA-CII) as predictors.

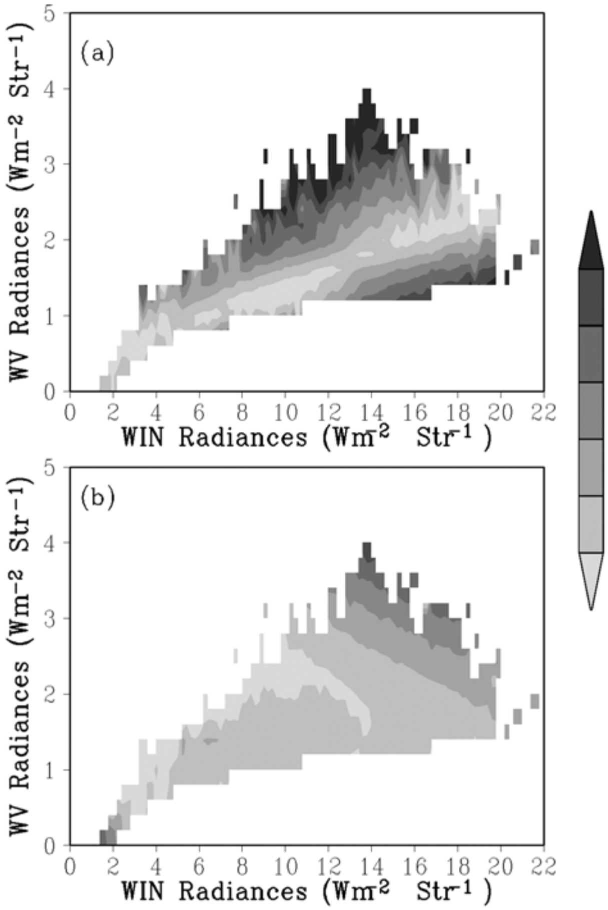

Figure 2. Variation of improvement parameters (η_1, η_2;Wm^{-2}) with WIN and WV radiances, for (a) GA-CI versus GA-CII and (b) GA–CII verses MLR-CII for Sample II data set.

The rmse in case of MLR is almost twice as compared to empirical function developed using GA technique (equation 3).

4. Assessment of Retrieval Accuracy

4.1. Comparison With RT Model Simulations

[17] The equations (equations 2–4) are used to get OLR for the test data (Sample II). The assessment of GA-CI, GA-CII and MLR-CII retrieved OLR with respect to model calculated OLR is made by computing the bias and rmse for Sample-II dataset (which is not used in the development phase of the retrieval algorithm). The rmse, bias, and correlation for GA-CI are 5 Wm^{-2}, 0.1 Wm^{-2}, and 0.99, respectively. GA-CII agrees well with those of model calculated OLR with bias of 0.2 Wm^{-2}, rmse of 2.5 Wm^{-2}, and correlation coefficients of 0.99. For MLR-CII rmse, bias and correlation coefficients are 4 Wm^{-2}, 0.01 Wm^{-2}, and 0.99 respectively. In all the cases (GA-CI, GA-CII, and MLR-CII) the rmse in the test data (Sample-II) is slightly higher than the rmse in the training dataset. The GA-CI error range between ±10 Wm^{-2} and the majority are within ±5 Wm^{-2}. In GA-CII, the errors are between ±4 Wm^{-2}, and are primarily confined between ±2.5 Wm^{-2}. The comparison between GA-CII and MLR-CII retrieval clearly shows the advantages of GA based technique over MLR.

[18] We computed an improvement parameters η_1 = ((rmse between model and GA-CI) – (rmse between model and GA-CII)) to show relative superiority of 2-channel algorithm over single-channel algorithm. Another improvement parameter η_2 = ((rmse between model and MLR-CII) – (rmse between model and GA-CII)) is also computed. The positive values of η_1 indicate improvement due to use of WV in addition to WIN in case of GA while the positive values of η_2 show the improvement in the OLR retrievals by GA as compared to MLR. Figures 2 show the variation of η_1 (Figure 2a) and η_2 (Figure 2b) with WIN and WV radiances for Sample-II data set. Over most of the regimes the values of η_1 (Figure 2a) are positive and indicate that WIN channels is not sufficient to estimate the OLR, particularly in regions like subtropical oceans and warm and humid regimes. Similarly over most of the regimes the value of the η_2 is also positive, which indicate the advantage of the GA over MLR.

4.2. Comparisons With Meteosat OLR

[19] Due to the unavailability of broadband measurements of OLR, we used Meteosat-7 observations for comparison. Meteosat-7 does not provide OLR products operationally, but algorithms are available for conversion of Meteosat-7 WIN and WV radiances into broadband flux (OLR). We used hourly Meteosat-7 and Kalpana WIN and WV radiances for 8th June 2007. The algorithm of *Schmetz and Liu* [1988] is used to compute OLR from Meteosat-7 narrowband radiances. The hourly as well daily mean Kalpana OLR are derived using GA-functions for different angular bins (e.g., Table 1) and were compared with Meteosat-7 OLR over common areas of observation. Figure 3 shows the scatter plots of the Meteosat-7 and Kalpana daily mean OLR at 0.5° × 0.5° resolution. The daily mean difference is about −0.03 Wm^{-2} with an rmse of about 5.8 Wm^{-2}. The hourly OLR comparison between

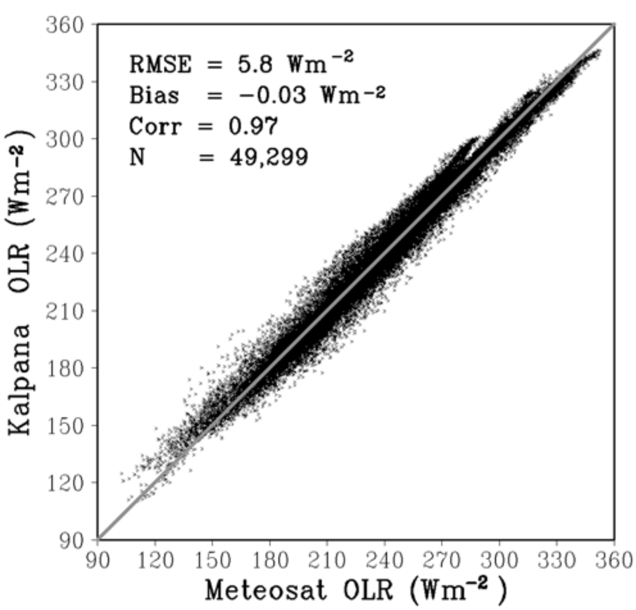

Figure 3. Comparisons between Meteosat-7 and Kalpana derived daily mean OLR (Wm^{-2}) on 8th June 2007.

Kalpana and Meteosat shows an rmse of the order of 6.5 Wm^{-2} and 8 Wm^{-2} for day and night respectively. To further validate Kalpana OLR we have obtained NOAA/HIRS orbital OLR products and the comparison is underway.

5. Conclusions

[20] A new technique is presented to compute the outgoing longwave radiation from radiance observations in the infrared (WIN) and water vapor (WV) channels of Indian National Satellite (INSAT) Kalpana VHRR. Optimum relationship between radiative transfer model calculated narrowband radiances and broadband flux were developed using Genetic algorithm, an advance empirical technique (GA). The use of WV radiances in addition to WIN radiances significantly improves the accuracy of the OLR retrieval. The relationship between OLR and WIN/WV radiances appears to be non-linear, particularly over warm and dry atmospheric conditions.

[21] When compared with an independent data containing radiative transfer model simulations, the root mean square error of retrieved OLR is 2.5 Wm^{-2} with negligible bias. The accuracy of our algorithm is comparable to that of 4-channel HIRS algorithm by *Ellingson et al.* [1989]. This improvement is due to the use of more advance empirical data fitting technique (GA). Very soon India will be launching INSAT-3D, which will be having a sounder. The present technique can then be extended to estimate OLR more accurately using a suitable combination of Imager and Sounder.

[22] The derived empirical functions were applied on Kalpana observed WIN and WV radiances for computing the OLR. Kalpana derived OLR agrees reasonably well with Meteosat-7 derived OLR. The extensive validation of the Kalpana derived OLR with other operationally available OLR products (NOAA/HIRS) is underway. Observations of OLR from geostationary platforms like Kalpana can be helpful in filling the gaps in the global coverage of OLR with high temporal resolution.

[23] **Acknowledgments.** We would like to thank Hai Tien Lee of Cooperative Institute for Climate Studies, Department of Meteorology, University of Maryland, College park, Maryland, for useful discussion during this study. The Meteosat-7 narrowband radiances provided by EUMETSAT are gratefully acknowledged. Useful discussions with Kiran Kumar of Space Applications Centre (SAC) about Kalpana sensors are also acknowledged. The SeeBor atmospheric profiles for radiation model calculation were obtained from University of Wisconsin.

References

Alvarez, A., C. Lopez, M. Riera, E. Hernandez-Garcia, and J. Tintore (2000), Forecasting the SST space-time variability of the Alboran Sea with genetic algorithms, *Geophys. Res. Lett.*, *27*, 2709–2712.

Ardanuy, P. E., and H. L. Kyle (1986), El Nino and outgoing longwave radiation observations from Nimbus-7 ERB, *Mon. Weather Rev.*, *114*, 415–433.

Ba, M. B., and R. G. Ellingson (2001), A study of diurnal cycle of OLR using GOES sounder data, in *Current Problems in Atmospheric Radiation*, pp. 505–508, A. Deepak, St. Petersburg, Russia.

Ba, M. B., R. G. Ellingson, and A. Gruber (2003), A validation of a technique for estimating OLR with GOES sounder, *J. Atmos. Oceanic Technol.*, *20*, 79–89.

Borbas, E., S. W. Seemann, H.-L. Huang, J. Li, and W. P. Menzel (2005), Global profile training database for satellite regression retrievals with estimates of skin temperature and emissivity, paper presented at 14th International ATOVS Study Conference, NASA, Beijing, China, 25–31 May.

Cheruy, F., R. S. Kandel, and J. P. Duvel (1991), Outgoing longwave radiation and its diurnal variation from combined ERBE and Meteosat observations. 1. Estimating OLR from Meteosat data, *J. Geophys. Res.*, *96*, 611–622.

Ellingson, R. G., and R. R. Ferraro (1983), An examination of a technique for estimating the longwave radiation budget from satellite radiances observations, *J. Clim. Appl. Meteorol.*, *22*, 1416–1423.

Ellingson, R. G., D. J. Yanuk, H. T. Lee, and A. Gruber (1989), A technique for estimating outgoing longwave radiation from HIRS radiance observations, *J. Atmos. Oceanic Technol.*, *6*, 706–711.

Ellingson, R. G., H.-T. Lee, D. Yanuk, and A. Gruber (1994), A validation of a technique for estimating outgoing longwave radiation from HIRS radiances observations, *J. Atmos. Oceanic Technol.*, *11*, 357–365.

Gruber, A., and A. Krueger (1984), The status of the NOAA outgoing longwave radiation dataset, *Bull. Am. Meteorol. Soc.*, *65*, 958–962.

Gruber, A., and J. S. Winston (1978), Earth-atmosphere radiative heating based on NOAA scanning radiometer measurements, *Bull. Am. Meteorol. Soc.*, *59*, 1570–1573.

Gruber, A., R. G. Ellingson, P. Ardanuy, M. Weiss, S. K. Yang, and S. N. Oh (1994), A comparison of ERBE and AVHRR longwave flux estimates, *Bull. Am. Meteorol. Soc.*, *75*, 2115–2130.

Harries, J. E. (1997), Atmospheric radiation and atmospheric humidity, *Q. J. R. Meteorol. Soc.*, *123*, 2173–2186.

Minnis, P., D. F. Young, and E. F. Harrison (1991), Examination of a relationship between outgoing infrared window and total longwave fluxes using satellite data, *J. Clim.*, *4*, 1114–1133.

Ohring, G., A. Gruber, and R. Ellingson (1984), Satellite determination of the relationship between total longwave radiation flux and infrared window radiance, *J. Clim. Appl. Meteorol.*, *23*, 416–425.

Ricchiazzi, P., et al. (1998), SBDART: A research and teaching software tool for plane-parallel radiative transfer in the Earth's atmosphere, *Bull. Am. Meteorol. Soc.*, *79*, 2101–2114.

Ricchiazzi, P., et al. (2000), SBDART: A research and teaching software tool for plane-parallel radiative transfer in the Earth's atmosphere, http://www.crseo.ucsb.edu/esrg/pauls_dir/, Earth Space Res. Group, Univ. of Calif., Santa Barbara.

Schmetz, J., and Q. Liu (1988), Outgoing longwave radiation and its diurnal variation at regional scales derived from Meteosat, *J. Geophys. Res.*, *93*, 11,192–11,204.

Singh, R., C. M. Kishtawal, P. K. Pal, and P. C. Joshi (2006), Surface heat fluxes over global ocean exclusively from satellite observations, *Mon. Weather Rev.*, *134*, 965–980.

Szpiro, G. G. (1997), Forecasting chaotic time series with genetic algorithms, *Phys. Rev. E*, *55*, 2557–2568.

P. C. Joshi, C. M. Kishtawal, P. K. Pal, R. Singh, and P. K. Thapliyal, Atmospheric Sciences Division, Meteorology and Oceanography Group, Space Applications Centre (ISRO), Ahmedabad-380015, India. (randhir_h@yahoo.com)