Use of a Dense Rain-gauge Network over India for Improving Blended TRMM Products and Downscaled Weather Models

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Abstract

This study makes use of a network of nearly 2100 rain gauges over India in order to statistically modify the Tropical Rainfall Measuring Mission (TRMM) algorithm 3B42. The validation and usefulness of the modified product is determined against rain gauge datasets and from the training and forecast phase of the Florida State University (FSU) multimodel superensemble. We use downscaled member model forecasts to construct superensemble forecasts. The member model forecasts are scaled down using the modified high-resolution TRMM rains during the training phase of the multimodel superensemble. We demonstrate that a mesoscale superensemble thus constructed has forecast efficiencies superior to those of all of the member models and to the ensemble mean (ENSM) and bias-corrected ensemble mean (BcorENSM). The forecast procedure includes a high-resolution downscaling of the model forecast rain and the construction of a multimodel superensemble. This procedure clearly provides a much-improved forecast of rain using metrics such as equitable threat scores (ETSs), anomaly correlations, root mean square (RMS) errors, and their bias scores. We also demonstrate that the performance of this modified TRMM algorithm provides results very clearly comparable to those obtained from the direct use of rain gauges throughout India and the TRMM 3B42 covering a domain of 50°S to 50°N.

1. Introduction

Over the last decade, considerable progress has been made in validating rainfall estimates derived from the TRMM Microwave Imager (TMI) and from the Precipitation Radar (PR) (Shige et al. 2007; Bhatt and Nakamura 2005; Aonashi and Liu 2000; Hou et al. 2000). A vast effort was made to validate these

datasets using gauge and ground-radar-based estimates by the U.S. and Japanese Tropical Rainfall Measurement Mission (TRMM) scientists. The estimates from TMI and PR are in mutual agreement within 20%. One of the most popular products being used by forecasters for validation is the 3B42 algorithm. This high-quality (HQ) combined instrument rain-calibration algorithm utilizes the rainfall estimates from microwave instruments and infrared (IR) precipitation instruments of geostationary and polar orbiting satellites. The 3B42 algorithm uses an optimal combination of the 2B31, the 2A12, the Special Sensor Microwave/Imager (SSM/I), the Advanced Microwave Scanning Radiometer (AMSR), and the

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(a)

(b)

Number of Raingauges in a 0.5° x 0.5° box on a typical Day

Fig. 1. Rain gauge distributions. APHRODITE data sources over the domain of interest (top). (Bottom) number of rain gauges on a typical day, in a 0.5° x 0.5° grid box over the IMD gauge analysis domain.

Advanced Microwave Sounding Unit (AMSU) precipitation estimates. The 2B31 algorithm combines Level 2 PR and TMI rainfall with details of drop size distribution (DSD) and rain rates, and the 2A12 estimates rain from TMI sensors (Kummerow et al. 1998). Near-global estimates are made by calibrating the IR brightness temperatures to HQ estimates. These gridded estimates are produced at a three-hourly temporal resolution and a nearly 25 km horizontal resolution between the latitudes of 50°S and 50°N. Currently, a large number of rain gauge sites have been deployed in many land areas, providing a unique opportunity to examine the TRMM-based rainfall estimates over such land areas.

Over tropical oceans and the land areas away from the TRMM ground-validation sites, no dense network of rain gauges is present; here, the TRMM database is clearly one of the best available datasets. However, in many land areas (e.g., the Middle East and the entire Asian region), dense networks of rain gauges are maintained (Yatagai et al. 2008, Fig. 1a). Figure 1 reveals the impressive distribution of sites in the Indian region, based on a recent collection that was completed by the India Meteorological Department (IMD) (Rajeevan et al. 2005, Fig. 1b). This collection includes rain from as many as 2,140 gauge stations. This precipitation dataset was prepared by the National Climate Data Center, IMD, in Pune, India; it covers daily rainfall totals from 1950 to 2007. These datasets were interpolated (Shepard 1968) on a $0.5^\circ \times 0.5^\circ$ latitude/longitude grid (Rajeevan et al. 2006) for research purposes. Figure 1b indicates the number of rain gauges used to prepare IMD analysis on a typical day. The number in each $0.5^\circ \times 0.5^\circ$ grid box represents the number of rain gauges reporting on that particular day. It is evident from Fig. 1b that a very dense network of rain gauges exists over the Indian mainland. A separate dataset was also prepared on a $1^\circ \times 1^\circ$ latitude/longitude grid and has been used for climate studies (Chakraborty and Krishnamurti et al. 2009). This dataset is considered to be one of the most comprehensive for this region. Most of the operational Numerical Weather Prediction (NWP) models issue forecasts at either 2400 GMT or 1200 GMT, and IMD gauge analysis is available at 0300 GMT. Time correction is applied using a three-hourly TRMM 3B42 diurnal cycle to align IMD gauge data with model forecast hours (i.e., 12 GMT). In our recent study (Krishnamurti et al. 2008), we examined multimodel forecasts using a combination of downscaling and superensemble; we used the IMD rain data over India

and performed time correction. This study involves the continuation of downscaling and multimodel forecasting of precipitation, in order to examine the TRMM and rain gauge datasets over India.

2. Datasets

One use of the global tropical TRMM datasets has been model validation of rainfall for short- to medium-range forecasts. Improving the initial rains of numerical prediction models using physical initialization has been addressed by Krishnamurti et al. (2000, 2003). Here we demonstrate that improving the models' nowcasting of precipitation positively impacts short- to medium-range forecasts. Different data assimilation schemes have been successfully used for the U.S. Weather Service operational model (Treadan 1996); examples include three-dimensional variational data assimilation (3D-Var) (Parrish and Derber 1992) and physical initialization of observed initial rainfall estimates. Similar efforts on the initialization of observed rainfall estimates have been addressed by Krishnamurti et al. (1991, 2000), Peng and Chang (1996), and Nunes and Roads (2007).

A reliable precipitation database is useful for validating numerical models, and vice versa. Models also have a role in assessing the usefulness of precipitation datasets. The Xie and Arkin (1997) precipitation data is another useful dataset for large-scale precipitation estimates. This dataset provides monthly and 5-day means at $2.5^\circ \times 2.5^\circ$ horizontal resolution. The World Climate Research Program (WCRP) established the Global Precipitation Climatology Center (GPCP) to archive rainfall analysis at better temporal and spatial resolutions in near real time, in order to obtain daily averaged global rainfall estimates at a horizontal resolution of $1^\circ \times 1^\circ$ (Huffman et al. 1997, 2001; Adler et al. 2003). These datasets have been extensively used in model validations for weather and climate studies. Comparison of these precipitation datasets derived at different resolutions reveals vast differences. Figure 2a illustrates a typical difference among the daily rainfall totals (mm) of the GPCP, TRMM, modified TRMM (discussed later), and the IMD rain-gauge-based field. The illustrations in this figure are for the total rain observed during the 24 h of Aug 8, 2007. The horizontal resolutions of these datasets are $1^\circ \times 1^\circ$ for GPCP, $0.25^\circ \times 0.25^\circ$ for TRMM, $0.5^\circ \times 0.5^\circ$ for modified TRMM, and $0.5^\circ \times 0.5^\circ$ for the IMD rain-gauge-based field. It is clear that higher resolution does not necessarily imply more horizontal details in the precipitation patterns. The GPCP rainfall dis-

Fig. 2. (a) An example of 24h total rain (mm) valid on August 8, 2007, observed through GPCP, TRMM 3B42, modified TRMM, and IMD gauges. (b) Spatial correlation of GPCP (line with cross marks), TRMM 3B42 (dashed blue line with filled rectangle marks), and modified TRMM (green line with no marks) rains with IMD gauge analysis.

tributions are somewhat smoothed and lower magnitude than those of the TRMM 3B42 and the rain-gauge products. The rain-gauge product seems to have more details on local rains. Heavier rains along the southwest coast of India were missed by the GPCP and the TRMM. Some noticeable discrepancies are apparent over the Himalayan foothills and the north-eastern part of India in the TRMM, IMD, and GPCP. Although the resolution of the TRMM 3B42 (25 Km) was finer than that of the IMD rain data (50 Km), we often noted some finer details in the rain gauge data of IMD; such details were somewhat smoothed in the TRMM product. Because of the large number of IMD rain gauges, the grid points of the half-degree resolution in fact indicated local rains, whereas the TRMM 3B42 is a blended product where the geostationary-satellite-based rainfall estimates from IR often contribute to a smoother field because of the smooth cold cloud top temperature fields of the high cirrus clouds. An overall assessment of the TRMM and the GPCP is presented in Fig. 2b. Here we present the spatial correlations of the GPCP-based (heavy dashed line) and the TRMM-based (thin dashed line) rains computed against the rain-gauge-based estimates covering a three-month period (June through August 2007). These correlations cover the entire domain of India depicted in Fig. 2a. Overall, it indicates that the TRMM 3B42-based estimates have a higher correlation than the GPCP-based estimates. In Fig. 2b, the green curve consistently indicates much higher correlations, based on the modified TRMM 3B42 product that is described in this paper. Figure 2a clearly illustrates differences among GPCP, TRMM 3B42, modified TRMM, and IMD gauge analyses.

This paper addresses multimodel forecasts of precipitation over India, using diverse datasets. This study is a sequel to a recent study by Krishnamurti et al. (2008) on precipitation forecasts over India. In that study, the sequence of steps was as follows.

- (1) Collection of TRMM 3B42 and IMD gauge-based $0.5^\circ \times 0.5^\circ$ latitude/longitude analysis, applying time correction to IMD gauge data using the diurnal cycle of TRMM
- (2) Prediction by the Florida State University (FSU) superensemble method (Krishnamurti et al. 2003), using multimodels where TRMM rains are used for training and model validation of forecasts
- (3) Downscaling of each member model's forecasts of precipitation towards the high-resolution IMD rains for a training and forecast phase
- (4) Construction of multimodel superensemble fore-

casts, using the downscaled forecasts from member models by using IMD gauge data for training

- (5) Model validation, using TRMM 3B42 and the IMD gauge datasets over India.

The present study carried out the same five steps, but the TRMM 3B42 rains over India were replaced by a modified TRMM rain that had been statistically corrected with the gauge data as a reference. The statistically modified TRMM 3B42 replicated most of the details of the heavy precipitation seen by the gauge datasets; thus, it was possible to improve superensemble forecasts through day 5 from a suite of models. That is the goal of this study.

2.1 Modified TRMM 3B42

The IMD gauge datasets that cover most of India are located over hills, river basins and deltas, semi-arid regions, coastal areas, deserts, and steep mountain ranges; therefore, they cover a large spectrum of land-surface conditions. The TRMM datasets are not based on a specific algorithm for such a variety of surfaces. Basically, we first carried out a simple extraction (interpolation) of the TRMM 3B42 rainfall on the IMD's $0.5^\circ \times 0.5^\circ$ latitude/longitude grid. To do so, we analyzed daily datasets of 24-hourly rains from these products, covering June 1, 2007, to September 30, 2007. A simple linear regression was next performed to modify the TRMM 3B42 rain over the same grid points of the Indian domain (Fig. 2a).

$$\text{GaugeRain}_i = a * (\text{TRMM 3B42})_i + b. \quad (1)$$

Here, i denotes the number of observations at each grid point, and a and b vary geographically. Regression coefficients (slope a and intercept b) are stored by using a time linear regression for 92 days (June 1 to August 31, 2007). These coefficients are then used to correct the TRMM rain for the entire period of our study (June to September 2007). The slope and intercept distribution indicate the nature of corrections that were made to the TRMM 3B42 towards the observed IMD gauge rainfall. In effect, these linear regressions define the modified TRMM 3B42 algorithms.

Figures 3a and b illustrate slope a and intercept b of the linear regression, also plotted along with the normalized difference vegetation index (NDVI) for the month of August 2007 (National Aeronautics and Space Administration (NASA) Earth Observations). Slope a indicates the ratio of the rate of increase of the

Fig. 3. Regression coefficients (a) slope (b) intercept of 92-day regression between IMD gauge data and TRMM 3B42 rain. The color bar legends represent the values of the regression coefficients. (c) NDVI for August 2007.

TRMM 3B42 rains to those from the IMD rain gauges. A 45° slope (equal to one) would indicate equal rates of increase for these two products. In some regions over India, the slope is less than one, and in others it is larger than one. Thus, we can obtain a geographical measure of the systematic error when we use the IMD rains as a benchmark. Intercept b denotes an overall shift of the rain. A high positive value of slope a ($a > 1$) denotes underestimation of the TRMM 3B42 rains compared to the IMD rain gauge product, while a low positive value (where slope values are between 0 and 1) indicates that TRMM is overestimating rain. Large values of a indicate that the distribution of precipitation intensity in the TRMM 3B42 is too flat (i.e., not enough heavy precipitation or too much light precipitation, or both). Areas over the Western Ghats and the northeastern region, along with some scattered areas over central India, indicate a higher slope value ($a > 1$) (Fig. 3a), indicating that TRMM underestimated rain and confirming the earlier discussion of Fig. 2a. Similarly, regression coefficient b (intercept) represents the systematic error in TRMM 3B42. As the value of b tends toward zero, IMD gauge rain becomes a factor of TRMM 3B42 rain. A higher value of b denotes a large systematic error in TRMM estimates. This was very useful in assessing the geographical distributions of the systematic errors of the TRMM

product. In the downscaling, we used only one variable, the high-resolution rainfall from the rain gauges and models. It might have been desirable to include additional information, such as the NDVI, which is an estimate of vegetation health and a means of monitoring changes in vegetation (Fig. 3c), which does seem to bear some relationship with the slope parameter of the precipitation. Regions with a very small slope seem to be present, in general, over regions of low NDVI value.

Using the regression coefficients presented in Figs. 3a and b, TRMM 3B42 is corrected to the modified TRMM. The new rainfall product should correct the problem areas. Figure 2b presents the time series of daily spatial correlations of the GPCP, TRMM (3B42), and modified TRMM (green line) for June through August 2007. With the highest spatial correlation to the IMD gauge analysis, the modified TRMM is the best among these products.

3. Florida State University multimodel superensemble

The notion of the multimodel superensemble for weather and seasonal forecasts was first proposed by Krishnamurti et al. (1999). This method is based on producing a weighted average of model forecasts to construct a superensemble forecast. This procedure

includes two phases, training and prediction. During the training phase, past forecasts from a number of member models and the corresponding observed (analyzed) fields are used. The training entails determining statistical weights for each grid location in the horizontal and vertical levels for all variables, for each day of forecasts and for each of the member models. For global NWP, the procedure brings in as many as 10^7 statistical weights. These weights arise from a statistical least square minimization using multiple regressions, where the member model forecasts are regressed against the observed (analyzed) measures. As the outcome of this regression, the weights are assigned to the individual models in the ensemble, which are then passed on to the forecast phase to construct the superensemble forecasts.

The temporal anomalies of a variable, rather than the full fields, are used in the multiple-regression technique. Hence, in formulating the superensemble forecast, the weights are multiplied by the corresponding model anomalies. The constructed forecast is

$$S = \bar{O} + \sum_{i=1}^N a_i (F_i - \bar{F}_i), \quad (2)$$

where $\bar{O}$ is the observed climatology, a_i is the weight for the i th member in the ensemble, F_i is the forecast value, and $\bar{F}_i$ is the forecast climatological value for the training period for the i th model's forecast. The summation is taken over the N member models of the ensemble. The weight a_i is obtained by minimizing the error term G :

$$G = \bar{O} + \sum_{i=1}^{N_{\text{train}}} (S'_i - O'_i)^2, \quad (3)$$

where N_{train} is the number of time samples in the training phase, S'_i is the superensemble field anomaly, and O'_i is the observed field anomaly at training time t . This exercise is performed for every grid point and vertical level in the dataset during every forecast phase. In other words, one weight is given to every

Fig. 4. Schematic representation of the FSU multimodel superensemble methodology. In the training phase, the model forecasts are regressed against the observation to obtain differential weights. These weights are then passed on to the forecast phase to create superensemble forecasts.

Fig. 5. Regression coefficients of ECMWF forecasts for days 1, 3, and 5 using IMD gauge rain. Top panels denote slope a , and bottom panels denote intercept b . The color bar below the panels represents the coefficients' magnitude.

Fig. 6. Regression coefficients of JMA forecasts for days 1, 3, and 5 using IMD gauge rain. Top panels denote slope a , and bottom panels denote intercept b . The color bar below the panels represents the coefficients' magnitude.

model at every grid point in the three-dimensional space for each forecast.

Figure 4 schematically outlines the superensemble strategy for constructing the multimodel superensemble. This method has been applied most recently to improve large-scale NWP forecasts of the monsoon (Shin and Krishnamurti 2003; Krishnamurti et al. 1999, 2000, 2001, 2003; Mishra and Krishnamurti 2007), hurricane track and intensity forecasts (Krishnamurti et al. 1999, 2000a; Williford et al. 2003; Vijay Kumar et al. 2003), and seasonal climate forecasts (Krishnamurti et al. 2000b; Krishnamurti et al. 2006a; Chakraborty and Krishnamurti 2006). In these studies, a common result has been that the multimodel superensemble consistently provides superior forecasts in terms of forecast accuracy, compared to the participating member models. However, the usefulness of such forecasts to meet the needs of the user community is not always assured.

4. Statistical downscaling of model forecast

At FSU, we receive five-day precipitation forecasts from the operational center in real time. Model forecasts available for this study are from the operational centers National Centers for Environmental Prediction (NCEP) (U.S.), European Centre for Medium-Range Weather Forecasts (ECMWF), Bureau of Meteorology Research Centre (BMRC) (Australia), and Japan Meteorological Agency (JMA). These models are members of the FSU multimodel superensemble suite. Model forecasts are made available roughly at $1^\circ \times 1^\circ$ spatial resolution; models are first interpolated to the IMD gauge analysis grid on a $0.5^\circ \times 0.5^\circ$ lat/long horizontal resolution. We once again used the least square method of minimization of error to downscale the model forecasts on the IMD grids by performing linear regression of the models' interpolated forecasts and modified TRMM rain. For this exercise, modified TRMM rain is used as observed rain.

This procedure is followed during the entire training and forecast phases of the multimodel superensemble. During the training phase, we have a collection of 92 forecasts for each day of forecast (day 1 through day 5) for each of the member models. The observed rains for each of the validation days are also available. We perform different regressions for each separate day of forecasts, using the entire history of forecasts of the training phase. Each grid location is treated separately in these calculations. The downscaling relation is a simple linear regression expressed by

$$\text{Observed Rain} = a * (\text{Model Rain}) + b. \quad (4)$$

Slope a and intercept b of the linear regression provide useful information as the bias of forecasts for the different models for different days of forecasts for each geographical location (i.e., grid points). This entire exercise was repeated twice, once using the modified TRMM 3B42 rain and once using IMD gauge rain (on the $0.5^\circ \times 0.5^\circ$ lat/long grid).

5. Results and discussions

In a recent study, Krishnamurti et al. (2008) examined multimodel forecasts using the combination of the downscaling and superensemble. We used the IMD rains and TRMM 3B42 over India, which also carried geographically distributed slope a and intercept b separately for each day of forecast of precipitation, for days 1 through 5. These fields provided useful information on the systematic errors and the error growth of the member models. The major findings of that study were that members had different behaviors from one model to the next. Some models had excessive rains in orographic regions, while others underestimated the rain. During the summer monsoon periods, some models had excessive rain over the rain shadow regions of southeastern India, reflected in the slope and intercept parameters of these forecasts. The present study investigates how close we can make the TRMM 3B42 product to the IMD rain gauge-based product, using the proposed simple downscaling. To achieve that goal, we must demonstrate that the slopes and intercepts of the forecasts based on the two products have very similar geographical distributions. Figures 5 and 6 depict the slopes and intercepts for days 1, 3, and 5 of the member model ECMWF and JMA forecasts using the modified IMD gauge precipitation, and Figs. 7 and 8 depict those using the modified TRMM (FSU-TRMM)-based rains. These results are for only ECMWF and JMA models.

5.1 Regression coefficients (slope and intercept) of member model forecasts of precipitation against gauge rainfall estimates

The purpose of this downscaling of model forecasts towards observed rainfall estimates during the training phase of the superensemble is to obtain a higher-resolution forecast product. Such a product can be obtained for the training phase when the geographically distributed observed estimates are available. Linear regression of the model forecasts against the observed

Fig. 7. Regression coefficients of ECMWF forecasts for days 1, 3, and 5 using FSU-TRMM rain. Top panels denote slope a , and bottom panels denote intercept b . The color bar below the panels represents the coefficients' magnitude.

Fig. 8. Regression coefficients of JMA forecasts for days 1, 3, and 5 using FSU-TRMM rain. The top panels denote slope a , and the bottom panels denote intercept b . The color bar below the panels represents the coefficients' magnitude.

estimates of rain provides useful statistics on slope a and intercept b from the least-square linear regression. The statistics of a and b (geographically distributed) are next used during the downscaling of the large-scale models in the forecast phase.

A slope of 1.0 is an indication that the model forecast matches those of the IMD gauge-based rainfall estimates; a slope less than 1 implies that the model rain is higher than those for the gauge estimates. Separate downscaling of the forecasts of the member models was carried out for each day of forecast. We will illustrate the performances of the ECMWF and JMA here. The ECMWF model's forecast was first examined in the context of slope and intercept distribution with respect to the IMD gauge rainfall. Figure 5 illustrates the results for days 1, 3, and 5 of forecasts. The top panels indicate the slopes. In three regions, the slopes were large. Over the far northern parts of Kashmir near 36°N , the slopes were underestimated by the ECMWF model, where they were in the range of 0 to -0.5.

Rainfall over the orographic hills of the Western and Eastern Ghats were, in general, underestimated by the ECMWF model. Over most of India, the slopes were close to 1.0. The intercepts of the ECMWF model (Fig. 5) were generally very small (i.e., the order of 0 to -0.1). Over a few regions of central India, these intercept values were slightly larger (i.e., -0.2 to -0.4). Overall, most models had very small intercepts. The slopes of the JMA model (Fig. 6) are reasonable, in the range of $0.5 \leq 1 \leq 1.5$ for most of India. The problem areas are near the orographic region of the southwest coast of India and along the foothills of the Himalayas. In these regions, the slope error increases slowly on days 1 through 5 of the forecasts. Slopes are < 0.5 in the semi-arid regions where the model rainfall is overestimated. The intercepts indicate a systematic shift. These values are generally very small for all models. For the JMA model, these values were generally between 0 and -0.05. Over very spotty regions, the intercepts were between -0.1 and -0.05.

Fig. 9. Time series of 24 h precipitation forecasts' RMS errors. The black line with circles represents the superensemble forecast prepared using downscaled member models (Dwn MM Superensemble), and the light gray line with rectangles indicates the Superensemble forecast prepared after downscaling the large-scale superensemble (Dwn LS Superensemble).

Fig. 10. Day 1 forecast valid at 1200 Z on September 3, 2007, using FSU multimodels. The color bar on the bottom right panel indicates the distribution of rain (mm day^{-1}). The numbers at the top of each forecast box indicate the spatial correlation of the forecast with modified TRMM.

Fig. 11. Day 1 forecast valid at 1200 Z on September 5, 2007, using FSU multimodels. The color bar on the bottom right panel indicates the distribution of rain (mm day^{-1}). The numbers at the top of each forecast box indicate the spatial correlation of the forecast with modified TRMM.

5.2 Regression coefficients (slope and intercept) of member model forecasts of precipitation against modified TRMM (FSU-TRMM) rain estimates

We next consider the slope and intercept distributions for the model forecasts validated against the modified TRMM algorithms. These slope distributions exhibit somewhat smaller values than those of the slopes that were computed from the use of gauge rain. The slopes (Fig. 8) indicate that the JMA model systematically underestimates rain compared to the modified TRMM estimates. Furthermore, a spread of these values is observed by day 5 of forecasts. The intercept values are generally very small for the JMA model, regardless of gauge- or modified TRMM-based validations. Such spreads of slope coefficients were not observed as much for the ECMWF model (Fig. 7). The ECMWF models slopes were quite similar, regardless of the rain data (modified TRMM or gauge rain) used for the regression. The intercept coefficients of the ECMWF were generally quite small over the semi-arid regions of western India and parts of the Western Ghats. These corrections for the slope and intercept provide the downscaled model forecasts. These statistics are used regionally for downscaling during the forecast phase. Given these downscaled model forecasts for the forecast phase, the last step in our exercise is the construction of a multimodel superensemble for the downscaled forecast. We have included the slopes and intercepts for all of the models (JMA, ECMWF, BMRC, and NCEP) in our superensemble construction. The geographical distributions of the slopes and intercepts are not displayed for all models. Those values lie within the range of values that are displayed in this section.

5.3 Sample forecasts using the modified TRMM 3B42 algorithm

Figure 9 plots day 1 superensemble forecast errors that were computed using two entirely different approaches and compared against each other. In our first experiment, we simply made use of our large-scale models and prepared the conventional superensemble (Fig. 4) forecasts; next, referring to the past statistics of the superensemble forecasts, we used our downscaling strategy to downscale the conventional superensemble to the $0.5^\circ \times 0.5^\circ$ grid over the domain of our study. In the second experiment, we applied the downscaling strategy to the multimodels and used these downscaled multimodels for the construction of superensemble forecasts. In Fig. 9, the ordinate denotes the root mean square (RMS) errors (magni-

tude in mm day^{-1}), and the abscissa denotes the time axis (with the first value representing the 24 h forecast issued on 1200 Z 1 September 2007). The heavy black line with circles denotes the 24 h forecast errors (RMS errors) of the superensemble forecasts prepared using the downscaled multimodels (Dwn MM Superensemble), and the gray line with rectangles denotes the time series of 24 h precipitation forecast RMS errors for the downscaled large-scale superensemble (Dwn LS Superensemble) for the same period. It is clear from Fig. 9 that the superensemble forecast prepared using the downscaled member model forecasts is consistently better throughout this entire forecast period. Similar efficiencies were noted for day 2 through day 5 forecasts (not shown). Figures 10, 11, and 12 indicate the observed FSU-TRMM rainfall and day 1 forecasts from four downscaled member models, and the downscaled superensemble. These forecasts are valid for September 3, 5, and 7, 2007, at 1200 UTC. In each of these panels, we included the spatial correlation of the model forecasts and the observed rain (based on FSU-TRMM). The spatial correlation of the downscaled superensemble is invariably the highest of all the member models and the ensemble mean (ENSM) (not shown here). It is possible to improve the efficiency compared to those of the downscaled member models (e.g., correlation values for superensemble were 0.693, 0.620, and 0.633; those for JMA were 0.426, 0.262, and 0.553 for the three mentioned examples). In these figures, the mesoscale details could be provided because of the consistency of the systematic errors that were provided by the linear regression-based downscaling. Such consistency is more easily handled by the multimodel superensemble. For day 5 of forecasts, we present similar diagrams in Figs. 13, 14, and 15. These are day 5 forecasts valid on September 7, 9, and 24 of 2007 at 1200 UTC. Here we see the same levels of improvement in forecast efficiencies for mesoscale rainfall forecasts. In these three forecasts, the spatial correlations for superensemble are 0.517 for September 7, 0.481 for September 9, and 0.433 for September 24. The corresponding correlations for the JMA model's downscaled day 5 rain forecast are 0.352, 0.292 and 0.216. We noted a quite similar improvement in forecast efficiencies for each of the 30 forecasts made for September 2007. When we used the high-resolution IMD rain to validate these improvements in forecast efficiency for the superensemble, a number of questions arose in the interpretation of the above results. When we used the lower-resolution model rains that

Fig. 12. Day 1 forecast valid at 1200 Z on September 7, 2007, using FSU multimodels. The color bar on the bottom right panel indicates the distribution of rain (mm day⁻¹). The numbers at the top of each forecast box indicate the spatial correlation of the forecast with modified TRMM.

Fig. 13. Day 5 forecast valid at 1200 Z on September 7, 2007, using FSU multimodels. The color bar on the bottom right panel indicates the distribution of rain (mm day⁻¹). The numbers at the top of each forecast box indicate the spatial correlation of the forecast with modified TRMM.

were not downscaled, the spatial correlations were of the order of 0.3 for day 1 of forecasts and 0.15 for day 5 of forecasts. Those rains have a lower spatial resolution and do not have mesoscale details. Spatial correlations of the TRMM rain interpolated to a half-degree latitude/longitude with the IMD gauge rain are of the order of 0.1. Given those details, it is important for a superensemble based on downscaled models to have mesoscale spatial correlations of the order of 0.65 and 0.45 for day 1 and day 5 forecasts.

5.4 Comparison of equitable threat scores (ETSs) of various superensemble forecasts

Here we compare efficiencies of forecasts over India for the entire month of September 2007. The training phase for these forecasts included the daily forecasts for June, July, and August 2007. Figure 16 presents the equitable threat scores (ETSs) (left panels) and the bias scores (right panels) for the member models. These scores are computed using the modified TRMM rains as a benchmark. Here, the scores for the multimodel superensemble (based on downscaled models) results for BMRC, JMA, ECMWF, NCEP, ENSM, and the bias-corrected ensemble mean (BcorENSM) are included in each panel. The panels include results for days 1, 2, 4, and 5 of forecasts. The ordinate for the left panels denotes the ETSs, and the abscissa denotes the thresholds of rain rates (mm day^{-1}) (e.g., the number 15 denotes a rain rate equal to or in excess of 15 mm day^{-1}).

The left panels clearly demonstrate that it was possible to improve forecast efficiencies from the multimodel superensemble compared to all other models and including ENSM and the BcorENSM. The bias scores in the right panel have a normalized score of one for a perfect bias score. Bias score values (ordinate) above one denote an overestimation of rains for a given threshold (abscissa), and values lower than one denote an underestimation of rains. Here again, we note the best bias scores for the multimodel superensemble. For low rain rates (less than 10 mm day^{-1}), we see a high bias (greater than one); and for higher rain rates, we see a low bias (less than one). The results are very promising, considering that we were able to improve forecast efficiency even through day 5 for mesoscale downscaled forecasts.

6. Concluding remarks and future work

The use of advanced Global Telecommunication System (GTS) has helped operational meteorology immensely; however, obtaining gauge-based rainfall

observations around the globe in real time does not yet seem feasible. Operational meteorologists consider gauge-based rainfall data in real time for validation purposes, and the main objective of this study was to explore the possibility of using modified TRMM rain for real-time operations and validation. We have attempted to provide an alternative source of precipitation data that combines the positive features of gauge and satellite (TRMM) data. This data can then be used for various purposes.

Simple linear regression-based downscaling for the model forecast towards the observed estimates of rains (from the modified TRMM) removed systematic errors of forecasts quite nicely. This capability is the strength of the simple least-square-based linear regression. The systematic errors are removed at each grid location for each member model during the training phase of the multimodel superensemble. We did not try higher-order regression methods, which may be worth examining following the context of the present study. A dense rain-gauge global network may be used to improve the TRMM-based algorithm over land areas. Figure 1a depicts the vast distribution of rain-gauge sites that have been collected during Akiyo Yatagai's APHRODITE's water resources project (<http://www.chikyu.ac.jp/precip>) and that are widely used by several research groups. The present study uses dense rain-gauge data collection over India (Rajeevan et al. 2005, 2006). Our study includes the following components.

- (1) Collection of TRMM 3B42 and India rain-gauge datasets on a $0.5^\circ \times 0.5^\circ$ latitude/longitude grid.
- (2) Point-by-point statistical regression of TRMM-based rain against rain gauge rain, and preparation of a new dataset.
- (3) Downscaling of over 100 five-day forecasts from each of diverse member models.
- (4) Validation of member model forecasts against TRMM 3B42, modified TRMM 3B42, and the gauge datasets.
- (5) Construction of downscaled superensemble forecasts.
- (6) Validation of downscaled superensemble forecasts against TRMM 3B42, modified TRMM, and gauge datasets.

The most promising results are that the downscaled member models and the superensemble exhibit high skills when validated against the observed high-resolution precipitation for days 1 through 5 of forecasts. The skills from the downscaled superensemble are consistently superior to those of each member model.

Fig. 14. Day 5 forecast valid at 1200 Z on September 9, 2007, using FSU multimodels. The color bar on the bottom right panel indicates the distribution of rain (mm day^{-1}). The numbers at the top of each forecast box indicate the spatial correlation of the forecast with modified TRMM.

Fig. 15. Day 5 forecast valid at 1200 Z on September 24, 2007, using FSU multimodels. The color bar on the bottom right panel indicates the distribution of rain (mm day^{-1}). The numbers at the top of each forecast box indicate the spatial correlation of the forecast with modified TRMM.

Fig. 16. Average (September 2007) ETS and bias for member models (black line) and superensemble (red line) are calculated against FSU-TRMM rain.

The revised TRMM 3B42 algorithm over land contributes equally well as the high-resolution gauge datasets for downscaling and construction of the multimodel superensemble. This dataset has been found to be very useful for evaluating the ENSM, BcorENSM, and superensemble-based studies. A similar study can be done using a suite of mesoscale models. Such studies are necessary to explore forecast improvements for precipitation at high resolutions. A successor to the

TRMM is the Global Precipitation Mission (GPM), which will consist of a constellation of satellites to provide radar- and microwave-based precipitation estimates. The present study is an effort to propel us towards that direction.

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Table 1. List of acronyms used in this paper.

AMSR	Advanced Microwave Scanning Radiometer
AMSU	Advance Microwave Sounding Unit
BcorENSM	Bias-Corrected Ensemble Mean
BMRC	Bureau of Meteorology Research Centre
DSD	Drop-Size Distribution
ECMWF	European Centre for Medium-Range Weather Forecasts
EMC	Environmental Modeling Center
ENSM	Ensemble Mean
ETS	Equitable Threat Score
GFS	Global Forecast System
GPCP	Global Precipitation Climatology Center
HQ	High Quality
IMD	India Meteorology Department
IR	Infrared
JMA	Japan Meteorological Agency
NASA	National Aeronautics and Space Administration
NCEP	National Centers for Environmental Prediction
NOGAPS	Navy's Operational Global Atmospheric Prediction System
NWP	Numerical Weather Prediction
PR	Precipitation Radar
RMS	Root Mean Square
SSM/I	Special Sensor Microwave/Imager
TMI	TRMM Microwave Imaging
TRMM	Tropical Rainfall Measuring Mission

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