An analysis of the performance of hybrid infrared and microwave satellite precipitation algorithms over India and adjacent regions

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Abstract

The measurement of precipitation is fundamental to our understanding of the hydrological cycle. Increasingly, there exists the capacity to independently determine components of the hydrological cycle from remote sensing data. Developing techniques to combine effectively the multiple streams of information required for a water budget assessment provides a difficult challenge, particularly given the disparities in spatial and temporal scales between measurements and predictions. Two research groups, the Naval Research Laboratory Monterey (NRL) and the University of Arizona (UA), are using a combination of geostationary infrared and polar-orbiting microwave satellite data to derive 6-hourly precipitation estimates over a global 0.25° grid. We examine the performance of these two algorithms for estimating the 24-h rainfall accumulation over India and Sri Lanka for the years 2002 and 2003. The derived values are compared with observations from a network of 39 national weather stations. In addition, two locations, Minicoy in the Laccadive Islands and Port Blair in the Andaman Islands were selected as being representative of the ocean environment to compare these satellite rainfall products against measurements from local rain gauges and Tropical Rainfall Measuring Mission (TRMM) satellite data. The NRL technique was accurate to within 25% of observed precipitation for only 33% of station locations, while the UA technique was accurate to within 25% of observed precipitation for about 47% of station locations.

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1. Introduction

Given the profound influence of the Global Water Cycle on human activities, and the growing demand for water in the face of a steadily increasing human population, it is no wonder that research into all aspects of the water cycle is a high priority (NASA Earth Science Enterprise Strategy, 2003; USGCRP Water Cycle Study Group, 2001). Having studied the evidence of recent increases in natural disasters and the climate model projections of such trends, the World Meteorological Organization (WMO)/United Nations Environment Programme (UNEP) Inter-governmental Panel on Climate Change (IPCC) in 2001 concluded that more intense precipitation events were very likely in the future over many areas and would thus cause increased flash-floods, landslides, soil erosion and avalanches. The IPCC also concluded it was likely (66–90% probability) that there would be an increase in summer drying over most mid-latitude continental interiors with an associated risk of drought and an increase in intensity (but not frequency) of the strongest tropical cyclones (IPCC, 2001).

From the conditions outlined in the IPCC report, we find that a logical candidate for the study of the hydrological cycle is the Indian Subcontinent. For the purposes of this study we will focus specifically on the Bay of Bengal, the Andaman Sea, and their respective catchment areas. The Bay of Bengal is characteristically different from other tropical ocean basins of the world. Although the geographical setting is very similar to the Arabian Sea, the Bay of Bengal is vastly different from the Arabian Sea in its physical, chemical, and biological features. The prime reason for this is the immense quantities of fresh water runoff and associated sediment load it brings into the basin. In fact, the Brahmaputra, Ganges and Irrawaddy Rivers discharge approximately $1.43 \times 10^{13}$ tonnes $\text{yr}^{-1}$ of fresh water into the Bay of Bengal and Andaman Sea (Martin et al., 1981), exceeded only by three other rivers, the Amazon, Congo and Orinoco. In addition, the Bay receives annually about $70 \times 10^{10} \text{m}^3$ of net freshwater influx (precipitation minus evaporation) at the surface (north of $15^\circ \text{N}$) (Shetye & Gouveia, 1998). Defining
the surface area of the Bay of Bengal to be 2,173,010 km² (Encyclopedia of Oceanography, 1966) this amounts to an equivalent layer thickness of about 32 cm.

The dominant force in this region driving the water cycle is the Indian Monsoon System (IMS). The IMS is a large-scale atmospheric circulation that results from complex ocean, atmosphere, and land interactions. From June to October, IMS precipitation provides much needed water for this semi-arid region. The timing and intensity of the summer monsoon is critical to human health, agriculture and the economy. Extreme hydrological hazards such as flood or drought are commonplace. Indeed, in already arid and semi-arid regions like India, a small decrease in rainfall and an increase in evaporation can result in significant declines in runoff (WMO, 2004). To cope with floods on large rivers, international collaboration is necessary to provide adequate forecasts and warnings, especially in large river basins shared by two or more countries (WMO, 2004) as is the case with Brahmaputra and Ganges basins. India’s hydrologic forecasters need better tools to issue warnings of floods and to more effectively manage their water assets. Prediction and validation of IMS rainfall, therefore, becomes very important.

Finer-scale rainfall data are required to make further significant progress with hydrological models. Streamflow models need to be validated by forcing them with observed data that can resolve individual storms and catchment basins (Huffman et al., 2001). NASA’s Earth Science Enterprise Strategy (2003) envisions that by 2014 seasonal forecasts of precipitation could be made with 75% accuracy at order 10 km resolution. At present the water budget can be balanced over global scales and long-time frames to within 20% with large uncertainties on regional to local scales and seasonal to annual time frames. Precipitation itself is measured remotely from space only over the tropics while other important variables such as soil moisture and snow water equivalent are largely unknown globally.

The fundamental barrier to finer-scale estimates is the lack of accurate, dense regional data, either in situ or remote sensors. Some regions do have the possibility of detailed precipitation estimates thanks to local networks of sensors (Huffman et al., 2001). Rain gauge networks are costly to establish and maintain and there may be non-uniform standards for collection and reporting. Finally, an additional barrier is the need to work with several international partners to obtain administrative permissions and maintain routine data deliveries. Thus, for those locations around the world without the resources to establish extensive ground networks or where the process of accessing data is cumbersome, the best potential for meeting these fine scale requirements will depend on satellite-based sensors (Huffman et al., 2001). The Indian Subcontinent is one region where the use of satellite-derived precipitation could be most beneficial.

2. Satellite-derived precipitation

We can quantitatively and qualitatively describe the hydrological cycle using various satellite remote sensing data sets from either polar orbiting platforms or geostationary satellites (Kumar & Schulz, 2002). The first set of techniques for deriving precipitation are based on using visible and infrared (VIS/IR) imagery to discriminate the brightness of the cloud in the visible spectrum and/or the low temperature of the cloud top as seen in the thermal spectrum (e.g., Arkin & Meisner, 1987; Barrett & Martin, 1981; Lovejoy & Austin, 1979). Other VIS/IR techniques focus on adding sophisticated criteria such as cloud area extent, time history, and textural features (e.g., Adler & Negri, 1988; Scofield, 1987; Wu et al., 1985). The VIS/IR techniques, however, are inherently indirect depending only in a statistical sense on the presence of rain below the cloud top (Petty, 1995).

Another set of techniques rely on passive microwave (MW) sensors onboard low-Earth orbit (LEO) satellites operated by government agencies, such as the US Department of Defense-Special Sensor Microwave Imager (SSMI) on Defense Meteorological Satellite Program (DMSP) platforms (Ferraro, 1997); the National Oceanic and Atmospheric Administration (NOAA)-Advanced Microwave Sounding Unit (AMSU-B) (Ferraro et al., 2000); and the National Aeronautics and Space Administration (NASA)-Advanced Microwave Scanning Radiometer (AMSR-E) on the Earth Observing Satellite (EOS) Aqua (Wilheit et al., 2003) and the TRMM Microwave Imager (TMI) and Precipitation Radar (PR) mentioned above.

Microwave instruments respond in a more physically direct way than infrared sensors to the presence of precipitation-size water and/or ice particles within clouds while remaining relatively insensitive to non-precipitating clouds. Atmospheric transmittance windows below 20 GHz, from 30 to 40 GHz, and at 90 GHz are used for rainfall monitoring. Below 20 GHz, rainfall absorption and emission are predominant, and ocean surfaces are warmer than the background radiation. Above 60 GHz, evidence of rainfall is primarily from scattering, where areas of heavy rainfall are colder than their backgrounds.

Collocating PMW and IR satellite observations

Fig. 1. Basic concept for a hybrid algorithm, combining the superior sampling of GEO IR measurements with the more physically based measurements of LEO PMW sensors. Some averaging is necessary to account for spatial and temporal offsets (fallout rate × time = vertical height) when aligning these data on a per-pixel basis (adapted from Turk et al., 2002a,b).
Between 20–60 GHz, a combination of absorption and scattering is present.\(^1\) Besides considering sensor measurement techniques, we also need to take into account sensor sampling styles. Microwave radiometers on polar-orbiting satellites may produce reasonably accurate instantaneous estimates, but their sparse temporal sampling (generally twice a day) constrains the time/space averaging needed to reduce random errors in a regional or global precipitation dataset. Sun-synchronous polar-orbiters can introduce biases in the mean precipitation intensity because they cannot sample the complete diurnal cycle of rainfall with a single instrument. The TRMM satellite helps overcome this difficulty by having a LEO that is not sun-synchronous. Its low inclination (35\(^\circ\)) orbit will pass over a given location at progressively later local sun times. However, for numerical weather prediction (NWP) and nowcasting applications requiring a rapid-update global precipitation analysis on time scales of 3 to 6 h, the current and near-future LEO satellite systems still leave significant temporal and spatial coverage gaps. Geostationary IR methods offer the spatial and temporal sampling required for our purposes, but they also have a few drawbacks such as diurnal biases due to changing solar illumination on the satellite (Wick et al., 2002) and requiring very high angular resolution in order to achieve a reasonable surface footprint size. Unfortunately, it is this same high angular resolution constraint that effectively precludes the use of current-generation MW radiometers on geostationary platforms (Petty, 1995).

Land is very different from oceans in terms of the emitted microwave radiation, appearing to have a surface emissivity of 90%. Thus, there is little contrast to detect the “warm” raindrops. Also, the background signal from a land surface may not be as spatially uniform as an ocean surface. These factors make determining rainfall intensity over land more difficult than over the ocean.

One area of focused study is the effort by some research groups to combine MW and VIS/IR techniques into hybrid algorithms in order to exploit both the physical directness of the microwave observations and the superior sampling and resolution of the infrared data (Fig. 1). Research groups at the Naval Research Laboratory Monterey (NRL) and the University of Arizona (UA), are using a combination of geostationary infrared and polar-orbiting microwave satellite data to derive near real-time 6-hourly precipitation estimates over a 0.25\(^\circ\) grid between 60\(^\circ\)N and 60\(^\circ\)S. These estimates are produced using separate and unique algorithms that are described below. Both research teams’ products are posted on their respective Internet websites.\(^2\)

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\(^2\) NRL’s Experimental Geostationary Rain Estimation (GEO) can be found at http://www.nrlmry.navy.mil/sat-bin/rain.cgi covering 60\(^\circ\)N to 60\(^\circ\)S, and the UA’s Hydrological Data and Information System (HyDIS) Precipitation can be found at http://hydis.hwr.arizona.edu/precip/index.html covering 50\(^\circ\)N to 50\(^\circ\)S.
The purpose of this study is to compare the performance of these two algorithms for 2002 and 2003 over the Indian Subcontinent against surface weather station observations within the study area of 0°N to 30°N and 70°E to 100°E (Fig. 2). We also examine the performance of these algorithms over the ocean by comparing them against a standard level-3 NASA TRMM product. Finally, we examine the suitability of the derived rainfall data as input into regional hydrological models such as the University of New Hampshire’s Water Balance Model/Water Transport Model (Vörösmarty et al., 1989) or the University of Washington’s Variable Infiltration Capacity (VIC) macroscale hydrologic model (Liang et al., 1994) (Fig. 3) using a simulated river network (Fekete et al., 2000) (Fig. 4) to generate river discharge estimates.

2.1. NRL Monterey GEO rain algorithm

The central core process of this hybrid IR–MW technique involves localized, accurate space and time alignments of all MW and IR pixels as each MW-based sensor passes over the various geostationary satellite coverage regions. The newly acquired MW rain rate estimates are paired with their time and space co-located (within 10-km), frequently acquired geostationary IR data (10-min maximum allowed time offset between the pixel observation times). The idea is to keep track of the latest MW-based rain rate observations over 2.5° box regions, and align the probability density functions (PDFs) of these rain rates with the PDFs of the IR observations from whatever geostationary satellite is applicable. The geostationary configuration used for the study period consists of GOES-8 (western Atlantic), GOES-10 (eastern Pacific), GMS-5/GOES-9 Back-up (western Pacific), Meteosat-5 (Indian Ocean), and Meteosat-8 (eastern Atlantic).

The statistics of these observations are then updated as soon as the next MW-based sensor over pass occurs. To accomplish the updating process, histograms of the IR-temperature and MW-rain rate pairs are built for a 0.25° grid box and are accumulated until the percent coverage of a given box exceeds a threshold, currently set to 90%. The overall age of the data used typically ranges from 2–10 h. Probability matching is then performed on the histograms in each box, which adaptively tunes subsequent geostationary satellite data into rain rate estimates. Thus, the “adjustment” of the IR-temperatures to a corresponding MW-rain rate is dynamic, adapting to the rain conditions observed by the blend of MW-based sensors. So the technique statistically adapts itself to MW-based rain rates. To work as accurately as possible on an operational basis, the technique requires a real-time or near-to-real-time set of data from a constellation of 11 satellite sensors (3 SSMI, TMI, 2 AMSU-B and the 5 geostationary satellites). Lastly, forecast model winds are used along with a topographic database to apply a correction in regions of likely orographic enhancement. The method is completely autonomous, self-adapting (as long as satellite data latency time is under 2–3 h),

Fig. 3. The University of Washington’s Variable Infiltration Capacity (VIC) macroscale hydrologic model (Liang et al., 1994). Satellite-derived precipitation will be used as input $P$ into the model to derive $R$. 
and requires no user intervention. Further details are given in Turk et al. (2002a,b, 2000). Fig. 5 shows how the NRL algorithm process works.

2.2. University of Arizona PERSIANN algorithm

The fundamental algorithm is based on a neural network and can therefore be easily adapted to incorporate relevant new information as it becomes available. An adaptive training feature facilitates rapid updating of the network parameters whenever independent estimates of rainfall are available. The independent estimates are provided by the TRMM 2A12 instantaneous rain rate product, which is derived by matching the nine-channel brightness temperatures measured by the TRMM microwave imager (TMI) with model-based Bayesian estimates of these temperatures (Kummerow et al., 1998, 1996).

PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) uses a neural network function approximation procedure to compute an estimate of rainfall rate at each 0.25° × 0.25° pixel of the infrared brightness temperature image provided by a geostationary satellite every 30 min. The system scans the infrared pixel array with a 5 × 5 moving window surrounding the central pixel, and five features (pixel temperature, 3 × 3 mean temperature, 5 × 5 mean temperature, 3 × 3 standard deviation, 5 × 5 standard deviation), are extracted from this window. Next, a neural network is used to classify these five features into groups associated with different cloud spatial characteristics. For each group, a multivariate linear function mapping is developed that relates the values of the input features to the output rain rate using available satellite rainfall data. The rainfall rate at each pixel is averaged to 6-h resolution. The University of Arizona PERSIANN method is described in detail in Soroosh et al. (2000). Fig. 6 is a schematic of the PERSIANN algorithm.

3. Observational data and methods

3.1. Hybrid algorithm data

Daily rainfall accumulation data for the years 2002 and 2003 were computed from each group’s satellite precipitation product. The UA PERSIANN 6-hourly precipitation files have units of mm/6 h and are labeled according to the start of their respective six hour period in Greenwich Mean Time (GMT). So to calculate 24-h rainfall accumulation for any given day one would add up each 6-h file: 0000Z, 0600Z,
Fig. 5. The NRL GEO product uses whatever MW sensor happens to pass over a given location and compares its rain product against those from the geostationary product (here SSM/I is shown). Statistical coefficients are then updated until the next MW sensor passes over the same location. (Turk, 2003 personal communication).

1200Z, and 1800Z. Fig. 7 shows an example of a 6-h PERSIANN precipitation product. The NRL 6-hourly files, on the other hand, have units of average mm/hour per 6 h and are labeled according to the end of their respective six hour period in GMT. So to calculate 24-h rainfall accumulation for a certain day one needs to add up each 6-h file: 0600Z, 1200Z, 1800Z, and 0000Z, and

Fig. 6. The University of Arizona’s PERSIANN product uses a $5 \times 5$ moving window to capture five features. Next, a neural network is used to classify these five features into groups associated with different cloud surface characteristics. For each group, a multivariate linear function mapping is developed that relates the values of the input features to the output rain rate using available rainfall data. The rainfall rate at each pixel is averaged to 6-h resolution. Simulations using previously calibrated neural network mapping functions generate error statistics for pixels with TRMM instantaneous rainfall estimates. These error statistics are then used to adjust the parameters of the associated mapping function. (Soroosh et al., 2000).
multiply that total by 24 to be comparable to PERSIANN.

Fig. 8 shows an example of a 6-h NRL GEO precipitation product. These daily rainfall accumulations were then compared to their respective daily observed precipitation reported by surface weather stations within the area of study.

3.2. Weather station observations

Historically, both ground based radar and rain gauge data have been used for “ground truth data” for precipitation (AMSR Rainfall Validation Implementation Strategy 2001–2005 draft of January 11, 2002). However, few wide-area networks exist with a dense, homogeneous spatial coverage and time sampling fine enough to permit meaningful comparison with the fundamental “instantaneous snapshot” nature of moving platform satellite measurements. A dense, rapid-time-update rain gauge network can reduce (but not eliminate) some of the intrinsic sampling offsets typical of intermittent and sporadic rain events, e.g., the so-called “rain-sneaking-between-the-gauges” effect (Turk, 2003). While the rain gauge network used for this validation study is not very dense or rapid, we expect these shortcomings will be compensated by the continuous nature and large area extent of the Indian Summer Monsoon.

Indian weather station data came from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (NCPC) and NOAA’s National Climatic Data Center (NCDC). There are 79 stations covering the Indian Subcontinent available online at the NCPC Global Precipitation Time Series website. The data are divided into two regions Pakistan/Northern & Central India (Fig. 9a), and Southern India/Sri Lanka (Fig. 9b). We will consider only reporting stations from India (56) and Sri Lanka (5) within the area of study, thus we will not include station 10 Khanpur, Pakistan shown in Fig. 9a. Indian stations 14–17 (Srinagar, Amritsar, Patiala, and Dehra Dun) are just north of the area of study and station 31 (Bhuj) is just west. This leaves a total of 61 stations to consider.

The NCPC’s Global Precipitation Time Series are available only in graphical form, but they show clearly the yearly progression of rainfall. Fig. 10a and b show the daily rainfall for Port Blair, in the Andaman Islands for 2002 and 2003. The accumulated actual rainfall (thick line) can be compared easily against the accumulated climatological mean rainfall (thin dashed line). Regions shaded green show precipitation surpluses; regions shaded brown show precipitation deficits. Blank areas indicate missing data. Since these images are not archived by NCPC they must be downloaded within a limited window of opportunity.

Daily rainfall accumulation data in numerical form were downloaded from the NCDC Climate Visualization (CLIMVIS) Global Summary of the Day version 6 dataset (Example data not shown). According to the NCDC website, version 6 data (available from January 1994 onward) incorporate enhancements to the precipitation data (not publicly listed). These data are referenced to GMT similar to the satellite data.

There are a total of 103 stations listed on the CLIMVIS website covering the Indian Subcontinent, 92 for India, and 11 for Sri Lanka. Only 86 stations listed for India are within the area of study. Twelve stations (11 India, 1 Sri Lanka) did not have the minimum of 5 days of data required for display and data download, leaving a maximum of 85 stations available to consider. The two sets of weather station observations provide a useful quality control check on one another, so we use only stations that are common to both sets. All stations except two (Calicut and Trivandrum, India) listed with the NCPC website are also listed on the NCDC website. Of the 57 remaining common NCPC/NCDC stations (52 India, 5 Sri Lanka) 4 stations are missing NCPC charts for either 2002 or 2003 Jabalpur, Indore, East Akola and Sholapur. No NCDC data exist for the Sri Lankan station Mannar. This leaves 49 Indian stations and 4 in Sri Lanka. The final quality control check is to consider only those remaining stations that have 60 days or less of missing NCDC data in each year. This cuts another 9 Indian stations from the data set and all 4 Sri Lankan stations (each missing between 212 and 228 days of NCDC data). After applying

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each of these criteria we are left with 40 Indian stations for testing the performance of the NRL and UA satellite precipitation algorithms. There is one station (Nellore) that has no recorded rainfall in the NCDC numerical data but has a regular seasonal rainfall pattern in the NCPC graphical data. Removing Nellore leaves 39 stations.

The NRL product had no missing data for 2002 and several days of missing data for 2003, while the PERSIANN product had only a few days of missing data in each year. This study will focus only on days having data common to all three data sets (i.e., only those days that have rain data from each source will be compared).

Fig. 9. a, b. Northern and Central India and Pakistan station locations (left) as well as the Southern India and Sri Lanka station locations (right) listed on the NOAA Climate Prediction Center global precipitation monitoring website. http://www.cpc.ncep.noaa.gov/products/global_monitoring/precipitation/global_precip_accum.shtml.

Fig. 8. The NRL GEO 6-h product for November 7, 2003 0000Z.
3.3. Performance characterization methodology

Performance by each of the satellite algorithms were characterized into three basic types: underestimation, overestimation and approximately equal (within 10%), and a given station could have various combinations. The data were characterized into 9 groups of algorithm performance for the years 2002 and 2003. For each station a series of operations were conducted: (1) raw daily rainfall accumulations, (2) raw accumulated rainfall through the year, (3) common data daily rainfall accumulations, (4) common data accumulated rainfall through the year, (5) histogram of common data rainfall intensities, (6) common data daily satellite algorithm rainfall minus daily observed rainfall (common daily difference error), and (7) accumulated common daily difference error through the year. Figs. 11a–d and 12a–c show these seven characteristics for WMO station #428090 Calcutta, India. Table 1 shows the results for the 39 criteria stations described in Section 3.2 based on the year-end common data accumulated rainfall (item #4).

Examples of stations in groups 1, 2, 8 and 9 are shown in Fig. 13a–d.

3.4. Oceanic rainfall data

To continue our study of the hydrological cycle for the Bay of Bengal and Andaman Sea, we need also to quantify the contributions of rain to the ocean. The satellite-derived precipitation products from NRL and UA can also be used for this purpose. We examine the performance of these algorithms by comparing them against the standard NASA TRMM level-3 product, 3B42.

The TRMM satellite, launched in 1997, was designed specifically to provide improved observations of rainfall over the oceans. A visible/infrared instrument (Visible and Infrared ScannerVIRS) was incorporated to establish a connection between TRMM and operational geostationary platforms, thus allowing TRMM to serve as a “flying rain gauge” (Kummerow et al., 2000).

Comparison of TRMM-based estimates of rainfall with independent, surface-based measurements over both ocean and land is a way of understanding the validity of the TRMM retrievals. For oceanic validation data, the TRMM Science Team used monthly atoll rain gauge data from the Comprehensive Pacific Rainfall Data Base (Morrissey et al., 1995) and ground-based radar estimates from the Kwajalein primary validation site (Schumacher & Houze, 2000). Kwajalein is the only permanent site where ground-based radar coverage is almost entirely over water. A key component to the TRMM validation effort was the comparison of TRMM rainfall products to the pre-TRMM state-of-the-art global precipitation analysis of the Global Precipitation Climatology Project (GPCP; Huffman et al., 1997). These atoll rain gauge data were analyzed in 2.5°×2.5° boxes similar to the GPCP analysis grid. TRMM 1°×1° rainfall products were smoothed to 2.5° for comparison (Adler et al., 2000). The TRMM
product and GPCP estimates showed significant scatter in comparison with the atoll rain gauge analysis with a near-zero positive difference (1 mm month$^{-1}$) for the TRMM analysis and a larger, negative difference for the GPCP analysis ($-26$ mm month$^{-1}$). Adler et al. (2000) stated that if the atoll rain gauge estimates are representative of the open ocean surrounding the atolls, then their statistics would lead to a tentative conclusion that the TRMM estimates were very good in terms of absolute magnitude. However, the Kwajalein radar observations (adjusted by gauges) suggested that the TRMM estimates were high by 21%. The GPCP estimates, on the other hand, were low compared to the atolls and roughly (within 6%) matched the Kwajalein results (Adler et al., 2000).

In a similar fashion, we selected two locations—Minicoy station in the Laccadive Islands and Port Blair station in the Andaman Islands as being representative of the ocean environment to compare the NRL and UA satellite algorithms against TRMM. Despite a lingering question on how representative atoll/island reports are of the open ocean (Adler et al., 2000), we feel these two stations should still provide a more valid ocean example than any continental land station. While the Port Blair station is nestled near some mountains, the
Minicoy station is on an atoll similar to the Kwajalein validation site.

The TRMM data set chosen was the standard level-3 3B42 product obtained from NASA’s TRMM Online and Visualization and Analysis System (TOV AS) website. Descriptions of each algorithm used to create TRMM products are available from the TRMM Data and Information System (TSDIS) and the TRMM website. The 3B42 product is based on the Adjusted Geostationary Operational Environmental Satellite Precipitation Index technique described by Adler et al. (1994).

The online data are available for latitudes from 40°S to 40°N (the latitudinal range of the TRMM satellite) with spatial resolution of 1° × 1° and 24-h temporal resolution. Daily accumulated rainfall in ASCII format was downloaded and formatted in the same fashion as the rainfall observations from the weather stations. There were no missing days of TRMM data from this website (example data not shown).

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5 NASA TOVAS website: http://lake.nascom.nasa.gov/tovas
4. Results

4.1. Hybrid algorithms versus observations

Fig. 14a,b show the number of stations meeting the selection criteria described in Section 3.2 where the hybrid algorithms either underestimated, overestimated, or were approximately equal to the observed daily rainfall (±10% — dotted red, ±25% — dashed magenta). The performance for the satellite algorithms is summarized in Fig. 14a for calendar year 2002 and in Fig. 14b for calendar year 2003.

The NRL GEO product behaves similarly for both years. For the 39 land stations the ratio of overestimation to underestimation is about 1:1 with a slight bias to overestimation. The NRL product is accurate to within 10% of the land stations only about 17% of the time. By expanding our definition of acceptable accuracy to be ±25% of observed precipitation, we find the NRL product to be accurate for only about 47% of land station locations.

In 2002 PERSIANN was approximately equal for 31% of the stations while for the remainder of other stations, overestimation was more common than underestimation by a factor of ~3:2. In 2003, PERSIANN was approximately equal for only 8% of the stations. The remainder of the stations showed a shift in the other direction with the UA product overestimating by a ratio of about 5:4. For both years combined the PERSIANN product is accurate to within 10% of the land stations only 19% of the time. By expanding our definition of acceptable accuracy to be ±25% of observed precipitation, we find the UA product to be accurate for about 47% of station locations.

4.2. Hybrid algorithms versus TRMM 3B42

For 2002 at Port Blair (Fig. 15a) the TRMM 3B42 product begins to diverge around yearday 195 underestimating the rainfall as does the PERSIANN product. The NRL product closely matches the station observations until about yearday 260 when it starts to underestimate the rainfall. All products show divergence around yeardays 260 and 325. For 2003 (Fig. 15b) the NRL product grossly underestimates the rainfall for most of the year showing the largest divergence on yeardays 85, 150, and 260. The PERSIANN product more closely matches the observed rainfall than the NRL product but it also shows large divergence the same yeardays. The TRMM 3B42 product does the best in matching the weather station rainfall observations but also misses the heavier rainfall on yearday 85, 150, and 260. Its performance is better through the end of the year.

For 2002 at Minicoy (Fig. 15c) both the NRL product and the PERSIANN product perform remarkably well in comparison to the observed rainfall and in comparison to each other. The TRMM 3B42 product on the other hand greatly overestimates the rainfall showing large divergence on yeardays 160, 215, 280, and 310. For 2003 (Fig. 15d) all the satellite derived rainfall products do relatively well with the PERSIANN product just slightly underestimating due mainly to missing the heavy rainfall around yearday 85.

4.3. Effects of geography and elevation

Although rain gauge data are taken here as the reference standard, they have sources of inaccuracy. This includes effects of local orography. Given the overall performance results from our study, we wanted to see if there were any localized effects that could explain some of the distribution. The relationships between the NRL and UA hybrid algorithm performance and their geographical location and elevation are shown in Figs. 16a–d and 17a–d. The hybrid algorithms underestimate significantly the observed rainfall for those stations located on the Indian west coast; one clear example is that of Bombay (Mumbai) (Fig. 13a). In the opposite case the hybrid algorithms overestimate the observed rainfall for those stations located on the Indian east coast. Some of these stations (Kakinada, Nellore, and Cuddalore, India) show no recorded precipitation a yearly accumulation of rainfall of 675 & 1075 mm (Kakinada), 1050 & 890 mm (Nellore), and 1125 & 1000 mm (Cuddalore) for 2002 & 2003, respectively. When we take these observed values and compare the hybrid algorithms again we find they perform as shown in Table 2.

Using the graphical NCPC data we see that there is a systematic difference between the years 2002 and 2003. The three stations show the NRL and UA algorithms estimating the accumulated rainfall in a similar fashion for 2002, but behaving very differently for 2003. Indian Meteorological Department records indicate that the Summer Monsoon rainfall over India during July 2002 was the lowest since rainfall records have been available with the 2002 summer seasonal rainfall 19% below normal (Srivastava et al., 2004). While for July 2003, climate monitoring products from NCDC show large positive precipitation anomalies (~80–100 mm) for the southeast coast of India. Thus, it appears that the NRL and UA algorithms
exacerbate the actual rainfall trend. The algorithms could be picking up on the decreased amount of cloud cover and then decreasing further the amount of rainfall produced by these clouds by using inappropriate assumptions of the cloud microphysics. Another possible explanation could be that the constellation of available LEO MW sensors used to dynamically adjust the GEO IR rainfall estimates was different in 2002 than it was in 2003, making the algorithm performance characterization between the two years less valid.

These values above do not account for any missing data from the hybrid algorithms as this would be impossible to find the corresponding days in the NCPC graphical data. By using the NCPC data in locations where the NCDC data were suspect, the performances of the hybrid algorithms did not improve in absolute accuracy (i.e., increase the number of stations within 25%), but did improve relative accuracy by reducing the numbers of stations being excessively overestimated to zero. The three examples listed above also illustrate one of the problems associated with surface observations — whether they can be relied upon being reported, archived or even shared within institutions completely and accurately. Indeed, the NCPC data are not subjected to the

Fig. 13. a, b. Type 1 — both NRL and UA underestimate (top left). Type 2 — NRL approximately equal, UA underestimates (top right). c, d. Type 8 — NRL approximately equal, UA overestimates (bottom left). Type 9 — Both NRL and UA overestimate (bottom right).
same quality controls as the NCDC data (John J. Bates, NCDC, 2005 pers. comm.). Another local effect apparent in the data can be seen with Coimbatore, India (Fig. 13d). This station is located in what looks like a “rain shadow” caused by the nearby mountains. This could explain why the hybrid algorithms both significantly overestimate the observed rainfall.

The influence of elevation showed no clear patterns with both algorithms having about the same distribution of under and overestimation throughout the elevation range of the criteria stations (Fig. 17a–d).

5. Discussion and conclusions

The NRL and UA precipitation products provide greater spatial and temporal resolution than the standard level-3 NASA TRMM products (1° × 1° daily or monthly) that are currently available. Indeed, the 0.25° × 0.25° resolution allows individual pixels to be matched with individual land reporting stations and will fit within the 0.5 grid domain of a simulated river network. There is a fine balance between grid size and time scale as the correlation between satellite rainfall intensities and rain gauge observations falls off rapidly below 24-h and 1°. Turk et al. (2002b) found that the correlation drops below 0.5 close to these time-grid size pairs: 12-h at 0.25°, 6-h at 0.5°, 3-h at 0.75°, and 1-h at 1°.

Problems occur when comparing 0.1° individual satellite observations to ≤ 1 m² rain-gauge measurements (e.g., sporadic rain, location of rain gauge, topography, etc). Despite careful efforts to provide climate quality validation data, ground-based measurements themselves have limitations. The greatest shortcoming is in the treatment of uncertainties, particularly when applied to relatively few satellite overpasses containing rainfall in any given month. In our case study this shortcoming is alleviated during the Indian Summer Monsoon and for the near year-round rainfall found over Sri Lanka and the southern tip of India. The ground validation (GV) paradigm of radars and individual rain gauges has been effective at verifying to first order that satellite precipitation algorithms are not making any egregious errors. Indeed, validation studies in the late 1980s and early 1990s proved the GV paradigm could differentiate between products that often differed by more than a factor of two (AMSR Rainfall Validation Implementation Strategy 2001–2005 draft of January 11, 2002).

However, the TRMM validation program found that more subtle biases, in the 10–20% range, are very difficult to detect in this manner due to the problems inherent with these ground-based observations. If only the area over the rain gauges is considered, the TRMM team estimated that 2–3 years of data would be required in even the rainiest locations before random errors reduce to less than 10%. Even subtle topography or urban influences can cause systematic differences in excess of 20% (AMSR Rainfall Validation Implementation Strategy 2001–2005 draft of January 11, 2002).

Other errors can come from missing data from individual satellite passes. Even with a full constellation of LEO satellites a three-hour latency period can exist before these data are manifested in the hybrid algorithms (Turk, 2003). Light rain conditions pose another type of problem due to the MW rain/no-rain screening techniques used (Turk et al., 2002a). Under certain conditions, light rain can be misidentified over land surfaces that scatter radiation similarly to a precipitating cloud. Likewise an opposite effect can occur when the screen fails to identify regions of light rain.

Fig. 14. a, b. Scatter plot showing satellite algorithm performance versus NCDC observation for 2002 (left) and 2003 (right). ±10% is shown by the dotted red line and ±25% is shown by the dashed magenta line.
One type of rain that produces relatively few, if any, large ice particles is the persistent orographic rain encountered on sloping terrain in the tropics and subtropics, especially over parts of India and elsewhere in tropical Asia during the Summer Monsoon. In these situations, collision–coalescence is thought to be an important mode of precipitation formation, and ice particles may occasionally be absent altogether (Petty, 1995). Petty (1999; J. Climate) has also undertaken an initial survey of the apparent prevalence of rain from warm-topped clouds and found it to be non-negligible in at least certain parts of east Asia and the western Pacific. This applies directly to the stations on India’s west coast. However, for our current purposes, these same coastal stations lie outside the watershed basins that drain into the Bay of Bengal. While the NRL algorithm makes an orographic correction, the method used is ad hoc and under corrects in steep small-scale topography (Turk, 2003). In general, though, this study shows that rainfall of this type can be observed at least somewhat reliably over large portions of the Indian Subcontinent using hybrid IR/passive MW (PMW) techniques.

While hybrid algorithms reduce sampling errors, other sources of uncertainty in rainfall retrievals associated with...
PMW sensors also exist. These include beam-filling error (sub-pixel inhomogeneity in the rainfall field), uncertainty in the vertical distribution of hydrometeors, and errors in estimating the freezing level. The determination of the freezing level is important due to the inversion problem of converting brightness temperatures into surface rain rates. This involves two steps: 1) retrieving a profile of precipitating hydrometeors from the measured brightness temperatures, and 2) relating the hydrometeor profile to a surface rain rate (usually by applying an assumed fall speed to the hydrometeor profile). The inversion problem, however, is often under-determined, meaning that the same set of brightness temperatures may correspond to several different profiles of precipitating water and ice (Wilcox, 2002). The hybrid algorithms address these issues with a statistical approach in the case of NRL and with the use of a neural network in the case of UA PERSIANN.

In the future, as model and measurement resolution time and space scales shrink, three-dimensional cloud effects will need to be taken into account. At fine scales, cloud morphology and satellite-view geometry become important. Cloud-resolving radiative transfer models as well as high-resolution remote sensing approaches are required to capture these effects.
resolution, limited area numerical models of cloud dynamics need to be developed or improved. From such models it is possible to generate candidate profiles of precipitating hydrometeors, and corresponding simulated brightness temperatures, to compare with observed brightness temperatures (Wilcox, 2002). With the proposed international Global Precipitation Mission (GPM), satellite view geometries will also be a factor. For example, when the AMSR-E sensor passes over a given location followed by a GPM sensor a few minutes later, these sensors despite having the same zenith angle would have different azimuth angles due to their different swath paths and thus have different view geometries. This becomes important with satellites using narrower beam width channels (\textasciitilde 85 GHz) sensing higher in clouds (more horizontal variation) and follow-on satellites using wider beamwidth channels (\textasciitilde 10, 19 GHz) sensing lower in clouds (less horizontal variation) (Bidwell et al., 2002).

Table 2

India east coast station performance

<table>
<thead>
<tr>
<th>Station</th>
<th>2002 Performance</th>
<th>2003 Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kakinada, India</td>
<td>NRL +3% in 2002, (-44% in 2003)</td>
<td>UA +7% in 2002, (-22% in 2003)</td>
</tr>
<tr>
<td>Nellore, India</td>
<td>NRL (-36% in 2002, -11% in 2003)</td>
<td>UA (-29% in 2002, +14% in 2003)</td>
</tr>
<tr>
<td>Cuddalore, India</td>
<td>NRL (-53% in 2002, -51% in 2003)</td>
<td>UA (-58% in 2002, -32% in 2003)</td>
</tr>
</tbody>
</table>

Fig. 17. a, b. NRL elevation versus performance for 2002 (top left) and 2003 (top right). c, d. UA elevation versus performance for 2002 (bottom left) and 2003 (bottom right).
Despite the limitations mentioned above, the NRL Monterey GEO and University of Arizona PERSIANN data sets reproduce well the progression of the seasonal rainfall. They also reproduce the natural variability of daily rainfall accumulation. While these hybrid algorithms may not reproduce each day’s rain-gauge recorded rainfall quantities they are adequate on a watershed/catchment area scale where time delays exist between a specific rainfall event and its eventual drainage into a stream/river network as runoff. These products should prove to be especially useful for estimating precipitation in regions with no, or unreliable, surface reporting stations and as “gap-fillers” in between radar coverage.

Gottschalck et al. (2005) conducted a comparison study of various precipitation data sets, including PERSIANN, to determine the best precipitation forcing for Global Land Data Assimilation System (GLDAS) simulations for the continental USA. They found that PERSIANN had the largest overall errors during the March 2002–February 2003 study period. PERSIANN typically underestimated rainfall on the west coast and overestimated rainfall in the US central and eastern regions. However, during the summertime, PERSIANN performed better than NWP models, capturing the timing of intra-daily and inter-daily precipitation associated with mesoscale convective systems. They found that large differences in precipitation forcing lead to large differences in land surface states such as soil temperature and soil moisture with the land surface models “dampening” the impact somewhat. Unfortunately, Gottschalck et al. (2005) did not generate surface runoff or river discharge estimates from these simulation runs.

Given the mixed results from the Gottschalck et al. (2005) study, we find that satellite-derived precipitation products, such as those from NRL and UA, should still be well-suited as input into hydrological models for the purposes of generating river discharge estimates. This is especially true for application during the Indian Summer Monsoon season when the rainfall is of high intensity, long duration and relatively uniform over large area extent. Indeed, one of the main motivations for assessing satellite-derived rainfall products is to provide a counter argument to one view held by the Hydrology community — namely, that since the accuracy of river discharge estimates are in the range of 10–20% (Fekete et al., 2000) and that since this level of accuracy is much higher than what can be achieved in measuring precipitation (Hagemann & Däumenil, 1998), “it would be desirable to develop new techniques, which could incorporate discharge estimates into the estimation of distributed precipitation” (Fekete et al., 2000). Instead of the traditional approach of estimating runoff from precipitation data (Runoff, $R = \text{runoff coefficient}, \ w \times \text{Precipitation}, \ P$), it was suggested that the inverse calculation be used to estimate precipitation from runoff data ($P = 1/\ w \times R$). The next step will be to take these satellite rainfall products, enter them into hydrological models and compare the resulting discharge estimates to discharge observations.

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References


NASA earth science enterprise strategy (2003).


