Satellite Rainfall Estimation Using Combined Passive Microwave and Infrared Algorithms

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(Manuscript received 10 October 2002, in final form 30 April 2003)

ABSTRACT

The development of a combined infrared and passive microwave satellite rainfall estimation technique is outlined. Infrared data from geostationary satellites are combined with polar-orbiting passive microwave estimates to provide 30-min rainfall estimates. Collocated infrared and passive microwave values are used to generate a database, which is accessed by a cumulative histogram matching approach to generate an infrared temperature–rain-rate relationship. The technique produces initial estimates at 30-min and 12-km resolution ready to be aggregated to the user requirements. A 4-month case study over Africa has been chosen to compare the results from this technique with those of some existing rainfall techniques. The results indicate that the technique outlined here has statistical scores that are similar to other infrared/passive microwave combined algorithms. Comparison with the Geostationary Operational Environmental Satellite (GOES) precipitation index shows that while these algorithms result in lower correlation scores, areal statistics are significantly better than either the infrared or passive microwave techniques alone.

1. Introduction

Water in the form of precipitation is a valuable commodity and therefore the monitoring of it, and the subsequent management of freshwater resources, is economically important and internationally sensitive. Unfortunately rainfall, unlike other meteorological parameters, is highly variable both spatially and temporally, with precipitation limited to a few percent of the earth’s surface at any one time. Surface-based observation of precipitation is accomplished primarily by gauges and, where economically viable, by radar. Over the world’s oceans these measurements are often nonexistent, and even over the land areas the coverage from surface observations is not uniform. Estimates of rainfall from satellite data address this shortcoming in that they provide spatially uniform coverage over both land and ocean; however, comparisons between the available surface observations and satellite-based estimates are complicated by the nature of the measurements from gauge data: rainfall is conventionally measured as an integral of time at a point in space, whereas satellites measure an integral of space at a point in time. Radars can provide measurements similar to satellite-based systems, but suffer from reflectivity to rain-rate conversion errors and limited spatial coverage.

There is an increasing demand for improved rainfall estimates from satellite systems throughout the entire range of scales in space and time, from global–climate down to local–instantaneous resolutions. Applications requiring rainfall products cover a range of hydrometeorological sciences, including water resources, flood forecasting, numerical weather prediction, and moisture budgets. To meet these demands a range of techniques has been developed to produce estimates of rainfall from satellite data. Visible (Vis) and infrared (IR) techniques...
rely upon the information provided by cloud-top characteristics and although the cloud-top to rain-rate relationship is not direct, they have the advantage of frequent observations. In addition, since clouds are larger and last longer than individual rain events a pseudo time integration of rainfall is possible enabling better satellite-gauge comparisons. Rainfall estimates produced by techniques using passive microwave (PM) data are more direct since they are primarily sensitive to the concentration of ice particles or droplets associated with precipitation. However, since PM observations are less frequent than Vis–IR observations they suffer from larger sampling errors when dealing with short-term rainfall estimates.

A number of intercomparison projects have taken place to assess the validity of satellite estimates at different spatial and temporal scales (see Ebert et al. 1996; Adler et al. 2001). Results from the third Global Precipitation Climatology Project (GPCP) Algorithm Intercomparison Project (AIP-3), summarized by Ebert and Manton (1998), showed that the PM estimates produced the best instantaneous results and the IR-based estimates provided the best long-term estimates. This was consistent with earlier work (e.g., Adler et al. 1993), which noted that the combination of the frequent observations of the IR with the accuracy of the instantaneous PM data would be advantageous.

This paper outlines a technique that provides PM-calibrated IR estimates of precipitation at a high spatial and temporal resolution. Unlike other combined techniques that produce coefficients at monthly or large spatial scale, this technique uses short-duration local calibration. Two scenarios are presented using an operational and a climatological–historical calibration. These, together with two other satellite estimates—the Geostationary Operational Environmental Satellite (GOES) precipitation index and PM estimates—are compared with gauge data over Niger.

2. Background

The development of Vis and IR techniques has a long history and relies upon the relationship between cloud-top characteristics and the rainfall falling from their bases. Although this relationship can be somewhat tenuous many techniques have been developed. One of them, which has become an operational technique, is the GOES precipitation index (GPI; Arkin and Meisner 1987). The technique relies upon the fraction of cloud colder than 235 K in the IR with a fixed rain rate and, although simple, provides a useful benchmark by which to assess other algorithms. More complex algorithms have been developed with varying degrees of success. Recent techniques have included the operational GOES IR rainfall estimation technique, or Auto-Estimator, described by Vicente et al. (1998, 2001) and the GOES Multispectral Rainfall Algorithm (GMSRA) described by Ba and Gruber (2001). The Auto-Estimator utilizes data from the GOES 10.7-μm channel through a regression against radar to generate rainfall estimates, while the GMSRA uses all five channels from the GOES instrument. Information provided by the growth rate of clouds and the spatial gradients is used to discriminate between rain clouds and nonraining cirrus clouds, with the GMSRA incorporating cloud-top particle information. Both techniques use an additional moisture correction factor to account for evaporation of rainfall falling from the clouds and not reaching the surface. Correlations between the surface data and the Auto-Estimator were slightly less than that of the GPI but substantial improvements are seen in the bias and rmse. Similar improvements were seen with the GMSRA not only in the rmse and bias, but also the correlation (Vicente et al. 1998; Ba and Gruber 2001).

The main drawback, however, of IR-based techniques is that they infer the surface rainfall from the cloud-top characteristics. However, more direct measurements of rainfall are possible with algorithms utilising PM data. These algorithms exploit the observation of the hydrometeor particles themselves (rather than the cloud tops) to produce estimates of rainfall. Over oceans these techniques rely upon increased radiation emitted from hydrometeors over a radiometrically cold surface. However, over the radiometrically warm land surfaces the emission signal is obscured necessitating the use of higher frequencies that utilize the scattering signature resulting from ice at the top of the rain column. Although the reliance upon ice scattering is less direct than the emission technique, it is more direct than the IR data, and benefits from the improvement in spatial resolution at higher microwave frequencies. Current PM sensors used for estimation of rainfall include the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave Imager (SSM/I) and the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI). The SSM/I is a (near) polar-orbiting sensor, and although there are usually two or three usable sensors at any one time resulting in a maximum of six overpasses per day, some regions receive only one overpass per day. The addition of the TMI sensor, in a low inclination orbit, only provides a modest increase in the daily coverage. Results from the series of Precipitation Intercomparison Projects (PIP) (Barrett et al. 1994; Smith et al. 1998a; Alder et al. 2001) and the Algorithm Intercomparison Programme (AIP) (Ebert et al. 1996) showed that the PM algorithms are more accurate than the IR-based algorithms in terms of instantaneous rainfall estimates. However, the IR techniques provide better long-term estimates than the PM techniques due to better temporal sampling: geostationary IR data nominally provides 48 samples each day (from Meteosat) compared with a maximum of 6 from the SSM/I sensors. Adler et al. (1993) noted that opportunities exist to improve precipitation estimates by combining two types of data so that the strengths of individual algorithms are maintained rather than the weaknesses.
Several forms of combined IR–PM techniques have been devised to exploit the individual strengths of the IR and the PM data. Adler et al. (1993) modified the GPI and the convective–stratiform technique (Adler and Negri 1988) rain-rate values by comparing the IR results with that of an 85-GHz-based algorithm over monthly timescales. This work has been extended to multisensor combined precipitation techniques currently employed by the GPCP (see Huffman et al. 1997, 2001), which combine estimates by using weights based upon error estimates assigned to the individual components derived from monthly rainfall products. Kummerow and Giglio (1995) tested both fixed IR/variable rain-rate and variable IR/fixed rain-rate techniques over the Pacific atolls, again based upon monthly relationships. The Universally Adjusted GPI (UAGPI), described by Xu et al. (1999) used the scattering index (SI) of Ferraro and Marks (1995) to produce an optimal IR rain/no-rain threshold and optimal conditional rain rates in order to reduce the total error between the IR-based and the PM-based rainfall estimates. These techniques have a similar methodology: the adjustment of the IR product by the PM product(s). Other methods use the PM rainfall retrievals to calibrate against the IR temperatures so that the IR temperatures alone can be used to generate the rainfall. Kidd (1999) describes the calibration of the IR temperatures over the AIP-3 region while Todd et al. (2001) generated calibrations over Africa using a moving 1° x 1° window to generate 0.25° x 0.25° calibrations. Miller et al. (2001) developed a technique that generates rainfall from IR data using a linear brightness temperature ($T_b$) to rain-rate relationship.

The common problem with the IR–PM techniques has been the choice of the calibration domain. Many techniques, such as Adler et al. (1993) and Xu et al. (1999), use temporal domains spanning entire months to provide robust calibrations. However, while the monthly calibrations will reflect the climatological variations in the IR–PM relationship they do not respond to the sub-monthly changes in the relationships. Instantaneous calibrations based upon coincident IR–PM values have been utilized by Miller et al. (2001) and Turk et al. (2000), and have the advantage of responding to changes in the calibration over short-term periods. Since the number of samples is much less for instantaneous calibration methods the spatial domain size needs to be increased. In the case of Turk et al. (2000) calibrations are generated on a 5° x 5° basis within a 15° x 15° moving window. There is therefore a tradeoff between the temporal and the spatial detail possible from the data used for calibration purposes. Todd et al. (2001) noted that the choice of the domain over which the calibration is generated could be critical in the accuracy of the final rainfall product. Kummerow and Giglio (1995) ably outlined the shortcomings of the different calibration regimes: if the most recent satellite information is used to generate the calibration coefficients, which are then applied until the next satellite overpass, the coefficients may not be representative of data for the period over which they are applied. Conversely, a more stable method of accumulating rainfall based upon monthly calibration coefficients does not necessarily preserve the rain volume (Kummerow and Giglio 1995).

More importantly, the latter technique provides only a climatological calibration and may not respond adequately to variations in the meteorology.

More recently the use of neural networks to combine IR and PM data has been explored by Sorooshian et al. (2000) and Bellerby et al. (2000) using a combination of GOES-IR and TRMM data. The Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) technique, described by Sorooshian et al. produces rainfall estimates using a single IR channel at a nominal resolution of 0.25° x 0.25° every 30 min using five feature parameters, and training regions based upon a mosaic of overlapping subareas. Bellerby et al. took four channels of GOES data together with temporal information in order to take advantage of available spectral and temporal information.

The results from the application of the IR–PM techniques are variable due to the regions over which they have been tested. Most of the techniques indicate reduced rmse and bias compared with the GPI technique (Adler et al. 1993; Kummerow and Giglio 1995; Xu et al. 1999) and similar or slightly worse correlations (Xu et al. 1999; Miller et al. 2001). Todd et al. (2001) note that the application of the Microwave-IR Rainfall Algorithm technique over the Etude des Precipitations par Satellite (EPSAT) gauges in Africa produced a daily 1° x 1° correlation of 0.96, exceeding the correlations of the GPI and the UAGPI; however, when the products were compared with the Global Precipitation Climatology Centre (GPCC) pentad dataset poorer correlations than the GPI and UAGPI were found.

The technique presented here is based upon earlier work of Kidd (1999). This study focused on the combination of IR and PM information over the AIP-3 study region in the western Pacific. Using the region coincident with the radar coverage, a number of periods were investigated to evaluate the optimal period for the calibration of the IR brightness temperature with rain rates derived from passive microwave rain retrievals. Four calibration scenarios were evaluated ranging from the entire period (four months), three periods defined by the three cruises, instantaneous (i.e., for each satellite overpass), and a minimum rainfall occurrence. While the overall relationship was represented by the calibration derived over the entire period, variability in the shorter-term calibrations suggests that a single calibration would not be appropriate. The use of the instantaneous calibration produced significant overpass-to-overpass variations in the calibration. However, Turk et al. (2000) use such a scheme but with a calibration region of 5° x 5° with a 15° x 15° moving window, compared with the AIP-3 radar region of about 1.5° x 1.5° equivalent:
the variations in the relationship caused by the number of samples are reduced by selecting a large spatial calibration domain. However, since the calibration is instantaneous, the PM data may introduce a diurnal bias that is kept until the next overpass. Todd et al. (2001) noted the choice of the domain over which the calibration is generated could be critical in the accuracy of the final rainfall product. The final calibration scenario studied by Kidd (1999) was a minimum rainfall occurrence scheme that necessitated a minimum number of raining data to be included in the calibration dataset. The advantage of such a method is that sufficient rain values are available for the calibration to be generated effectively: the disadvantage is that the period over which the calibration is generated is determined by the rainfall events, so that if little rainfall occurs the calibration period can be unacceptably long. The results using this minimum rainfall occurrence calibration scheme indicated that for instantaneous rainfall retrievals the combined technique had a similar correlation as the GPI using a frequency difference algorithm as the PM calibration source, but poorer correlations when using the Goddard Profiling algorithm (see Kummerow et al. 2001) and the scattering index (Ferraro and Marks 1995). The frequency difference algorithm used here is outlined by Ebert et al. (1996), and was originally calibrated by the UK FRONTIERS radar network for the AIP-3 study. The calibration of this algorithm has been upgraded through calibration against the TRMM precipitation radar (PR; Kidd 2000).

This study uses a fixed calibration period rather than the minimum rainfall occurrence method of Kidd (1999) to reduce the complexity of generating the calibrations. A period of five days was chosen that coincided with the mean calibration period of the minimum rainfall occurrence method. The spatial domain of 1° x 1° was chosen so that the smaller scale meteorological features could be resolved in the calibration process. This is slightly smaller than the ~1.5° x 1.5° regions of the AIP-3 study (Kidd 1999), but interestingly when aggregated over the five day period results in a similar number of input data values as the Turk et al. (2000) method that relies upon instantaneous 5° x 5° calibration.

3. Methodology

This technique has been developed through the exploitation of near real-time datasets now readily available over the Internet that provide algorithm developers with a new source of high quality data. Data from SSM/I have been available for more than 15 yr, while global IR data, combined from multiple geosynchronous satellites has only recently been available.

a. Datasets

Two main datasets are required for the current technique. The IR dataset is acquired from the source described by Janowiak et al. (2001), which is available from the Climate Prediction Center three days after collection. The data, an example of which is shown in Fig. 1, covers a global region from 60°S to 60°N using data from five geostationary satellites. The US GOES satellites provide data over the United States and Eastern Pacific, the Japanese Geostationary Meteorological Satellite covers the western Pacific and eastern Asia, while the European Meteosat satellites cover central Asia and Europe/Africa. The data is remapped to a resolution of approximately 4 km with a temporal resolution of 30 min, although some data gaps exist because not all the geostationary satellites operate at this temporal scale. Figure 2 shows the typical number of samples that are available during a 24-h period using this dataset. Several artifacts are corrected including parallax, viewing angle, and intersatellite calibration. The differences in the observation wavelengths between the satellites result in brightness temperature variations of less than 2% and are deemed to be significantly less important that the viewing angle correction (Janowiak et al. 2001).

The PM data is collected from the SSM/I sensors of the DMSP satellites via the Global Hydrology Climate
Center at the National Aeronautics and Space Administration (NASA) Marshall Space Flight Center. The data is available about two days after the observation time and is obtained for each available SSM/I sensor. Utilizing the currently available sensors (on the F13, F14, and F15 satellites) a maximum of six overpasses each day can be obtained for small regions, although two to four overpasses is more common (see Fig. 3). Rainfall estimates from the PM data are obtained via a combined frequency difference technique: this technique utilizes the frequency difference algorithm (see Ebert et al. 1996) at 85 and 19 GHz with different calibrations for land and ocean surface types. The original algorithm, as used in the AIP-3 and PIP-3 intercomparison projects, was calibrated against UK FRONTIERS radar data but has subsequently been recalibrated against the TRMM PR rainfall data. The removal of some surface features is performed using the method outlined by Ferraro and Marks (1995), although some residual contamination does remain primarily due to snow and ice.

b. Algorithm processing

The combined rainfall algorithm uses three key stages to process the datasets:

1) Database generation
   - Rainfall estimates from the PM are remapped to a 0.1° grid (approximately 11 km) for each 30-min period centered on the hour and half-hour.
   - IR data is subsampled to a 0.1° grid by using a 3 × 3 filter to average the 4-km data and generate a mean cloud-top temperature over a 12 km × 12 km area. This approximates the maximum resolution of the PM rainfall estimates.
   - Each collocated PM and IR pixel for each 30 min (±15 min) and 1° × 1° area is entered into a database that records histograms of the IR temperatures (75–329 K) and PM rainfall estimates (0.0–51.1 mm h⁻¹). All data-present regions of the database are then saved onto disk for later use.

2) Calibration procedure

The calibration procedure requires that sufficient data be used to ensure a stable relationship between the IR and PM datasets. The current technique carries out a calibration procedure once per day using a temporally and spatially weighted aggregation of the data from the database. The “operational” scenario uses data for \( d_0 \) (current day) back to \( d_{-4} \) (day minus four) and is accumulated using an arbitrarily derived linear weighting function (i.e., \( d_0 \)

Fig. 2. Number of IR images available for 26 Feb 2002.

Fig. 3. Number of PM overpasses per day for 1 Aug 2002 from 3 SSM/I instruments (F13, F14, and F15).
has a weight of $d_{-1} = 0.8$, $d_{-2} = 0.6$, etc.). The "climatological-historical" scenario uses data from $d_{-2}$ to $d_{-1}$ using the weighting function centered on $d_0$ (0.6, 0.8, 1.0, 0.8, 0.6, respectively). After the data has been aggregated temporally it is then smoothed spatially through the use of a $5^\circ \times 5^\circ$ Gaussian filter. Thus separate histograms of collocated IR temperatures and PM rainfall rates are generated. These are converted into cumulative histograms and are then matched through the use of a cumulative histogram matching approach (outlined below) so that the coldest IR temperatures are assigned the highest rainfall. These relationships for each $1^\circ \times 1^\circ$ area are saved as a lookup table that enables efficient processing of subsequent calculations.

3) Application

Each 30-min image is then processed using the current calibration at the subsampled IR resolution of 12 km to generate rainfall estimates.

c. Cumulative histogram matching technique

A major problem facing the calibration of satellite estimates with validation data is the matching of the datasets both temporally and spatially. Errors noted by Kidd and Bailey (1997) include systematic errors due to satellite-ground misregistration that lead to a significant drop in statistical accuracy. Temporally coincident data are rarely achieved and several minutes leeway between the two datasets is often required. This can lead to displacement in position and changes in the spatial form of the precipitation. Finally, physical differences between satellite retrievals and validation retrievals exist and it is not realistic to assume that the satellite measurements will replicate those of the validation data precisely. These include resolution differences, viewing angles, and response to hydrometeors.

The characteristics of rainfall also need to be recognized: instantaneous rain rates are heavily skewed toward low rain rates (with zero being the modal value). Relying upon a simple regression between satellite algorithm and measured rainfall leads to a bias due to the dominance of the zero and light rainfall observations. Some techniques attempt to overcome this problem by binning the data into categories (Ferrarro and Marks 1995; Smith et al. 1998b), but the low rainfall skew is still present within each bin. Barrett et al. (1991) noted that the low rain-rate skew leads to overestimation of subsequent rainfall retrievals, and proposed the use of cumulative histograms to relate the observed rainfall to the satellite algorithm. In this way the observed frequency distribution of rain rates would be reflected in the resulting algorithm product. The technique can also be used to evaluate the relationship between two datasets where a regression line would not be meaningful (see Adler et al. 2001).

The premise of the cumulative histogram matching technique is that the measured rainfall is correct and that the satellite retrieval should produce a frequency distribution of rainfall rates similar to the microwave distribution over a certain region. Thus for a selected region the values of the satellite IR brightness temperatures and collocated measured rainfall (the PM estimates) are accumulated into histograms that in turn is transformed into a cumulative histogram. These cumulative histograms are then matched so that the occurrence of heaviest measured rainfall is associated with the values of the satellite IR $T_{b,S}$ linked to be heaviest rainfall. A lookup table can then be generated of satellite IR $T_{b,S}$ to rainfall. Using this technique, if the observed rainfall indicates 100 points above 10 mm h$^{-1}$ the output of the satellite algorithm will also produce 100 points above 10 mm h$^{-1}$. The region over which the data is accumulated is primarily dependent upon the number of data points available: this needs to be large enough for a reasonable sample size, but small enough to represent any local characteristics.

An example of the technique is shown in Fig. 4 using the $1^\circ \times 1^\circ$ entry of the database centered on the crosshairs in Fig. 4f. Histograms of IR data and rainfall estimates are generated (Figs. 4a and 4c) and then accumulated into cumulative observations (Figs. 4b and 4d). Note that the IR cumulative histogram is inverted since high temperatures are associated with no rain. The IR rain-no-rain threshold is the temperature with the same cumulative frequency as that of the PM defined non-raining frequency. Increasingly colder IR temperatures are assigned increasingly higher rain rates so that the final distribution of IR assigned rain rates is the same as that determined by the PM data. The technique therefore assumes a monotonically increasing rain-rate relationship with decreasing IR temperature with the premise that colder IR cloud-top temperatures are associated with higher rainfall than warmer clouds. The final relationship is shown in Fig. 4e indicating, in this case, that the rain-no-rain threshold is set at about 240 K, with temperatures of 220 and 210 K having rain rates of about 5 and 12.5 mm h$^{-1}$, respectively.

4. Results

To evaluate the current technique a set of data was processed covering the whole of Africa for June–September 2001, and compared with gauge data over Niger. A total of six algorithms were generated using the IR and PM data:

1) GOES precipitation index, as described by Arkin and Meisner (1987).
2) The UAGPI, using optimal IR thresholds based upon the PM delineated rain areas, and a rain rate derived from the mean rain rate when raining as defined by the PM frequency difference algorithm (described above) rather than the SI used by Xu et al. The IR
thresholds and rain rates are generated on a monthly basis.

3) A variable rain-rate version of the UAGPI has been developed here (termed the UAGPIv), using the same rain–no-rain threshold as the UAGPI, but modified here to use a cumulative histogram matching rain rate lookup table relationship based upon monthly IR–PM statistics.

4) A PM-calibrated IR algorithm using the cumulative histogram matching approach (described in section 3c), based upon the operational scenario (PM–IRo).
5) A PM-calibrated IR algorithm based upon the climatological–historical scenario (PM–IRc).
6) A frequency difference (19–85 GHz) PM algorithm, calibrated over land and over water using TRMM PR data. The daily rainfall totals are based upon the mean of the satellite observations during that day.

a. Qualitative assessment

An example of the monthly rain–no-rain IR thresholds for June–September 2001 is shown in Fig. 5 for the whole of continental Africa. Each $1^\circ \times 1^\circ$ square represents the IR cloud-top temperature that matches the PM-identified rain–no-rain boundary. Regions of coldest IR rain–no-rain boundaries are evident along $15^\circ$N with temperatures as low as 210 K being associated with precipitation from July through September. This region marks the northerly extent of the intertropical convergence zone (ITCZ). Other cold rain–no-rain boundary regions are also observed from Yemen to Oman during July and August, over central Africa ($20^\circ$–$30^\circ$E at the equator), in the south of the region, and over the western Mediterranean particularly during September. These very low values of the IR rain–no-rain threshold temperatures are associated with deep–high clouds:
a drawback of the monthly calibrations is that any cold cloud, precipitating or not, can be assigned rainfall values. The use of shorter-term calibrations alleviate this somewhat since if no rain is associated with nonprecipitating cirrus within the calibration period, no matter how cold, no rainfall will be retrieved. Over the eastern Mediterranean region very high temperatures for the rain–no-rain boundary can be observed, often exceeding 290 K during June, July, and August. These areas are associated with regions with little or no precipitation, as evidenced by the 0 conditional rain rate (Fig. 6). In regions of no PM-identified rainfall the methodology of the cumulative histogram matching technique sets the rain/no-rain boundary to the minimum observed IR temperature.

Figure 6 shows the conditional rain rate, used in conjunction with the IR rain–no-rain thresholds for the generation of the UAGPI estimates. The highest conditional rain rates are found along the ITCZ region (about 15°N), being most extensive during August with rain rates in excess of 6 mm h⁻¹. As the ITCZ migrates southward in September over central Africa conditional rain rates of over 4 mm h⁻¹ are identified. Subtropical regions show relatively low rain rates, although with a few exceptions such as the western Mediterranean during September. Combining the information from Figs. 5 and 6...
reveals some practical information on the different rain systems: cold rain–no-rain thresholds with high conditional rain rates suggest regions with significant convective activity with the ITCZ being the dominant feature over this region. Cold rain–no-rain thresholds and low conditional rate rates suggest large synoptic-scale features, such as frontal systems, as evidenced in the south of the region. Warm rain–no-rain thresholds and low conditional rain rates suggest low-level clouds, such as small-scale convection (e.g., trade wind cumulus) or subresolution precipitation systems (i.e., a combined signal of rainfall and surface).

Techniques, such as the UAGPI, produce the rain–no-rain boundaries and conditional rain rates on a monthly basis, compared with the short-term calibration of the current technique. The short-term calibration is designed to capture the current meteorological conditions rather than the climatological-scale events. Figure 7 shows the variations in the rain/no-rain boundary for a location 15°N, 10°W from 1 June 2001 through to 31 December 2001 generated for the PM±IRo scenario. It can be seen that the IR rain–no-rain boundary varies significantly over relatively short periods of time. For example, around day 310 the rain–no-rain boundary falls from about 240 to 210 K in a few days. Similar changes are also seen in the rain rates assigned to the IR temperatures associated with the passage of easterly waves across the region. These results are consistent with those of Kidd (1999) over the Tropical Ocean Global Atmosphere Coupled Ocean–Atmosphere Response Experiment region, which showed significant day-to-day variations in the IR–rain-rate relationships.

The application of four of the techniques to continental Africa is shown in Fig. 8. The daily products from the GPI, PM–IRc, UAGPIv, and PMW algorithms are shown for 27 August 2001 at 12-km resolution. Some notable differences are apparent:

• The GPI produces the greatest rain area of the algorithms, particularly over central Africa. The PM, due to its limited sampling produces the least.

• Over southern Africa the GPI identifies a significant area of precipitation to the east of the landmass, but in both the PM–IRc and the UAGPIv this is reduced in intensity, and both algorithms indicate activity in the west of the landmass that is also identified in the PM data.

• Significant differences exist between algorithms over the Arabian Peninsula, with the GPI suggesting fairly uniform accumulations of about 3–4 mm day\(^{-1}\). The PM–IRc shows isolated regions of high precipitation (>12 mm day\(^{-1}\)), while the UAGPIv suggest a more extensive line of precipitation with rainfall totals in excess of 16 mm day\(^{-1}\).

The full resolution satellite products and the gauge data for a single day (12 August 2001) are shown in Fig. 9 over the Niger region. For illustrative purposes only, the gauge data have been interpolated to within 0.5° of each gauge location to enable better visual comparison. As noted in Fig. 8, the GPI defines the largest rain area with daily rainfall in excess of 16 mm day\(^{-1}\) over a large area, while the PM retrieval shows the least rain area, again due to the temporal sampling of the SSM/I instruments. The two PM–IR methods show less rain area than the GPI, and a greater amount of light precipitation around the main rainbands. They also suggest much higher maximum rainfall totals with in excess of 32 mm day\(^{-1}\) retrieved. The UAGPI algorithm produces a greater rain area than the PM–IR methods but calibration artefacts can be readily observed. Xu et al. (1999) applied a smoothing to their calibration to eliminate this problem. The UAGPIv product based upon a variable IR–rain-rate conversion and smoothed calibration fields are shown, with the rain area being similar to that of the UAGPI, but with fewer calibration artefacts.

A comparison of the satellite products with the gauge data reveals some differences. The satellite algorithms capture the large rain feature in the center of the study area (14°–16°N and 6°–8°E), all the algorithms suggesting rainfall totals of at least 4 mm day\(^{-1}\). The gauge
data, while showing high rainfall in the south of the small region shows less rainfall in the north. However, the distribution of the gauges in this region precludes comprehensive coverage of this event. Areas centered on 12°N, 3.5°E and 13°N, 12°E show high rainfall totals in the gauge data, but little rainfall identified by the non-GPI rainfall algorithms. The maximum values suggested by the UAGPI, UAGPIv, and PM–IR are all higher than that measured by the gauges. This wet bias may be attributed to the distribution of gauges that will have a zero–low-rainfall bias due to their poor spatial coverage and also the fact the PM algorithm produces time-specific samples of instantaneous rainfall compared with the time-integrated rainfall recorded at the gauge locations.

b. Statistical comparison

Satellite retrievals and gauge data for Niger are compared for June, July, August, and September 2001 to coincide with the peak of the rainy season in this region. The Niger gauge dataset consists of up to 169 gauges and therefore provides a relatively dense gauge network over this region of Africa. The purpose of this study is to evaluate results at high resolutions rather than climatological scales; a resolution of 0.1° × 0.1° was chosen to approximately match the spatial resolution of the high-frequency SSM/I channels. A simple distance-weighted interpolation procedure is used to generate rainfall fields from the gauge data, but only those 0.1° × 0.1° boxes that have one or more gauges are included in the statistical analysis.
Fig. 9. Case study for 12 Aug 2001: GPI, PM–IRo, UAGPI, UAGPIv, and PMW algorithms, and gauge data (interpolated to 0.5° radius). Regions with no data coverage are in white.
Daily 0.1° × 0.1° results are shown in Table 1 and summarized below:

- The PM algorithm produced the least bias in three of the four months, although it had the highest bias in the month of July.
- The GPI technique had the lowest rmse of the techniques overall, but the combined algorithms have a substantially lower rmse than the PM algorithm alone, with the UAGPI algorithm performing best amongst the combined algorithms. The poor performance of the PM algorithm may be attributed to the low number of samples acquired each day, often leading to a large overestimation or underestimation of the daily rainfall.
- Correlation coefficient results are rather mixed with the UAGPI being best in two of the months, with the GPI and PM–IRo methods being best in the other two months. All the IR-based algorithms are an improvement upon the PM data alone.

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- The probability of detection (PoD) and false alarm ratio (FAR) scores show that the IR-based techniques produce a large number of FAR events with the GPI being the worst. The PM algorithm has the highest or second highest PoD with a low false alarm ratio, which is attributable to the smaller rain area caused by fewer samples.
- The Area-Weighted Error Score (Todd et al. 1995), designed to compensate for the biases produced by the large number of zero rainfall amounts in the dataset, shows the PM algorithm to have least errors in all but one month, and the combined algorithms to have lower error scores than the IR-only (GPI) technique. This indicates that the combined algorithms provide a better rain area retrieval than the GPI algorithm can provide.
- This result is also shown by the occurrence of rainfall where %occ indicates the occurrence of satellite rainfall at each gauge location compared with the gauge rainfall. In all months the GPI overestimates the occurrence of rainfall, while the combined algorithms produce occurrences between 92% and 128% of that observed by the gauges. Note that there is little difference between the different combined algorithms. The low rainfall occurrence identified by the PM retrievals is affected by the due to the low temporal sampling.

Scatterplots of the gauge (observed) versus satellite estimates are shown in Fig. 10. The GPI versus gauge
plot (Fig. 10a) shows that the GPI does not produce much rainfall above about 40 mm day\(^{-1}\). This lack of high rainfall totals is compensated for by a large number of low-medium rainfall events resulting in most days producing some rain (and hence the overestimation in the occurrence of rainfall). The other algorithms show a positive bias, retrieving higher daily rainfall totals than the GPI: the PM–IRo and PM–IRc techniques showing similar number of points close to the axes. The UAGPI appears to have the least spread of data points, but with a slight bias toward the identification of rainfall by the satellite estimates where gauge data records 0 rain. The UAGPIv tends to produce more light rain events when compared with the surface gauges, as evidenced by the number of points close to the x axis.

A summary of daily 0.1° × 0.1° resolution statistics is shown in Fig. 11 for plots of correlation, skill scores (see Ebert 1996), and rainfall occurrence. The corre-
Fig. 11. Plots of (a) percent satellite rain occurrence to gauge rain occurrence (b) algorithm skill scores, and (c) algorithm correlations, for 0.1° × 0.1° daily statistics. Vertical scale indicates the number of 0.1° × 0.1° boxes present.

lations, plotted in Fig. 11a, show that the GPI has a larger number of days with higher correlations than the combined algorithms, although the PM–IRc and UAG-Piv algorithms show a small peak in the number of days with correlations between 0.65 and 0.75. The poor correlations of the PM data are also evident. The skill scores of the algorithms are shown in Fig. 11b, with the PM algorithm showing a low skill score, while the other algorithms show higher skill scores. The combined algorithms indicate generally higher skill score statistics than the GPI technique. The distribution of the occurrence of rainfall statistic is shown in Fig. 11c and reinforces the results of Table 1. The GPI overestimates the occurrence of daily rainfall against the gauges, reporting rainfall on at least 50% more occasions. Conversely, the PM algorithm reports rainfall on only about a third of the occasions that the gauges do because of sampling issues. All of the combined algorithms show a similar slight positive bias in the peak occurrence of precipitation.

5. Discussion

The results of this comparison indicate that the combination of IR and PM data does not necessarily lead to better statistical results. The advantages of combined techniques envisaged by Adler et al. (1993) have only been realized in part, and while there are many cases of improvement among these techniques, not all have resulted in improved statistics for every case studied.

The final output of any combination technique is reliant upon two important factors:

1) the quality of the initial PM algorithm used to calibrate the IR data, and
2) the ability of the IR data to faithfully represent the rainfall (both in terms of its indirect nature, and the changing characteristics between calibration periods).

The first is a critical issue: since many of the techniques rely upon imposing the characteristics of the PM algorithm onto collocated IR data and then using that calibration over the estimation period: any inherent weaknesses in the PM algorithm will be transferred to the IR technique. Kidd (1999) and Xu et al. (1999) note that the success of any combination technique is reliant upon reducing any error of the PM algorithm. The choice of the initial PM algorithm is therefore vital in ensuring a reasonable result from the combined techniques. Among the favored techniques are the scattering index (Ferraro and Marks 1995) used by Xu et al. (1999) and Miller et al. (2001), and frequency difference techniques used by Kidd (1999), Todd et al. (2001), and Miller et al. (2001). Both algorithms have performed well in the PIP and AIP intercomparison projects. In this study, the high probability of detection and low false alarm ratio scores of the PM algorithm indicate that it is very good at identifying rainfall: if the algorithm identifies rain then the gauge will almost certainly report rain, but the temporal sampling restricts the ability of algorithm to improve upon the standard statistical results.

The second point raised is also important: while it has been shown that for long-term observation of rainfall a simple cloud-indexing technique performs well, for short-term rainfall estimates the relationship between the cloud-top temperatures and rainfall becomes more critical. This relationship is further complicated by the number of calibration values available, which in turn is determined by the spatial and temporal region over which the calibration is generated. It is reasonable to assume that the cloud-top temperature–rain-rate relationship varies with the life cycle of the storm and therefore any tendency of the PM imagery to be available only during a certain point in this life cycle can lead to biases. Similarly, calibration over a limited area can lead to local biases in the results; however, this is not critical as long as the data are spatially consistent over the region of interest. In this study, the Niger region lies at the northern boundary of the ITCZ where moist air interacts with the dry air of the Sahara desert. It is reasonable to assume therefore that very steep gradients occur across this region that would lead to changes in
the IR–rain-rate relationship over relatively short distances, and possibly at subcalibration resolutions. This would imply that the calibration region must therefore be adapted to the environment in which it is to be used.

An issue only just beginning to be addressed among the satellite rainfall estimation community is that of biases in statistical results due to the nature of the phenomena being observed (Ebert et al. 2003). Since rainfall distributions are highly skewed, statistics that rely upon a normal distribution may be misinterpreted. For instance, the overall performance statistics for an algorithm are heavily influenced by the skill for very light rain events since such events are much more heavily represented in the dataset than are heavier rainfall amounts. Thus, if an algorithm devised to retrieve light rainfall correctly were to be compared with one designed to retrieve heavy rainfall, the former would be favored due to preponderance of light rainfall occurrences that might be expected in the validation dataset. The effect of the statistical biases is therefore related to the spatial and temporal scale of the rainfall products being generated. Results of Turk et al. (2002) illustrate this: using data over South Korea, plots of rmse, correlation, and bias were produced for varying temporal and spatial resolutions. While daily, $1^\circ \times 1^\circ$ products resulted in an rmse of about 1.5 mm h$^{-1}$, the rmse quickly increases with finer resolutions so that for timescales of 1 h and $0.1^\circ \times 0.1^\circ$ the rmse is in excess of 6.0 mm h$^{-1}$. This is also reflected in the correlation coefficient results that range from about 0.65 to less than 0.15 for daily $1^\circ \times 1^\circ$ and hourly $0.1^\circ \times 0.1^\circ$ resolutions, respectively. However, it should be noted that the spatial and temporal aggregation of data would in itself reduce errors associated with the datasets. As shown by this study, an algorithm that produces a high correlation is not necessarily the “best” algorithm; it depends upon the application: for modeling purposes or drought relief it is probably more important to know the occurrence of rain rather than the amount. Further investigations of the spatial and temporal parameters are required so that suitable calibrations domains can be chosen.

The current calibrated IR techniques are useful compared to PM alone as long as the errors associated with cloud-top temperature to rain-rate conversion are less than those associated with the temporal sampling. At present it is feasible to retrieve hourly rainfall from IR data in this way due to the temporal sampling of the current generation of PM instruments (i.e., SSM/I and TMI). This also implies that certain regions of the globe, at certain times, will produce more accurate rainfall estimates due to better cloud-top temperature–rain-rate relationships. More critical however, is the consistency of the results: this analysis does not show any overall advantage of one technique over another from one month to the next. While accurate retrievals are desirable, for many applications it is probably more important to have a technique that has consistent and known errors.

6. Conclusions

The combination of IR data with PM rainfall estimates has been seen as having great potential in improving short duration rainfall estimates. Numerous techniques have been developed using different PM rainfall estimates and different calibration periods/regions with products generated at a range of spatial and temporal resolutions. The results from these techniques are varied: in certain situations the combined techniques are clearly superior to IR-only based techniques, while other situations suggest little or no improvement. Some of these variations in performance can be attributed to the algorithms and techniques used, and also to the rainfall systems being observed. Unfortunately there does not appear to be a single technique that is clearly better than any other one at present.

New observations from satellite missions such as the Meteosat Second Generation (MSG), launched in August 2002, should improve this situation through the use of observations from the 12-channel Spinning Enhanced Visible Infrared Imager instrument (see Levizzani et al. 2000). Use of the multichannel information should enable better precipitation delineation and rainfall “potential” information compared to that derived from the IR 10.7-$\mu$m channel data alone. In addition, the MSG will provide 15-min image capture capability, enhancing the use of life history technique with such data.

Additional rainfall information from PM sources is also likely to improve with the launch of new sensors. The Global Precipitation Mission (GPM) (Flaming 2002) will provide 3-hourly data that would prove very useful in the calibration of the IR datasets. The ability of the GPM mission would enhance this capability rather than replace the combination techniques since sub-three-hourly estimates would still be needed. The GPM data would not only greatly improve the temporal calibration, but also provide a validation source through the proposed dual-frequency precipitation radar data. However, it remains to be seen whether improved PM–IR results would be better than interpolated/advection rainfall information from the frequent data collection of the GPM.

Acknowledgments. This research is funded by the EU–RAINSAT project, shared-cost project (EVG1-2000-00030) cofunded by the Research DG of the European Commission with the RTD activities of a generic nature of the Environment and Sustainable Development sub-program (5th Framework Programme). Global infrared data is provided courtesy of the Climate Prediction Center and John Janowiak; passive microwave data from the SSM/I courtesy of the Global Hydrology and Climate Center, NASA/MSFC. The reviewers of the paper are also thanked for their comprehensive comments on this paper.

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