Errors and Uncertainties Associated with Quasi-Global Satellite Precipitation Products

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Abstract

Measuring precipitation on a global scale is only possible from satellite platforms. Satellite precipitation estimates are based on geosynchronous infrared sensors on geostationary satellites, characterized by high sampling frequency, and polar-orbiting microwave sensors on low-Earth-orbiting satellites with less-frequent sampling. Assessing satellite product performance is fundamental to infer the reliability of such estimates and effectively use them in water resources management, extreme event characterization, disease control, or weather forecasting. Nevertheless, errors and uncertainties associated with satellite precipitation products are often masked due to temporal and spatial sampling, as well as bias-corrections against a reference dataset. Moreover, the verification of satellite precipitation products is easier over land areas, where rain gauges and ground radars are available as benchmark, but extremely limited over the oceans. Substantial work still remains to better quantify relative and absolute errors and uncertainties within satellite-based precipitation products over land and oceans.

1 Introduction

Precipitation products that are based on satellite retrievals are affected by errors and uncertainty (Massari and Maggioni 2020). If errors are unintended, generally small and known problems that can (and should) be fixed, uncertainties are those we do not (fully) know and may be a consequence of assumptions, but may also be accounted for at a later stage. Quantifying such errors and uncertainties is essential for the appropriate use of quasi-global satellite precipitation products in any applications (Maggioni and Massari 2018; Serrat-Capdevila et al. 2014).

Errors and uncertainties are often quantified by comparing satellite products against a reference dataset. Common validation data over land are ground-based rain gauges and radar networks, which are limited by their local coverage (Maggioni et al. 2016; Kidd et al. 2017). Over oceans, validation is way more difficult because of their inaccessibility and extent. Past efforts have used weather radars located on islands and coastlines, rain gauges onboard cruise, merchant, and research ships, as well as buoy gauge arrays (Bowman 2005; Burdanowitz et al. 2018; Hayes et al. 1991; Khan and Maggioni 2019; Klepp 2015; Serra 2018; Serra and McPhaden 2003, 2004; Smith et al. 2009). Any reference dataset also carries errors and uncertainties that impact retrieval bias corrections as well as any validation of the satellite products themselves.

Errors and uncertainties associated with satellite precipitation products may be broken down into three main categories that are discussed in this chapter:

Sensor errors and uncertainties: physical limitations of engineering and knowledge;

Retrieval scheme errors and uncertainties: assumptions, information utilization, and the mechanisms of the retrieval algorithm itself.;

Product errors and uncertainties: progression from instantaneous to daily/monthly products, temporal and spatial sampling, and inheritance of errors and uncertainties.

2 Sensor Errors and Uncertainties

Some errors and uncertainties in satellite precipitation observations are due to physical limitations of the sensor itself which, in turn, impact resolution, sampling, accuracy, precision, and noise. Specifically, different remote sensors (radars, geostationary infrared sensors, passive microwave sensors) have different capabilities, in terms of diversity and number of channels used and their spatial resolutions. The spectral and design characteristics of the remote sensing technique along with the specific design of the mission determine both what kind of information about precipitation is retrieved and the associated type of errors and uncertainties.

Satellite weather radars are active sensors onboard spacecrafts that measure the backscattered radiation from precipitation particles and use frequencies in the 3-10 GHz range. Radar retrievals are complicated by several factors, which affect their performance and reliability. First off, the echoed power can be influenced by clutter, beam blockage and/or by the intermittent influence of anomalous propagation. Second, the measured backscatter is not a simple function of rainfall rate, as the relationship between reflectivity and rain rate depends on the drop size distribution but is also affected by beam spreading. Range corrections and vertical profile adjustments have been implemented in the past to tackle this issue (Fulton et al. 1998), but such corrections are unable to address all effects completely (Young et al. 2000). Furthermore, differences in the calibration of the reflectivity-rain rate relationship may translate into very different rain rates (Scofield and Kuligowski 2003).

Geostationary infrared (IR) sensors detect cloud-top properties, which are indirectly related with rainfall rate, i.e., larger rain rates are usually associated with larger, taller clouds with colder cloud tops. Thus, a simple measure like cloud top temperature can provide a rainfall estimate. Nevertheless, this relationship may vary within the lifetime of a single event, as well as among different rain systems and climatological regimes, causing large sources of uncertainty in the precipitation estimates (Kidd and Levizzani, 2011).

Passive microwave sensors (both imagers and sounders), commonly onboard low Earth orbiting satellites, have the capability to penetrate cirrus clouds and detect liquid and frozen hydrometeors, which are strongly related to surface precipitation and thus have a strong physical basis on which estimate precipitation. However, PMW retrievals are characterized by coarser spatial resolution and less frequent temporal sampling when compared to geostationary observations (Kazumasa et al. 2020). Specifically, microwave sensors spatial resolution depends on frequency of operation, orbit altitude, and antenna aperture size - the largest ever used is the AMSR2 one with a 2m diameter (Kummerow 2020).

Microwave imagers retrieve brightness temperature to quantify atmospheric water subsidence, precipitable water content, and cloud liquid water content over land and oceans, using a variety of channels that span from 7 GHz to 183 GHz (to detect frozen precipitation). Imagers are usually conically scanners, with a fixed incident angle. As an example, the Global Precipitation Measurement (GPM) Microwave Imager (GMI) precipitation retrievals (version 5) were compared to radar–radiometer retrievals between 40°S and 40°N by (Adhikari et al. 2019). A quasi-global ~7% GMI overestimation was observed, with specific regions (including central Africa, the Amazon, the Himalayas, and the tropical eastern Pacific) showing an overestimation up to 50% in the GMI retrievals.

On the other hand, microwave sounders observe the vertical distribution of temperature and water vapor and are mostly cross-track scanners with varying surface incident angles. Thus, sounder retrievals are characterized by wider swath width than imagers and by more uncertainties related to the image geometry, varying field of view sizes, and surface and atmospheric effects. Moreover, the same sensors may not exhibit the same characteristics. For instance, the Advanced Technology Microwave Sounder (ATMS) instrument, a cross-track microwave sounder, has four feedhorns, whose alignment differ between the Suomi National Polar-orbiting Partnership (SNPP) and the NOAA-20 satellite sensors (Figure 1). These differences are often small, but can be important, especially if retrieval schemes ignore them.

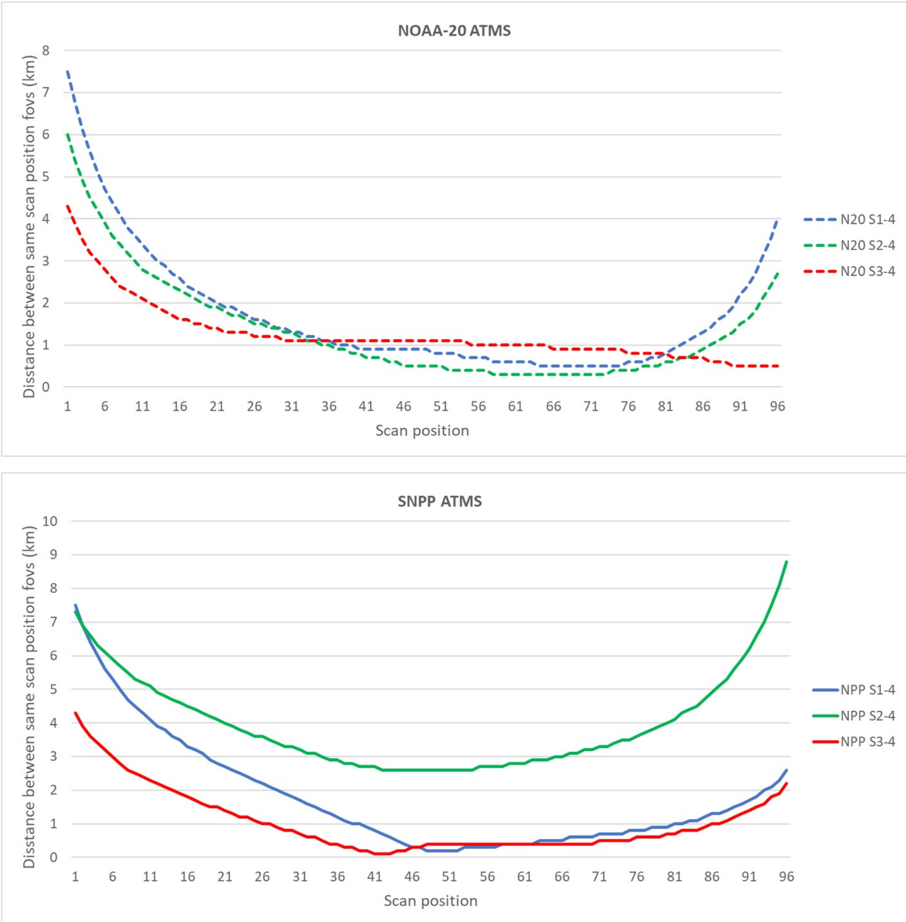

Figure 1: Distance between the same scan position for NOAA-20 ATMS (top panel) and SNPP ATMS (bottom panel).

Although this kind of errors and uncertainties applies to Level 1 data, they also impact Level 2 products that directly use the satellite retrievals, as well as Level 3 products as a consequence, as discussed in the following sections.

3 Retrieval Scheme Errors and Uncertainties

Level-2 satellite products are instantaneous swath-based precipitation products generated by a retrieval algorithm. For passive microwave sensors, such schemes are based on the knowledge that different channels peak at different depths within the raining column. However, there are more independent variables within raining clouds than the available channels (Kummerow et al. 2015), requiring additional assumptions and/or constraints. Bayesian approaches have been found particularly useful in this regard (e.g., the Goddard Profiling Algorithm, GPROF).

However, past studies have shown how the same retrieval scheme may perform very differently in different regions of the world and under different meteorological conditions (Kidd et al. 2018). The errors and uncertainties associated with any individual retrieval scheme can be essentially broken down into two main sources. The first relates to the information that the retrieval scheme has to work with, whether these data are satellite observations or ancillary data. The second relates to the mechanisms of the retrieval itself. These will be dealt with in turn below.

3.1 Information from Observations

As with any processing system, the information available to a processing system is crucial in determining the quality of any derived products: the same is true with precipitation retrieval schemes. There are two main sources of information used in retrieval schemes, the satellite observations themselves, and ancillary data. Satellite observations, as noted above may be derived from a range of sources, each with their own characteristics particularly, here, in terms of precipitation information.

Retrieval scheme built upon information using only visible observations clearly suffer from not being able to retrieve anything at night-time (despite some modern sensors are extremely sensitive), in addition to the fact cloud top characteristics are poorly related to the precipitation falling at the surface. Although infrared-based techniques, which can be used at night and have a more physical basis, in that deeper clouds which are more likely to precipitation are colder, are still limited by the cloud-top to surface indirectness. It is therefore clear that no matter how ingenious VIS/IR techniques are, even when information from both are available, they have significant uncertainties associated with their retrievals, at least at the instantaneous scale. However, where VIS/IR techniques do have an advantage, is in terms of temporal and spatial resolutions. Temporally, geostationary sensors can provide frequent and regular observations which allows the changes in clouds (and therefore indirectly, the precipitation) to be observed. Therefore, what the VIS/IR techniques lose in terms of accuracy at the instantaneous scale is compensated to a degree by the much-improved temporal and sampling. Despite their simplicity, techniques such as the Global Precipitation Index (GPI; Arkin and Meisner 1987) which use a simple threshold and single rain-rate, perform reasonably well even at daily, pixel-scale (e.g., 4 km) scales. Although newer multi-channel vis/IR sensors are now available on both LEO (e.g., MODIS) and GEO (e.g., ABI) sensors the limitation of any retrieval scheme is in the physical capabilities of the observations.

The more physically direct observations provided by passive microwave sensors allow retrieval schemes to exploit the characteristics of the hydrometeors themselves. The different types of sensors, operating across different frequencies allow a range of characteristics to be observed. Historically precipitation retrievals have been based largely upon observations from imaging sensors that operate within the window channels, with the main atmospheric attenuation being hydrometeors. More recently, sounding instruments which typically operate at higher frequencies, have started to be exploited, although with slightly less direct radiation-to-precipitation relationships. The availability of co-incident observations across a number of channels essentially determines how much information is available for the retrieval. Therefore, many retrieval schemes have concentrated on the AMSR/GMI-class of sensor which provide a core set of observations at frequencies ranging from 10 GHz through to 89 GHz (the AMSR-class have 6 GHz, GMI-class 166 and 183 GHz). This range of frequencies allows both emission and scattering signals to be observed and leads to a large diversity in the observed brightness temperatures. This diversity allows a greater differentiation of precipitation characteristics and subsequently, reduces the errors and uncertainties associated with the retrievals. Techniques such as the GPROF rely upon multi-frequency information to enable the observations to be matched against the a priori database. While GPROF has been applied across a range of sensors, it is clear from validation work (see Kidd et al. 2017), that sensors with a larger number of channels perform well, those with fewer channels perform less well.

The most direct satellite observations of precipitation are derived from active microwave systems, or radar. Although these observations are typically at a single frequency, or for the GPM DPR two frequencies, the directness of the backscatter to rain rate relationship makes up for the lack of channels. However, as with all retrieval techniques, there are some significant assumptions made to enable the retrievals work. Typically, when there is a paucity of information, ancillary data sets are used to better constrain the possible retrieval outcomes, and ultimately the final precipitation estimate.

3.2 Incorporating Ancillary Data

A large range of ancillary data is available which may be incorporated into a retrieval scheme. Key criteria relate primarily to data sets that are generally easily available and within a set time for the retrieval scheme to be useful. Basic ancillary data sets include surface information, primarily land/sea since the background surface is often a determinant in how a retrieval scheme processed the observations. Where available, dynamic ancillary data may be used, such as that from models. The GPROF retrieval scheme uses model information to better constrain the retrieval outcomes, and thus the information ancillary data augments the information that is gained from the satellite observations. The role of this information becomes more important as the information content of the satellite data sets decreases. Thus, at a simple level, model data incorporated into a retrieval using 5-channel MHS data will have greater importance than the same model data used in a retrieval using data from the 13-channel GMI sensor.

However, it should be noted, that any retrieval scheme that incorporates information from external sources will include any errors and uncertainties from those external sources into their retrieval. This is particularly true with model data. Until recently the GPROF scheme used ECMWF model data at a relatively coarse spatial and temporal resolution, far coarser than the features that were being retrieved. Consequently, significant uncertainties arose in heterogeneous regions. More recent iterations of the scheme utilize finer-scale model information allowing these finer features to be better resolved within the retrieval scheme. Nevertheless, there is a trade-off between including external information and the resulting improvements. (Kidd et al. 2021) showed that without model information a relatively simple GPROF-like retrieval scheme can perform nearly as well as GPROF itself, but without any external information, particularly for the observations from diverse-channel sensors (Kummerow 2020; Kummerow et al. 2015).

To date, it is fair to say that no retrieval scheme current provides information on the errors and uncertainties associated with their precipitation estimates, stemming from a number of factors. Fundamentally it is often difficult to define what is meant by 'errors and uncertainties' and how to translate the requirements of the user community into the products generated by the retrieval scheme developers. Some techniques provide a range of possible precipitation estimates, however, since instantaneous precipitation is heavily skewed towards zero, this measure of the range of possible values is more qualitative than quantitative. Similarly, validation of the instantaneous precipitation estimates against high-quality surface reference data sets may provide an insight into the differences and accuracies of the retrieval schemes. However, these comparisons tend to be limited in extend both regionally and temporally and may not be representative elsewhere over the globe.

4. Product Errors and Uncertainties

Beside errors inherent in sensors and in the retrieval schemes, other errors overlap at a product level which adds structural deficiencies in the precipitation estimation methodology. Satellites are not observing the all-Earth's surface continuously in space and in time. They rather provide snapshots of the cloud conditions for the same observing area for geostationary satellites (i.e., the full disk) and for different areas in time for low earth orbiting satellites (which are normally equipped with PMW instruments). Therefore, depending on the revisit time of the satellite and the frequency of acquisition, rainfall estimates might be subjected to significant errors, which can be exacerbated by the intermittent nature of rainfall and its high temporal and spatial variability. To overcome this and other problems related to the use of a single satellite estimate, a growing number of techniques have been developed to exploit the synergy between the polar-orbiting PMW retrievals (infrequent, more direct) with the geostationary observations (frequent, less direct) and to merge these combinations with gauge observations. However, this adds uncertainty to the processes related to the "blending" of these data and their inter-calibration including the procedures to bring swath-based L2 products to gridded based via spatiotemporally interpolation.

Although overall beneficial, the combination of multiple-source of rainfall estimates does not fully solve the sampling problem that propagates from lower level products and that leads to biases and missed precipitation events (Behrangi and Wen 2017). The sampling error is impacted by the satellite orbit and swath width, which influence the sampling interval (i.e., the number of satellite acquisitions in a particular area during a defined period of time, e.g., a day). When the sampling interval increases, a logical increase in the sampling error is observed (Nijssen and Lettenmaier 2003; Ciabatta et al. 2017), as well as diurnal-cycle bias errors (Gebremichael and Krajewski 2004).

Other errors may arise that are not strictly dependent upon the estimation technique but are, somehow, interrelated with it. These errors are linked to the physical characteristics of the rain, the climate and the condition of the Earth's surface and are able to impact significantly the uncertainty of L3 products (Gottschalck et al. 2005; Dinku and Anagnostou 2005; Ebert et al. 2007; Kummerow et al. 2006; Tian and Peters-Lidard 2010; Ebert et al. 2007; Stephens and Kummerow 2007; Tian et al. 2007; Tang and Hossain 2012; Oliveira et al. 2016). As each blended product respond differently to these factors, the characterization of such errors can extremely very challenging.

The study by Ebert et al. (2007) who explored the performance of different satellite precipitation products in different study regions and investigated the role of rain intensity, types of precipitation, season and surface conditions. Ebert et al. (2007) found significant uncertainty in precipitation retrievals for stratiform precipitation caused by IR sensors and large errors in higher rain rates during warm months. Moreover, a misidentification of light rain above cold land surfaces was linked to the confounding effects of snow and ice at the ground that scatter radiation similarly to a precipitating cloud (Villarini and Krajewski 2007; Stampoulis et al. 2013; Aghakouchak and Mehran 2013). High temperature might be another cause of error. For example, the effect of rainfall evaporation before it reaches the ground was identified by (Moazami et al. 2016) in the semi-arid region of Iran.

Because of snow and ice cover, orography-enhanced precipitation, and large weather and climate variability, high latitudes and complex terrain add a challenge in estimating precipitation (Maggioni et al. 2016). Mountainous regions are often defined as water Earth's towers, as they sustain life and society but are typically under-monitored and prone to extreme precipitation-triggered events, like flash floods and landslides, whose consequences can be devastating. In these environments, IR-based products suffer from the presence of warm orographic rain. Indeed, both IR algorithms use cloud-top temperature thresholds that are too cold for orographic clouds, thus leading to significant underestimation (Hirpa et al. 2010; Dinku et al. 2007). Even PMW products also underperform when observing warm orographic rain, due to the scattering of ice aloft that may be insensitive to this type of precipitation and therefore leading to underestimation of rain at the surface. Cold surface and ice cover over mountain tops could be also misclassified as rain clouds in PMW algorithms, leading to rainfall over-estimation.

5. Conclusions

Quantifying errors and uncertainty associated with quasi-global satellite precipitation product performances is essential to effectively use such products in several applications, including extreme event monitoring, crop management, and disease control activities. Errors and uncertainties in these gridded Level-3 products arise from a combination of sources at different levels from the physical limitations of the sensor engineering and process knowledge to the assumptions and methods used in the retrieval algorithm to the progression from instantaneous to aggregated products.

Quasi-global satellite products' performance is typically assessed through comparisons against a benchmark, commonly a rain gauge or radar network over land and weather radars located on islands and coastlines, rain gauges onboard ships, and buoy gauges over oceans. The presence of errors in the benchmark dataset itself increases the apparent error of the satellite observations and should be considered when evaluating such products.

Errors are usually estimated using a set of statistical tools, that commonly include continuous statistical measures as well as categorical metrics (Ebert et al. 2007). Continuous verification metrics measure the accuracy of rain amount. Common scores include (but are not limited to) bias, bias ratio, root mean square error, mean absolute error, correlation coefficient. Categorical metrics assess the ability of a product to capture the occurrence of rainfall events through a contingency table (or confusion metrics). Common categorical metrics are false alarm rate, probability of detection, critical success index, success ratio, among others. To overcome the issue of the benchmark dataset, alternative techniques have been developed for assessing the performance of satellite products. The most used technique is the Triple Collocation Analysis. Given three estimates of rainfall, the Triple Collocation Analysis provides errors and correlations for each of the three datasets, e.g., (Alemohammad et al. 2015; Massari et al. 2017; Roebeling et al. 2012).

Furthermore, modeling errors and uncertainties associated with quasi-global satellite precipitation products is fundamental for water resources and climate applications, especially where and when in-situ measurements are not accessible. There are several models currently available. Similar to validation methods, some models rely on a benchmark and others do not require one, focusing only on the uncertainty component. Some are based on additive errors, others use a multiplicative approach (Tian et al. 2013). Power law models have been proposed to quantify the standard deviation of the sampling error (Bell et al. 1990; Gebregiorgis and Hossain, 2013; Gebremichael and Krajewski 2004; Hong et al. 2006; Steiner et al. 2003), whereas more stochastic approaches have been applied to level-3 satellite products (Gebremichael et al. 2011; Hossain and Anagnostou 2004; Maggioni et al. 2014).

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