

3.2. Directions in error modeling

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3.2.1. Introduction

Past validation studies highlighted a myriad of factors, such as retrieval techniques, sensor types, topography, spatial and temporal sampling and algorithms, that contribute to uncertainties associated with satellite precipitation products. All these factors result in errors in precipitation products, whose estimation is fundamental for hydrological modeling, land data assimilation systems, water resources management and climate studies. The ability to model errors in precipitation is paramount for not only obtaining information about satellite products' accuracy and precision in regions and during periods in which in situ measurements are not available, but also to perturb input precipitation to force land surface and hydrologic models. Despite the importance of error models, there is a clear imbalance between research efforts dedicated to the assessment of the performance of satellite precipitation products (as highlighted in Chapter 1.2) and those related to the development of precipitation error modeling.

Nevertheless, in the recent past, several models have been developed to estimate errors and uncertainties in satellite precipitation datasets. Some rely on a reference, some focus on the uncertainty component alone and do not require a reference, some are based on an additive approach and others use a multiplicative error assumption. Error models highly depend on the product temporal and spatial resolution, on precipitation rates and products, and on a priori error model structure. Thus, error models are unlikely to be universal. This section reviews the most common techniques, discusses their limitations and provides recommendations for the agencies and the scientific community.

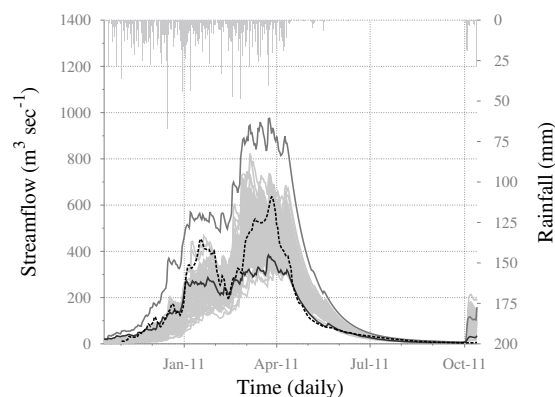
3.2.2. Results

Two main types of error models are commonly used to assess errors and uncertainties in precipitation data: additive and multiplicative. The multiplicative error model was found superior to the additive approach thanks to its ability to separate the systematic and random components of the error; its applicability to the large range of variability in daily precipitation; and its predictive skills (Tian et al., 2013). Most methods require a benchmark dataset to estimate such errors and uncertainties. However, Adler et al. (2009) proposed a framework, later expanded by Tian and Peters-Lidard (2010), to assess uncertainties in global satellite precipitation datasets using the spread of coincidental and co-located estimates from an ensemble of six different products. Nevertheless, this approach only provides a relative analysis and some of the products in the ensemble are not completely independent.

One of the first error models was proposed by Huffman et al. (1997) and applied to the GPCP analysis (Adler et al., 2003; Huffman et al., 2009) and the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA; Huffman et al., 2007). This model provides root mean square random error estimates for each grid box and at each time step (i.e., monthly and daily). Once again, the limitation of this approach is that the error estimates depend on the samples being functionally independent, which may not be the case when considering finer temporal resolution.

Several studies focused on the estimation of the sampling error and modeled its standard deviation using a power law (e.g., Bell et al., 1990; Gebremichael and Krajewski, 2004; Steiner et al., 2003; Hong et al., 2006). For instance, Gebregiorgis and Hossain (2013, 2014) proposed estimating the variance of daily satellite precipitation error using information such as rain rate and geophysical features. However, these techniques assume that: i) precipitation errors can be modeled with a lognormal distribution, which, at high rain rates, can be unrealistic (Gebremichael and Krajewski, 2005); and ii) the variance is an appropriate estimator of the satellite precipitation error. The Gebregiorgis and Hossain (2013, 2014) approach was shown to perform better when the false alarm and the hit components of the error are dominant, but the performance degraded when the missed precipitation represents a large component of the total error.

Solutions have been proposed to characterize uncertainties and errors associated with global high-resolution satellite precipitation datasets. For instance, Hossain and Anagnostou (2006) introduced the two-dimensional satellite rainfall error model (SREM2D), a stochastic model that estimates the joint probability of successful delineation of rainy and non-rainy areas. SREM2D has been successfully applied in hydrologic modeling for streamflow simulations and debris flow predictions (Maggioni et al., 2013; Falck et al., 2015; Nikolopoulos et al., 2017). An example of the SREM2D performance in adjusting a satellite precipitation product (Hydro Estimator, HYDRO-E), used as input to a hydrological model in the Tocantins-Araguaia basin in Brazil, is presented in Figure 3.2.1.



SREM2D Ensemble Q ——— Rainingauge Q ——— HYDROE rainfall —■—
 HYDROE Q ——— Observed Q - - - - -

Figure 3.2.1. Streamflow simulations in a sub-basin of Tocantins-Araguaia watershed in Brazil during October 15, 2010–October 14, 2011 using input precipitation from different sources: i) the satellite-based HYDRO-E product, ii) rain gauges and iii) HYDRO-E perturbed using the SREM2D error model (ensemble). This figure shows how SREM2D was able to push the satellite product closer to both ground observations of streamflow (black dashed line) and the simulation that uses reference rain gauges as input (black solid line).

Bellerby and Sun (2005) designed a methodology to quantify the uncertainty of high-resolution satellite precipitation products by generating probabilistic and ensemble representations of the measured precipitation field. Teo and Grimes (2007) presented a model for uncertainty estimation of satellite rainfall values based on a stochastic ensemble generation of rainfall. Many of these methods use a Monte Carlo approach to generate spatially correlated random fields and ensembles of precipitation error. However, describing the spatial dependence of precipitation fields is not straightforward, as different rainfall intensities are characterized by different correlation structures (that is, when observed values are low, they tend to be scattered

and intermittent with poor spatial dependence, while when the rainfall intensity is high, it tends to be more temporally spatially dependent; Bárdossy and Pegram, 2009).

Gebremichael et al. (2011) proposed a non-parametric method to estimate errors and uncertainties at fine resolutions (3-hourly/25 km), based on conditional density functions of satellite precipitation at each grid box, calibrated using a ground reference. Maggioni et al. (2014) introduced the Precipitation Uncertainties for Satellite Hydrology (PUSH) framework, which models errors as a combination of a random and a systematic component and considers missed precipitation cases, false alarms and hit biases. PUSH was later modified by Oliveira et al. (2018) to account for factors like seasonality and surface type and has been proven to have potential when estimating satellite precipitation errors on a global scale (Khan and Maggioni, 2020). On a similar note, Wright et al. (2017) proposed a simpler approach, based on a shifted gamma distribution, to characterize precipitation and produce a “best guess” distribution of the true precipitation by also considering hits, misses and false alarms. They were the first to explore the potential benefit of incorporating atmospheric variables such as humidity and precipitation from numerical weather models (specifically, atmospheric reanalysis) in a satellite precipitation error model.

As noted above, the complexity in error model formulation varies quite largely, from methods that estimate the variance of a precipitation product to others that also evaluate false alarms and missed cases. Very simple or more complex bias correction methods can significantly reduce errors in streamflow simulated by a hydrological model (Serrat-Capdevila et al., 2014). For instance, simple long-term bias correction was shown by Beck et al. (2017) to yield reasonable streamflow performance over tropical regions. However, such correction may not be appropriate anywhere and anytime, given the non-stationary nature of precipitation biases, or for any kind of application (Ciabatta et al., 2016; Bitew and Gebremichael, 2011).

3.2.3. Summary

Although in the recent past numerous attempts have been made to develop error models of satellite precipitation products, several issues limit their use in applications. First off, the majority of these approaches is based on assumptions regarding the distribution of precipitation (and/or associated errors). Second, simple error models may be preferable for some applications, but more complex solutions may be more appropriate for others. For instance, hydrological models used to simulate floods should be particularly sensitive to extreme precipitation events and the ability of detecting such events. Thus, an error model that accounts for missed precipitation cases and false alarms would be preferable. Third, precipitation errors and uncertainties depend on the product’s temporal and spatial resolution, seasonality, rain rate and geophysical features. Thus, the same error model would unlikely perform similarly everywhere in the world (for example, oceans versus land, complex topography versus plains, tropics versus high latitudes), at any time (for example, winters versus summers), for any precipitation event (for example, solid versus liquid precipitation, convective versus stratiform systems) and for any application (drought versus flood monitoring).

3.2.4. Recommendations

Based on this first and partial attempt to assess the current status of satellite precipitation error modeling, here are some recommendations for the agencies and the community:

- Encourage the use of satellite precipitation error models in applications;
- Elaborate on the limitations and capabilities of current error models;

- Investigate possible reference datasets for calibrating error model parameters (such as distribution parameters, missed precipitation fraction and false alarm rates), especially in those regions of the world where no dense ground observation networks exist;
- Communicate such limitations to support further research using these models;
- Incorporate ancillary information (for example, topography, land surface characteristics, climate variables) within model precipitation errors;
- Consolidate current modeling approaches targeting different applications (different applications may have different needs, and the “one fits all” model may not be the appropriate solution); and
- Assess the performance of error models of different complexity across regions characterized by a variety of land uses, topography and climatologies.

3.2.5. Acknowledgments

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3.2.6. References

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