Precipitation Rate Estimates *from* Satellite Infrared Imagery

A New PERSIANN Model

Adapted from “PERSIANN Dynamic Infrared-Rain Rate Model (PDIR) for High-Resolution, Real-Time Satellite Precipitation Estimation,” by **Phu Nguyen** (University of California, Irvine), **Eric J. Shearer**, **Mohammed Ombadi**, **Vesta Afzali Gorooh**, **Kuolin Hsu**, **Soroosh Sorooshian**, **William S. Logan**, and **Marty Ralph**, Published online in *BAMS*, March 2020. For the full, citable article, see [DOI:10.1175/BAMS-D-19-0118.1](https://doi.org/10.1175/BAMS-D-19-0118.1).

Rain gauges and radars are the most popular sources for precipitation measurement and estimation, but their distribution is limited. In recent decades, satellite-based precipitation products have proven to be an effective alternative. They provide the first quasi-global estimations, except for the polar regions. Near-real-time, satellite-based precipitation data are essential in weather, climate, and hydrological modeling—including managing drought and flash floods.

Satellite-based precipitation estimation algorithms primarily utilize input from longwave infrared (IR), visible (VIS), and passive microwave (PMW) sensors. Satellite observations do not read rain rate (RR) directly. An indirect relationship links the occurrence and intensity of rainfall to data from one or multiple sensors. Although PMW sensors are reliable sources for instantaneous precipitation estimations, their spatial and temporal resolutions are far coarser than IR/VIS readings. The spatiotemporal richness of IR and/or VIS helps balance

the relatively poor spatiotemporal resolution of PMW sensors and so is integral to many precipitation estimation algorithms. However, VIS observations do not capture nighttime precipitation variability, while IR only provides brightness temperature (T_b)—the cloud top temperature.

Over the last two decades, a number of widely used products estimate quantitative precipitation by combining information from various satellite sensors. Some products, such as the Tropical Rainfall Measuring Mission (TRMM), primarily utilize PMW measurements, and others are IR-based products. Some products combine other precipitation-estimating algorithms, such as the Integrated Multisatellite Retrievals for GPM (Global Precipitation Management; IMERG).

One of the biggest challenges for IR retrievals is warm cloud detection. Warm rain clouds offer little contrast between their T_b and the Earth's surface temperature, and they lack complementary ice scattering for estimation from PMW. Many methods either regularly fail to capture warm precipitation or elect to set T_b thresholds lower than warm precipitation temperatures, effectively reducing their detection rate to zero. In addition, many IR-based

*** The dynamic cloud-top brightness temperature (T_b)–rain rate (RR) model. In PERSIANN-CCS, clouds that are identical in shape, size, temperature distribution, and all other defining characteristics but spatial location have completely identical RR readings. However, in PDIR, the underlying climatology causes shifts in the T_b –RR curves that characterize cloud-based models like PERSIANN-CCS and PDIR. In PDIR, drier climatologies such as the Mojave Desert (MD) cause a leftward shift in the T_b –RR relationships, which results in lower precipitation rates than at identical temperatures in moderately wet regions such as California's Central Coast (CC), while wetter climatologies such as the Klamath National Forest (KNF) cause a rightward shift, which causes an increase in estimated precipitation rates for identical temperatures.**

algorithms do not have a built-in cloud-type model; nonprecipitating cold (low T_b) clouds such as cirrus will incorrectly be detected as a source of precipitation, which results in overestimating the occurrence and amount of precipitation.

Arguably, the primary limitation with IR-based algorithms is their reliance on T_b without

the incorporation of information from underneath the clouds. These algorithms have difficulty handling rainfall over the highly complex terrain of the western United States, where they must account for nonbrightband (NBB) rainfall, brightband (BB) rainfall, and hybrid rainfall. Typically, satellite-based precipitation algorithms underestimate rainfall in the mountains of the West but tend to overestimate rainfall in the dry regions of the Southwest.

In the western United States, orography makes warm, NBB rainfall a significant source of yearly precipitation. Clouds associated with NBB precipitation are strongly correlated with orographic lifting and frequently occur at lower levels than BB rainfall-associated clouds with temperatures of ~250–270 K. While BB and NBB designations are rooted in radar rather than satellite sensing, T_b values of these clouds can differ by tens of degrees while producing identical rainfall totals. Thus, NBB

*** Average annual rainfall (mm year⁻¹) for the validation period (2008–13) for the baseline product Stage IV (ST4) and the near-real-time Stage II (ST2)—both are primarily radar data but also gauge data—the three satellite-based precipitation products [CMORPH (CMO), TRMM, and PERSIANN-CCS (CCS)], and the new product, PDIR.**

rainfall must be a primary consideration in precipitation-measuring studies in the western United States. (However, we are using only temperature, not reflectivity, measurements, and will refer to shallow, higher-temperature, orographically linked precipitation as warm precipitation rather than NBB precipitation.)

To combat the failure of satellite precipitation algorithms to capture rainfall accurately in the western United States, we propose an algorithm that creates a model of T_b –RR curves that are dynamically shifted at

each pixel according to the relative wetness of the pixel's rainfall climatology. We call this the PERSIANN Dynamic Infrared–Rain rate model (PDIR). The central hypothesis of PDIR is that land surface characteristics (topography, elevation, climate type, temperature climatology, etc.) influence the T_b –RR relationship. Rainfall climatology represents these land surface characteristics. The dynamic T_b –RR curve introduced in PDIR can estimate identical rainfall for clouds of differing temperatures as well as different rainfall rates for identical clouds with the same temperatures—a necessary feature for detecting warm precipitation.

Methods

With the dynamic T_b –RR relationship technique and other steps, PDIR is based on—and further improves upon—the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Cloud Classification System (PERSIANN-CCS) framework. PERSIANN-CCS uses image segmentation and objective classification methods to process cloud images into cloud-patch regions. Characteristics of the cloud-patch regions are extracted and clustered to create 400 cloud types, each with characteristic rainfall curves. PDIR expands the classification scheme to include characteristics of warmer clouds and includes monthly sets of 100 cloud types, improving the scheme's ability to distinguish between different rainfall regimes from different times of year.

To increase the capture of warm precipitation, PDIR increases the contrast between warm clouds and Earth's surface by raising the maximum T_b threshold for segmenting from 253°K (which is used in PERSIANN-CCS) to 273°K. To distinguish warm precipitating clouds from clear-air pixels with similar T_b , PDIR uses a series of gradient and morphology filters designed to increase the contrast around the edges of clouds, which improves the effectiveness of the watershed method used to segment cloud patches. While increasing the temperature threshold to 273°K increases false alarms, the higher threshold increases overall skill. Furthermore, this technique can capture overlapping clouds—for example, a smaller cloud at a higher altitude whose boundary is completely encompassed by a large cloud at a lower altitude, which

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would normally be captured as one cloud patch in the PERSIANN-CCS system. PDIR's processing starts from large areal scales and gradually decreases down to the pixel level: input for PDIR is mosaic IR data; after the watershed segmentation step, PDIR begins to work at a cloud-patch level, then at the pixel scale for T_b –RR curve shifting.

PDIR solely utilizes longwave data (10.7 μ m) from geostationary satellites as input data, linking T_b and RR with machine learning. PDIR's T_b –RR relationships were calibrated during the 2014–16 period and validated for 2008–13 with NOAA's passive microwave combined (MWCMB) dataset. Local rainfall climatology data (WorldClim 2 over land; PERSIANN-Climate Data Record (CDR) over water) is used to adjust the precalibrated T_b –RR relationships. This adjustment—dynamic curve fitting—is unique to PDIR. Benchmarking and comparison both utilize National Centers for Environmental Prediction (NCEP) products that are primarily radar based; the main baseline dataset incorporates quality-controlled rainfall information from ground gauges and radars. IMERG is one of the satellite-derived comparison datasets.

Validation

For the 2008–2013 validation period, the three satellite-based precipitation products (CMORPH, TRMM, and PERSIANN-CCS) fail to reproduce the patterns of spatial variability in annual precipitation observed in the NCEP radar-gauge baseline product. All severely underestimate rainfall over the rainy northwestern regions of the Pacific coast states (the Cascade Range and Sierra Nevada). On the other hand, apart from slight overestimation in arid parts of Nevada, PDIR accurately reproduces spatial patterns of annual rainfall that are similar to the observed ones with a correlation coefficient (CORR) of 0.88, significantly higher than for the other products. Results also show that PDIR is superior to all other products in capturing rainfall over all intervals of rainfall intensity. Overall, these evaluation results highlight the difficulty of observing rainfall from satellites over the region's complex and heterogeneous topography.

At daily scales, however, differences between the products' performances were subtle until we investigated to what extent each

product's performance depends on rainfall quantity. PDIR significantly improves skill of detection. The comparison satellite products fail more regularly to accurately detect heavy rainfall events over the region. It is clear that PDIR is superior to all of the comparison products in capturing rainfall over all intervals of rainfall intensity in regard to volumetric Critical Skill Index (vCSI)—looking at how much rain falls, not just when and where. All the products, including PDIR, have lower skill in capturing heavy rainfall compared to low rainfall, but PDIR significantly improves both the detection of heavy ($>40 \text{ mm day}^{-1}$) rainfall (though with increased false alarms) and low rainfall ($<1 \text{ mm/day}$ and between 1 and 5 mm/day).

Atmospheric rivers (ARs) contribute one-third to one-half of the annual precipitation over much of the region and are the primary source of flooding on the West Coast. Thus, accurate observation of precipitation events associated with ARs is of utmost importance. We examined the performance of PDIR in detecting the extreme rainfall from two major landfalling ARs.

An AR event from 28 November to 7 December 2012 brought 200 mm of rainfall in 10 days along the coasts of Washington, Oregon, and northern California. PDIR detects the storm's spatial variability relatively well, suggesting that the near-real-time PDIR can

★ Rainfall during the period from 20 to 25 Mar 2018 associated with an extreme AR event over California. Observations from ground measurements: Stage IV and the near-real-time Stage II, satellite-based measurements: CMORPH (CMO), TRMM, IMERG, PERSIANN-CCS (CCS), and PDIR.

be effective for early flood warning in such extreme events.

The AR of 20–25 March 2018—a Pineapple Express—brought 230 mm of rain in some regions during the first day alone. Although all satellite-based products [the Climate Prediction Center MORPHing method (CMORPH), TRMM, IMERG, and PERSIANN-CCS] estimate heavy rainfall during the storm period, PDIR is the only product to mimic the observed spatial rainfall patterns. In addition, PDIR estimates more accurate rainfall amounts than other commonly used products.

Conclusions

Preliminary evaluations of PDIR show a meaningful advantage over established algorithms and much promise. PDIR solely utilizes IR as input data and proved that it was of comparable or greater relative skill to PMW-, radar-, and other IR-based products for annual accumulations and short-term extreme weather events. On the other hand, PDIR does have the tendency to overestimate rainfall totals and falsely detect rainfall in some situations, and its skill is often eclipsed by other products on the daily scale. However, its strengths outweigh its deficiencies.

PDIR's future direction is chiefly focused on its global implementation. Moving forward, there is great potential for the development of a high-resolution climate data record using PDIR. ☼

BAMS: What's your take-away message about PDIR?

Eric Jay Shearer (University of California, Irvine): *We would like readers to know that near-real-time subdaily quantitative precipitation estimates (QPE) on a global scale are rapidly improving. PDIR proves that it can be useful for real-time monitoring, a gap that satellite rainfall estimates have been working on filling.*

Mohammed Ombadi (University of California, Irvine): *Estimation of precipitation from satellite infrared data has come a long way since early efforts at the turn of the twenty first century.*

BAMS: How did you become interested in rain estimation with satellites?

Phu Nguyen (University of California, Irvine): *Satellite precipitation observation is especially useful for developing countries. At UC Irvine we have been developing advanced machine learning models for satellite precipitation estimation for more than two decades. We have been collaborating with UNESCO to provide training courses in Asia, Africa, and the Middle East for operational hydrologists and water resources engineers on the use of satellite datasets developed by our center. Improving the quality of satellite precipitation estimation is crucially important to us.*

Vesta Afzali Gorooh (University of California, Irvine): *There is a need for an accurate satellite precipitation dataset representing an alternative source to ground-based*

precipitation measurements. This product carries a potential for hydrologic applications and natural disaster management related to precipitation events.

EJS: *Also, as a researcher with a focus on the U.S. West Coast, I recognize how much trouble the region is for satellite QPE. Yet, the region houses some of the country's largest population centers. It became clear to me and all involved in the research that improving satellite QPE over the western U.S. is vitally important for water security and flood resiliency.*

BAMS: What surprises you the most about the work on PDIR?

MO: *It is surprising that we can make reliable precipitation estimates using solely infrared information.*

EJS: *The implication is that IR-based algorithms may soon have comparable skill to algorithms that utilize passive microwave readings.*

VAG: *I was surprised how considering a dynamic relation between brightness temperature and rain rate can improve the quantitative IR-based precipitation estimation, especially over the complex topography in the western states.*

Soroosh Sorooshian (University of California, Irvine): *I am not sure if I would label it as a surprise, but the level of creativity and vision by the younger members of the team working on this topic fascinates me.*

BAMS: What was the biggest challenge in developing PDIR?

PN: *Estimating precipitation solely from IR channel imagery is always challenging.*

VAG: *There are many satellite precipitation products with longer latency time and lower spatio-temporal resolution, and we are specifically working on improving pure GEO-based precipitation algorithms to take advantage of spatiotemporal richness of IR data. Despite our relatively narrow focus, we still experience difficulty in convincing the community not to make comparisons between multi-sensor products and solely IR-based datasets, which is an apples and oranges comparison.*

SS: *Application of machine learning and neural networks to process vast amounts of satellite observations has and will continue to be a very challenging area of research. The physical complexity of the precipitation process and ability to estimate the rates and amounts reaching the ground is no trivial matter.*

BAMS: What's next?

EJS: *Next, PDIR will be adapted to global implementation. The results will be used to build a climate data record over the entirety of the satellite age.*

PN: *We will introduce the new global near-real-time high-resolution precipitation product from the algorithm very soon.*

VAG: *Our global implementation and climate datasets will be publicly available through CHRS website (<http://www.chrs.web.uci.edu/>).*