**Evaluation of the performance of climate reanalysis products in reproducing spatial and temporal variation in precipitation in central Panama**

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**Introduction (~500 words)**

[motivation for study: precipitation is important but such data often not available]

* Tropical forests vary widely in their total annual precipitation and its seasonal distribution, and thus in the frequency, intensity and duration of drought stress, and this in turn drives considerable variation in tropical forest communities and ecosystems (Muller-Landau et al. 2021).
* Information on local climate, and especially precipitation, is thus critically important for ecological studies in tropical forests.
* Research on Barro Colorado Island (BCI) has benefited from an exceptionally strong meteorological monitoring program (Paton and Stallard, BCI climate, this volume).
* However, such high-quality ground-based meteorological data are relatively scarce in Panama and most other tropical forest regions (Malhi & Wright 2004; Clark 2007).

[Reanalysis datasets are a potential solution, but little evaluated in tropics]

* Global gridded climate products provide a potential alternative for characterizing climate when local ground data are not available (Burton et al. 2018).
* These global climate products are produced by combining data from ground-based and/or satellite sensors with statistical and/or mechanistic models.
* A plethora of such datasets now yields a wide array of options for researchers; e.g., an initial search for this study yielded 23 publicly available precipitation products (Table S2).
* Unfortunately, relatively few studies have evaluated the performance of any of these datasets in reproducing spatial and temporal climate variation in tropical forests, much less provided quantitative comparisons to inform choice among these datasets (Trenberth et al. 2001; Burton et al. 2018).

[Central Panama offers a great option for evaluating rainfall products in the tropics]

* Central Panama is an excellent region for evaluating the performance of global climate products in reproducing precipitation patterns in the tropics.
* Annual precipitation varies more than twofold due to a steep rainfall gradient from the drier Pacific to the wetter Caribbean side of the isthmus, as well as elevational rainfall variation (Paton and Stallard 2023 regional).
* And importantly, the region features a relatively large number of high-quality, long-term rainfall monitoring sites, reflecting the importance of rainfall for the operation of the Panama Canal as well as the legacy of the Smithsonian Tropical Research Institute (Paton, Steve & Equipo de Análisis de Calidad de Agua, Panama Canal Authority, 2022; Paton & Stallard 2023 regional,BCI).

[objectives and approach of this study]

* Here, we evaluate ten high-spatial-resolution gridded climate reanalysis datasets against ground-based rainfall data in central Panama.
* We first specifically assess their ability to capture spatial variation including the steep regional rainfall gradient, as well as elevational variation.
* For those datasets with high temporal resolution data, we further evaluate their accuracy and precision in reproducing seasonal and interannual variation.
* Our aim is to provide guidance for researchers seeking to choose among available datasets to estimate rainfall in tropical sites lacking nearby ground stations.
* We treated the ground data as “truth” in evaluating the reanalysis datasets, though we recognize that not all differences between the gridded climate reanalysis products and the ground data necessarily reflect errors in the reanalysis products.
* Most fundamentally, rain gauge data reflect rainfall at a single point (<0.1 m2), whereas reanalysis products estimate average rainfall over an area more than a million times larger (>1 km2).
* Rain gauges also systematically underestimate precipitation by ~9-23% due to wind effects and evaporation (Polluck et al. 2018).

**Methods (~800 words)**

*Study region*

The focal region is centered on Barro Colorado Island and the Panama Canal (Figure 1). It encompasses a narrow isthmus with a steep regional rainfall gradient from the drier Pacific to the wetter Caribbean side, as well as a 425 km2 manmade lake (Gatun Lake, since 1913) and orographic variation from sea level to 1340 m elevation.

*Datasets*

Ground-based rainfall data were collected at 79 stations, including 73 maintained by the Panama Canal Authority (ACP) and 6 maintained by the Smithsonian Tropical Research Institute (STRI). Rainfall data were collected using automated tipping buckets and manual rain gauges (REF – BCI met report). Data were pre-screened by Steve Paton. The temporal extent of ground records varied among sites, from 1 to 103 years of data per station. The ground data also contained gaps of missing data due to sensor failures or other problems. We restricted our analyses to subsets of sites having more complete data during the years covered by the reanalysis datasets, as detailed below.

We evaluated precipitation products from 11 publicly available gridded climate reanalysis datasets with spatial resolutions of 0.05 degrees (approximately 5.5 km) or better (Table 1, see also Table S2 for a complete list of datasets considered). We did not consider coarser resolution products because of the steepness of climate gradients in the focal region. Reanalysis datasets were resampled at 0.008333-degree resolution using the raster package (Hijmans et al. 2012). The time periods covered vary among reanalysis datasets and spanned 1970-2016 (Table 1). The climate products tested here are not independent – they share many of the same forcing datasets and/or algorithms (Table S2).

*Statistical analyses*

Our analyses of spatial variation focused on two response variables: total annual precipitation and total January to April precipitation, the latter a proxy for dry season precipitation. To visualize spatial patterns of precipitation for each reanalysis dataset, we computed average annual precipitation and average January to April precipitation for each grid cell of each dataset and mapped these across the region. For analyses of performance in capturing spatial variation, we used data for 31 ground station sites each having 32 or more complete years of data during 1970-2016. We used reanalysis data for the raster cells including the ground station locations, or the closest non-null values. (Some stations fell within grid cells that were largely water, which had null values in some reanalysis datasets.) We gap-filled the ground station time series of annual precipitation and January to April precipitation. Specifically, for each response variable (annual precipitation, January to April precipitation), we fit linear mixed models with random effects for year and fixed effects for site, including all site-year combinations with complete data. We then used the predictions of these models for missing site-year combinations. For each reanalysis dataset, we calculated the observed mean annual precipitation and mean January to April precipitation for each ground station from the gap-filled data, restricting to the years included in that reanalysis dataset. We evaluated the performance of each reanalysis dataset in capturing spatial variation in each response variable using scatterplots, linear regressions (for predicting the ground data from the reanalysis data), and the following metrics: the Pearson correlation coefficient, root mean square error (RMSE), mean absolute error (MAE) and mean bias across the 31 sites.

2. Mean bias=

where Y is reanalysis dataset value, X is rain gauge value, i is an index for site, and n is the number of sites.

We evaluated the performance of the reanalysis datasets in capturing temporal variation in precipitation at nine focal ground stations that each had 44 or more years of data during 1970-2016. These included two precipitation records for Barro Colorado Island. BCICLEAR is the STRI meteorological record from the lab clearing, which combines data from an automated tipping bucket with a manual rain gauge (the total in the manual rain gauge is distributed across days in accordance with the totals in the automated tipping bucket). BCI and the other seven stations were ACP sites monitored with electronic rain gauges. The nine sites ranged in mean annual rainfall from 2088 to 3947 mm/year during 1970-2016 (Figure 4). To evaluate performance in capturing seasonal variation, we first calculated the mean rainfall for each calendar month at each site for the year’s corresponding to each reanalysis dataset, then calculated Pearson correlation coefficients, RMSE, and MAE over the 12 calendar months for each site and dataset, and finally averaged these statistics over the nine sites for each dataset. To evaluate performance in capturing interannual variation, we calculated Pearson correlation coefficients, RMSE, MAE, and mean bias % for total annual rainfall across years for each site and dataset, and then averaged the results over sites. Missing values were not gap-filled, but simply omitted. Interannual variability could be assessed only for six reanalysis datasets with publicly available time series between 1979 and 2016.

All analyses were conducted in R version 4.2.1 (R Core Team, 2022) using the packages terra, sp, raster, tmap, and seegSDM (Hijmans et al., 2023; Pebesma, 2023; Tennekes et al., 2022; GitHub, oxford-seegSDM). Complete code is presented in online supplementary material in the Smithsonian Figshare repository.

**Results (500 words)**

*Spatial patterns*

All the reanalysis datasets show higher annual precipitation at higher elevation and on the Caribbean (northwest) side of the isthmus, consistent with ground observations, but they differ widely in the strength of these gradients and the details of the patterns (Figure 2, left). The datasets differ even more strongly in their spatial patterns of January to April (dry season) precipitation (Figure 2, right). All the reanalysis datasets except CHELSA W5E5, perform moderately well in capturing spatial variation in precipitation in this tropical region, with Pearson correlation coefficients between 0.56 and 0.85 for annual precipitation and between 0.47 and 0.85 for January to April precipitation (Figure 4, Table 2). However, they all have substantial errors, with RMSE of 324-598 mm for annual precipitation, and 85-125 mm for dry season precipitation. The spatial pattern in total annual precipitation across the ground stations is best captured by CHELSA 2.1, CHIRPSv2, CHPclimv1, and CHELSA EarthEnv, while TERRA and CHPclimv1 best capture the variation in Jan-Apr precipitation (Pearson r>0.8 in all cases). In general, the reanalysis datasets systematically underestimate precipitation at the wettest sites, those at high elevation and along the Caribbean coast (Figures 3, 4).

The datasets vary strongly in their biases relative to the recorded ground data. As expected, given the known bias towards under catchment in the ground-based rainfall measurements, the reanalysis datasets average systematically higher values for mean annual precipitation than the ground datasets, with biases ranging from -55 and -38 mm (TERRA, WorldClim) to +460 mm (PBCOR CHPclim). However, 10 of 11 reanalysis datasets systematically underestimate dry season precipitation, with average mean bias ranging from -65mm (TERRA) to +5 mm (CHELSA 2.1) across datasets. The PBCOR-corrected datasets have higher precipitation totals, and thus systematically shift the mean bias upwards.

*Seasonal and interannual patterns*

All reanalysis datasets did well at reproducing the broad patterns of seasonal variation in mean rainfall among calendar months (Pearson correlations between 0.93 and 0.98, Table 2). However, all underestimated dry season precipitation in the wettest sites (Figure 5). CHIRPSv2 had the highest Pearson correlation for seasonality (0.98) and the smallest RMSE(37mm)across sites. The various CHELSA-derived datasets version 1.2 and 2.1 achieved high Pearson correlations (r=0.97); and were biased upwards with respect to the ground data.

Interannual variability in the rain gauge data was less well reproduced in the gridded climate products (Figure 6). The best datasets – specifically CHIRPSv2 and CHELSA W5E5 had Pearson correlation coefficients of 0.75 and 0.69, respectively across sites, but other datasets did much worse (r=0.26 to 0.59, Table 4). The highest annual rainfall years observed in ground measurements at the wet sites were almost never mirrored in the reanalysis datasets (Figure 6). The two BCI record which is an electronic tipping bucket shows higher mean annual precipitation in comparison with the manually emptied bucket.

**Discussion (~800 words)**

*Performance of gridded climate products (250 words)*

[general results]

* The high-resolution gridded climate products analyzed here all did moderately well in capturing the broad trends of spatial and seasonal variation in precipitation in central Panama, as reflected in high Pearson correlations.
* However, all of them underestimated precipitation in the wettest sites, especially dry season precipitation.
* In general, the products performed less well at reproducing spatial variation in dry season precipitation and interannual variation in total annual precipitation.

[general issues with interpretation]

* Interpretation of differences among the climate products in RMSE, MAE and mean bias relative to the ground stations is complicated by the known systematic undercatch in ground-based rainfall measurements.
* Given that ground data are systematic underestimates, accurate climate products should show substantial positive mean bias relative to the ground stations, and this will elevate their RMSE and MAE.
* Most of the climate products show substantial positive mean bias (90-414mm) for total annual precipitation, on the order of what would be expected to compensate for undercatch.
* The exceptions are WorldClim and TERRA, which share a forcing dataset that is an observational network, thus approaching ground values. Another exception is CHELSA W5E5 which is a daily timeseries and performs badly when calculated as a long-time climatology.

[which dataset to use for what]

* Unsurprisingly, our analyses suggest that different climate products are best for different applications.
* For studies of among-site variation within central Panama, we recommend CHELSA 2.1, which best captured spatial variation in total annual precipitation and offers ~1 km spatial resolution (and includes values for grid cells that are mostly or entirely water).
* For analyses requiring historic time series at the monthly scale, we recommend CHIRPSv2 which best captured interannual variation. For daily timeseries, CHELSA W5E5 performs well and offers daily data at ~1 km resolution for 1979-2016.
* (For more recent time series, CHIRPSv2 provides near real time estimates, but at coarser spatial resolution.)
* The steep precipitation gradient of Panama, and the narrow isthmus requires high resolution products. Products with coarser than 0.05 degrees resolution miss most of the local variability.

*Caveats and comparisons with other studies*

[Caveats / shortcomings ]

* The main limitation of this study is the fact that we are comparing spatial point observations against gridded products which represent mean values across larger areas.
* A critical assumption is that the ground data is the actual precipitation, however given all the known biases a relatively higher value might be approximating better actual precipitation.
* Another shortcoming is that all datasets that we are comparing are not completely interdependent from each other and may vary very slightly, for example the seasonality analysis yielded very similar results for all CHELSA products.
* Other studies proposed alternative methods such as triple collocation to overcome poor quality of ground records, using three independent datasets sources to evaluate the linearity between datasets and statistics such as Kling-Gupta efficiency (Wild et al., 2022).

[Comparison with other studies]

* The most common method to evaluate precipitation products is a direct comparison with rain gauge values under the assumption that it is representative of the true value, however the smoothed profile of gridded products might miss the temporal and spatial variability (Tozer et al.2012).
* A similar study in the east Asian monsoon region had similar results, placing ERA5 the parent dataset of the CHELSA products as the dataset with the highest correlation coefficients (Kim & Lee, 2022).
* Another common method is to cross validate datasets to find the strengths and limitations of each relative to a reference dataset (Baudouin et al., 2020).
* Our results show a tendency towards overestimation in CHELSA 2.1 which is also observed in mountainous region in Himalaya by the forcing dataset ERA5 (Chen et al., 2021).
* Furthermore, a recent study using hydrological simulation highlight the reliability of ERA5 at the daily and monthly scale, surpassing satellite products such as the Global Precipitation Mission, in our case GPM was omitted from analysis due to a very poor-quality index in Panama (Ougahi & Mahmood, 2022).
* CHIRPSv2 has been evaluated in Colombia using around 75 rain gauges and shows to work well even under intense ENSO event and a tendency to underestimate, we found that CHIPRSv2 shows the lowest error metrics in all our analysis(López-Bermeo et al., 2022).

*Recommendations for future research*

[recommendations for future analyses]

* Future analyses should build on the work here by incorporating additional ground datasets, applying more sophisticated methods to assess the quality of the reanalysis products, and evaluating additional variables.
* We’ve included only rain gauges in our evaluation; data from local weather radar, weirs, and other measurements of river and lake levels could be integrated to more comprehensively assess precipitation patterns.
* Their inclusion would require more complex analyses, including accounting for distance effects in the radar data and applying hydrological models to link rainfall with runoff.
* The rain gauge data could also be better utilized by incorporating explicit, empirically supported models for how point measurements such as rain gauges are expected to differ from average values over large areas.
* Here we’ve evaluated only precipitation, but other climatic variables are important such as potential evapotranspiration. Though, there is higher scarcity of ground data in central Panama against which to evaluate them.
* Future analyses would ideally address additional dimensions of rainfall variation, including at daily scales – but comparing these between ground station points and climate product grids is tricky because of the difference in spatial grains.
* Our analysis encompasses spatial variation in mean annual and seasonal precipitation, seasonal variation in mean monthly precipitation, and interannual variation in total annual precipitation.

[conclusion]

* The available climatic products perform well to estimate general patterns of precipitation in Panama. The known biases and caveats need to be carefully considered when using the data as a proxy of actual precipitation. More high-quality ground data from Panama must make its way into observational networks to improve the estimates for the country.

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**Supplemental Materials**

Table S2. can be the complete datasets.xlsx table for now, but eventually needs to also include a column for the citation, the complete dataset reference, and the complete reference for a methods description paper.

Complete code for the analyses.

Supplemental figures

It would be good to make a figure that better captures the seasonal analysis, even though I think it will probably go in supplemental material. In particular, I suggest a figure with one panel per site, and one color per reanalysis dataset. x axis ground data, y axis reanalysis data. One point per calendar month per reanalysis dataset. I guess maybe fitted lines for each site x dataset too, to show the differences among the datasets. (Don’t write the equations on the figure, though.) The 1:1 line should definitely be graphed. An alternative longer version would be one 1-page graph per site, one panel per reanalysis dataset. That would definitely go in supplemental material.

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