Evaluation of high-resolution gridded climate products in reproducing spatial and temporal variation in precipitation in central Panama

Vicente Vasquez[1,2*] and Helene C. Muller-Landau[1]

[1] Smithsonian Tropical Research Institute, P.O. Box 0843-03092, Balboa Ancón, Republic of Panamá

[2] School of Forest, Fisheries and Geomatics Science, University of Florida, 349 Newins-Ziegler Hall, Gainesville, Florida, 32611, USA

* Corresponding author: vasquezvicente@ufl.edu, vasquezv@si.com, vicenteavv7@gmail.com

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Abstract

Tropical forests vary widely in their precipitation regimes and seasonal water availability, but high-quality in-situ (ground-based) meteorological data are rare, and few studies have evaluated the performance of global gridded climate products in the tropics. We compared the performance of eleven high-resolution gridded climate products against in-situ datasets spanning high rainfall variation in central Panama. The gridded products differed widely in their performance, although most captured the broad trends of spatial and seasonal rainfall variation in central Panama, and all underestimated precipitation in the wettest sites, especially in the dry season. Spatial, seasonal and interannual variation were best captured by CHIRPSv2; downscaled finer-resolution products performed similarly well in reproducing spatial variation. Our ability to quantify performance was constrained by limited data availability, even in this region with relatively many in-situ datasets, highlighting the need for more investment in ground-based data collection in the tropics.

Keywords: precipitation, Panama, climate reanalysis, satellite-based precipitation; rain gauge; validation; tropical forests

Introduction

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, 2023). However, such high-quality in-situ (ground-based) meteorological data are relatively scarce in Panama and most other tropical forest regions (Malhi and Wright, 2004; Clark, 2007).

Global gridded climate products provide a potential alternative for characterizing climate when local measurements are not available (Burton et al., 2018). These global climate products are produced by combining data from in-situ 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 S1). Unfortunately, relatively few studies have evaluated the performance of any of these datasets in reproducing spatial and temporal climate variation in tropical landscapes, much less provided quantitative comparisons to inform choice among these datasets (Trenberth et al., 2001; Burton et al., 2018).

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 (Muller-Landau et al., 2024; Paton and Stallard, in preparation). The region hosts a relatively large number of high-quality, long-term

rainfall monitoring sites, reflecting the importance of rainfall for the operation of the Panama Canal and for the scientific mission of the Smithsonian Tropical Research Institute (Paton, 2022; Paton, 2023; Paton and Stallard, 2023; Wright and Muller-Landau, 2024).

Here, we evaluate eleven high-spatial-resolution gridded climate datasets against in-situ rainfall data in central Panama. We (1) assess their ability to capture spatial variation including the steep regional rainfall gradient, and (2) evaluate their accuracy and precision in reproducing seasonal and interannual variation. Our aim is to provide guidance for researchers seeking to choose among available gridded datasets to estimate rainfall in tropical sites lacking nearby ground stations. We treated the in-situ data as "truth" in evaluating the gridded climate datasets, though we recognize that not all differences reflect errors in the global gridded climate products. Most fundamentally, rain gauge data capture rainfall at a single point (<0.1 m^2) in a region with high local stochastic rainfall variation, whereas gridded climate products provide values for average rainfall over an area more than a million times larger (>1 km^2). Rain gauges can also systematically underestimate precipitation by ~9-23% due to wind effects and evaporation (Pollock et al., 2018).

Methods

Study region

Our study region is located in Central Panama, extending from 8.8° to 9.5° N latitude and from 80.2° to 79.4° W longitude. This region includes the Panama Canal and Barro Colorado Island (Figure 1). It encompasses a narrow isthmus with a steep regional rainfall gradient from

77 the drier Pacific to the wetter Caribbean side, as well as a 425 km^2 artificial lake (Gatun Lake,
78 since 1913) and orographic variation from sea level to 1340 m elevation.

79 Rainfall is seasonally variable in this region, with a dry season extending on average
80 from late December to late April. The length and severity of the dry season vary among sites and
81 plays a major role in determining tree species composition (Condit et al. 2013) and patterns of
82 deciduousness (Bohlman 2010).

83 *Datasets*

84 We evaluated gridded climate datasets against in-situ rainfall data for 31 stations,
85 including 29 maintained by the Panama Canal Authority (ACP) and 2 maintained by the
86 Smithsonian Tropical Research Institute (STRI). Rainfall data were collected using electronic
87 tipping buckets for ACP data, and both manual and electronic sensors for STRI data, with some
88 changes in sensor models over time (Paton, 2022). The selected ground stations had relatively
89 complete data during the years covered by the gridded datasets and were a subset of 100 ground
90 stations that were initially considered for inclusion (Table S2). Analyses of temporal variation
91 were further restricted to just nine stations with the longest time records, as detailed below.

92 We evaluated precipitation products from 11 publicly available gridded climate datasets
93 with spatial resolutions of 0.05 degrees (approximately 5.5 km) or finer (Table 1, see also Table
94 S1 for a complete list of datasets considered). We did not consider coarser resolution products
95 because of the steepness of climate gradients in the focal region. The temporal coverage varied
96 among gridded datasets and spanned 1970-2016. The gridded climate products evaluated here
97 are not independent – they share many of the same forcing datasets and/or algorithms (Table 1).
98 For comparisons with ground stations, we extracted raster cell values at each station's

coordinates using a nearest-neighbor approach (implemented with the terra package, Hijmans et al., 2023). If this returned a null value (e.g., for stations located in grid cells dominated by water), we instead used the nearest non-null cell. Some stations are spatially close to each other and therefore fall within the same raster cell for some or all gridded datasets (Table S3). For visualization purposes, gridded datasets were resampled using nearest-neighbor at 0.008333-degree resolution (terra package, Hijmans et al., 2023).

Analyses of spatial variation

Our spatial variation analyses focused on two response variables: total annual precipitation and total January to April precipitation, the latter a proxy for dry season precipitation. We chose to evaluate dry season precipitation in addition to annual precipitation because dry season precipitation is especially important for the biota and ecosystem function. We also ran analyses of wet season precipitation initially, but those results paralleled those for annual precipitation, and thus we do not include them here. To visualize spatial patterns of precipitation for each gridded 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.

We evaluated the ability of the gridded datasets to reproduce spatial variation using in-situ data for 31 stations each having 30 or more years of data during 1970-2016 (Figure 1). The comparisons with gridded datasets were based on the means for each ground station over the relevant span of years (which varied among grided datasets). In computing site-specific means, in-situ data were used as reported for site-year combinations with complete records (annual

121 precipitation required data for all 12 months, and dry-season precipitation required data for all
122 four months from January to April). We gap-filled the remainder of the ground station time
123 series of annual precipitation and January to April precipitation before computing means for each
124 ground station. Specifically, for each response variable (annual precipitation, January to April
125 precipitation), we fit linear mixed models with fixed effects for site (*s*) and random effects for
126 year (*t*), using data from the entire historical record, and only including site-year combinations
127 with 12 months for the annual precipitation model and the 4 dry season months for the January to
128 April precipitation model. For example, for annual precipitation, *P*, we fit:

129 $$P_{st} = \beta_s + c_t + \epsilon_i$$

130 Where P_{st} is the annual precipitation in site *s* in year *t*, β_s is the fixed effect for site, c_t is the
131 random effect of year (normally distributed with mean 0 and fitted variance σ^2_{year}) and ϵ_i is the
132 residual error term. We then predicted P_{st} in year-site combinations without data from the fitted
133 β_s and c_t. In total, 136 out of 1457 values of mean annual precipitation for ground sites were gap-
134 filled in the 1970-2016 timeseries for the 31 sites. The proportion of gap-filled data varied
135 among gridded datasets, depending on the temporal extent of the gridded dataset and the
136 availability of station observations within that period (Figure S2).

137 We visualized and quantified the performance of each gridded dataset in capturing spatial
138 variation in each response variable using scatterplots, linear regressions (for predicting the in-situ
139 data from the gridded data), and the following metrics: the Pearson correlation coefficient (*r*),
140 root mean square error (RMSE), mean absolute error (MAE) and mean bias across the 31
141 stations. These metrics were calculated as:

142 $$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

143 $$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - x_i)^2}{n}}$$

144 $$MAE = \frac{1}{n}\sum|y_i - x_i|$$

145 $$Mean\ bias = \frac{1}{n}\sum(y_i - x_i)$$

146 where y_i is the value for the gridded dataset for site i, x_i is in-situ value for site i, and n is the
147 number of sites.

148 *Analyses of temporal variation*

149 We evaluated the performance of the gridded datasets in capturing seasonal variation and
150 interannual variation in precipitation at nine focal ground stations that each had 44 or more years
151 of data during 1970-2016. Mean total annual rainfall during 1970-2016 ranged from 2088 to
152 3947 mm/year among the focal stations. For interannual and seasonal temporal variation
153 analyses, missing values in the ground data were not gap-filled but simply omitted.

154

155 The temporal variation analyses included two precipitation records for Barro Colorado
156 Island which fall within the same grid cell. The station named BCICLEAR is the STRI
157 meteorological record from the lab clearing area, which combines data from an automated
158 tipping bucket with a manual rain gauge (an average of two manual gauges, with missing days

159 filled by prorating the rainfall recorded at the end of the gap based on electronic sensor data).
160 The station named BCI is the ACP electronic gauge located near the edge of Gatun Lake.

161 To evaluate performance in capturing seasonal variation, we first calculated the mean
162 rainfall for each calendar month at each site for the year's corresponding to each gridded dataset,
163 then calculated Pearson correlation coefficients, and RMSE over the 12 calendar months for each
164 site and dataset and finally averaged these statistics over the ten records for each dataset.

165 To evaluate performance in capturing interannual variation, we calculated Pearson
166 correlation coefficients and RMSE for total annual rainfall across years for each site and year
167 and then averaged the results over datasets. Interannual variability could be assessed only for six
168 gridded datasets with publicly available timeseries between 1979 and 2016.

169 All analyses and visualizations were conducted in R version 4.2.1 (R Core Team, 2022)
170 using the packages terra, sp, tmap, lme4, basemaps (Hijmans et al., 2023; Pebesma and Bivand,
171 2005; Tennekes, 2018; Bates et al., 2015; Schwalb-Willmann, 2024). Complete code is provided
172 in the associated repository (Vasquez, 2024).

173

174 **Results**

175 *Spatial patterns*

176 All the gridded datasets correctly capture the direction of regional precipitation trends,
177 showing higher annual precipitation at higher elevation and on the Caribbean (northwest) side of
178 the isthmus, but they differ widely in the strength of these gradients and the details of the
179 patterns (Figure 2, top). The datasets differ even more strongly in their spatial patterns of January

to April (dry season) precipitation (Figure 2, bottom). In general, the gridded datasets systematically underestimate precipitation at the wettest sites, those at high elevation and along the Caribbean coast (Figure 3). The gridded precipitation datasets perform moderately well in capturing spatial variation in mean annual precipitation, with Pearson correlation coefficients with in-situ data averaging 0.73 (range 0.35-0.88), and less well for January to April precipitation, with correlation coefficients averaging 0.61 (range 0.14-0.88) (Table 2, Figure 4). All gridded datasets exhibit substantial differences relative to ground measurements, with RMSE of 276-548 mm for annual precipitation, and 80-130 mm for dry season precipitation. The spatial pattern for total annual precipitation across the in-situ stations is best captured by CHIRPS v2.0, CHELSA 2.1, CHELSA EarthEnv, and CHPclim v1.0, while CHIRPS v2.0, TerraClimate and CHPclim v1.0 best capture the variation in Jan-Apr precipitation (Pearson $r>0.8$ in all cases). The CHIRPS v2.0 dataset had the lowest RMSE and MAE for both total annual precipitation and January-to-April precipitation.

The datasets vary strongly in their biases relative to the in-situ data. Given the known tendency towards under-catchment in rain gauge measurements, we expected all the gridded datasets to exhibit substantial positive biases relative to the in-situ data. For total annual precipitation, 7 of 11 gridded datasets average substantially higher values consistent with this expectation, but the remaining 4 showed small negative bias (mean bias ranged from -44 to +418 mm; Table 2, Figure 3). Further, 10 of 11 gridded datasets systematically underestimate dry season precipitation relative to in-situ data (mean bias ranged from -63 to +5 mm, Table 2, Figure 3). Inspection of the bias patterns across sites reveals that the gridded products all exhibit the expected modest positive bias (higher values than in-situ) in the lower rainfall lowland sites, and all have strong negative bias at high rainfall high elevation sites (Figures 3 and 4). The

PBCOR-corrected datasets have higher precipitation totals, and thus systematically shift the mean bias upwards.

Seasonal and interannual patterns

All gridded 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 at the wettest sites (Figure 5). CHIRPS v2.0 had the highest Pearson correlation for seasonality (0.98) and the smallest average RMSE (23 mm).

Interannual variability in annual precipitation was less well reproduced in the gridded climate products, especially at the wetter sites (Figure 6). The best datasets – specifically CHIRPS v2.0 and CHELSA W5E5 – had mean Pearson correlation coefficients of 0.74 and 0.69, respectively, and other datasets did much worse (r=0.26 to 0.59, Table 2).

Discussion

Performance of gridded precipitation products

The high-resolution gridded precipitation 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 than in total annual precipitation, and less well at reproducing interannual variation than seasonal variation.

Our results provide a basis for specific recommendations on which products are best for various applications, at least for the study region. For analyses requiring time series, we recommend CHIRPS v2.0, whose monthly product best captured seasonal and interannual variation, and which is available at daily resolution from 1981 to near real time. CHIRPS v2.0 also performed well in reproducing spatial variation among ground stations in our study region, even though it has only 0.05 degree (~5 km) spatial resolution, and thus it is also our top recommendation for studies of among-site variation in central Panama. For studies requiring finer spatial resolution, the best 1-km resolution dataset we evaluated was CHELSA 2.1, although it did much more poorly than CHIRPS v2.0 at capturing spatial variation in dry season precipitation among our 31 focal ground stations. We expect that downscaling of the CHIRPS product would likely perform even better (e.g., Retalis et al., 2017). We note that WorldClim datasets performed particularly poorly, and we advise against their use.

The steep precipitation gradient of Panama, the narrow isthmus, and high topographic heterogeneity creates high local variability in precipitation, which is inherently missed by coarser resolution products. We thus included only products with at least 0.05 degrees resolution in our evaluation. In other tropical regions without such fine-scale spatial heterogeneity, coarser resolution products such as IMERG(GPM) may perform equally well and should be considered.

Interpretation and comparisons with other studies

Interpretation of differences among the climate products in RMSE, MAE and mean bias relative to the in-situ data is complicated by the known systematic undercatch in rain gauge measurements, as well as by the fact that some of our in-situ datasets also directly contribute to some of the gridded climate products. Given that in-situ data can systematically underestimate rainfall, accurate climate products should show substantial positive mean bias relative to the in-situ observations, and this will elevate their RMSE and MAE in our analyses. Most of the climate products showed 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 approximating closer in-situ values. Some of our in-situ stations are included in the observational datasets that inform WorldClim, TERRA, and CHPclim v1.0, and thus we expect these products to exhibit higher performance relative to these in-situ datasets, even though they are likely to perform more poorly at independent validation stations. It's important to keep in mind that the gridded climate products evaluated here are not all independent – there are many shared forcing datasets among them, which can in part explain similarities in performance (Table 1).

Our findings on the performance of gridded precipitation products are broadly consistent with previous studies, although there have been few studies in the tropics, and most of those have included only one or a few gridded products. López-Bermeo et al. (2022) and Paredes Trejo et al. (2016) found that CHIRPSv2 does well in reproducing spatial, seasonal, and interannual variation in rainfall in the Antioquia region of Colombia and in Venezuela, respectively. Burton et al (2018) evaluated CHIRPS and three other satellite-based rainfall products in tropical South America and Africa, finding that CHIRPS and TRMM did best (we did not include TRMM in

our analysis because of its coarse resolution of 0.25 degrees). Bastidas Oejo et al. (2019) found that CHELSA1.2 and Worldclim both showed very good performance in reproducing rainfall patterns in northwest Colombia, with CHELSA1.2 doing better, also consistent with our findings.

Recommendations for future research

Future analyses should build on the work here by incorporating additional in-situ datasets, applying more sophisticated methods to assess the performance of the gridded climate products, and evaluating additional variables. We included only rain gauges in our evaluation; data from local weather radar, weirs, and 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, ideally also accounting for environmental heterogeneity within grid cells, and by incorporating sites with shorter time series. Furthermore, additional research is necessary to evaluate the electronic sensors' tendency to underestimate rainfall, considering the variability in sensor types utilized at each station and the potential impacts of climate and surrounding vegetation on point measurements. Here we evaluated only precipitation; a more complete treatment would also encompass other variables important for predicting drought stress and forest ecosystem function, notably including potential evapotranspiration, solar radiation, temperature, and windspeed.

Our ability to quantify performance was constrained by limited data availability, even in this region with relatively many high-quality, long-term in-situ datasets. For example, the gridded datasets exhibit quite different patterns of precipitation in the northwestern area examined, which lacked ground stations for evaluation (Figures 1 and 2). The relatively good performance of the gridded products should not be taken as a reason to reduce investment in ground data. These products ultimately depend on high-quality in-situ data, which are incorporated into these products in multiple ways. Especially given the high topographic and land cover heterogeneity in this region, a denser and more evenly placed network of stations is needed to fully capture regional climate variation, better evaluate the gridded products, and contribute to better products themselves. We thus recommend investing more in meteorological data collection and curation.

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411 Table 1. Key characteristics of the gridded climate products analyzed here. See Table S1 for the larger set of datasets considered for analysis.

Name	Forcing datasets	Resolution, degrees (km)	Time period	Native format	Citation
CHELSA 1.2	Reanalysis dataset: ERA interim	0.0083333 (~1 km)	1979-2013	Climatology, monthly timeseries	Karger et al., 2018
CHELSA 2.1	Reanalysis dataset: ERA5	0.0083333 (~1 km)	1981-2010	Climatology, monthly timeseries	Karger et al., 2018
CHELSA EarthEnv	Reanalysis dataset: ERA5	0.0083333 (~1 km)	2003-2016	Daily timeseries	Karger et al., 2021b
CHELSA W5E5	Reanalysis dataset: WFDE5	0.0083333 (~1 km)	1979-2016	Daily timeseries	Karger et al., 2021a
CHIRPS v2.0	Satellite products: TMPA. Observational dataset: GTS and GHCN.	0.05 (~5.5 km)	1981-2022	Monthly timeseries	Funk et al., 2015b
CHPclim v.1.0	Observational dataset: GHCN & FAO. Assisted with satellites	0.05 (~5.5 km)	1980-2009*	Climatologies	Funk et al., 2015a
TerraClimate	Spatially interpolated dataset: WorldClim v2.0. Reanalysis dataset: JRA-55	0.04166667 (~5 km)	1981-2010 1970-2016†	Climatology, monthly timeseries	Abatzoglou et al., 2018
WorldClim v2.1 (Spatially interpolated dataset)	Observational dataset: WMO & FAO	0.0083333 (~1 km)	1970-2000	Climatologies	Fick and Hijmans, 2017
PBCOR CHELSA 1.2	ERA interim & USGS, GRDC, etc.	0.0083333§ (~1 km)	1979-2013	Climatologies	Karger et al., 2018; Beck et al., 2020
PBCOR CHPclim	GHCN & FAO & USGS, GRDC, etc.	0.05 (~5.5 km)	1980-2009*	Climatologies	Funk et al., 2015; Beck et al., 2020
PBCOR WorldClim 2.1	WMO & FAO & USGS, GRDC, etc.	0.0083333§ (~1 km)	1970-2000	Climatologies	(Fick and Hijmans, 2017; Beck et al., 2020)

412 *Adjusted to 1980-2009, although FAO does not provide temporal extent for its climatology

†Temporal extent of the complete timeseries extends from 1958 to 2023.

§ PBCOR (Precipitation Bias Correction) versions of products are computed by multiplying the original product by the PBCOR factors. The native resolution of the PBCOR bias correction factors is 0.05 degrees; these are resampled to the resolution of the original datasets to produce the bias corrected datasets.

Table 2. Summary statistics for the performance of different gridded climate products in relation to the in-situ rain gauge observations in central Panama. Performance in relation to spatial variation is based on analysis of gap-filled data for 31 stations each having 30 or more complete years of data during 1970-2016. Performance in reproducing seasonal variation among averages for calendar months and interannual variation in total annual precipitation is based on nine ground stations with data for 1979-2016 (without gap-filling). Pearson r is the Pearson correlation coefficient, RMSE is root mean squared error, MAE is mean absolute error, and Bias is the mean error (see methods). Bold highlights the best performance within each column. Some gridded climate products lacked multiannual time series and could not be included in the evaluation of interannual variation, indicated here by "NA".

Gridded Climate Product	**Spatial variation in total annual precipitation (31 stations)**				**Spatial variation in January-to-April precipitation (32 stations)**				**Seasonal variation (9 stations)**		**Interannual variation (9 stations)**	
	Pearson r	**RMSE**	**MAE**	**Bias (mm)**	**Pearson r**	**RMSE**	**MAE**	**Bias (mm)**	**Pearson r**	**RMSE**	**Pearson r**	**RMSE**
CHELSA 1.2	0.82	310	250	53	0.63	107	63	-35	0.97	31	0.31	836
CHELSA 2.1	0.87	475	438	390	0.61	105	69	-6	0.97	42	0.57	608
CHELSA EarthEnv	0.85	318	258	68	0.66	91	61	**4**	0.94	24	0.59	625
CHELSA-W5E5v1.0	0.36	497	401	**-19**	0.15	125	83	-10	0.97	42	0.69	657
CHIRPS v2.0	**0.88**	**273**	**222**	92	0.82	**81**	**49**	-22	**0.98**	**23**	**0.74**	**463**
CHPclim v1.0	0.86	371	326	245	**0.86**	91	57	-46	0.96	29	NA	NA
TerraClimate	0.78	412	346	-50	0.84	112	74	-64	0.93	33	0.27	648
WorldClim 2.1	0.65	402	330	-24	0.47	121	84	-52	0.95	34	NA	NA
PBCOR CHELSA 1.2	0.75	377	306	107	0.60	108	66	-32	0.97	28	NA	NA
PBCOR CHPclim	0.77	547	463	413	0.81	89	54	-32	0.96	36	NA	NA
PBCOR WorldClim 2.1	0.56	423	337	-21	0.32	131	93	-57	0.96	36	NA	NA

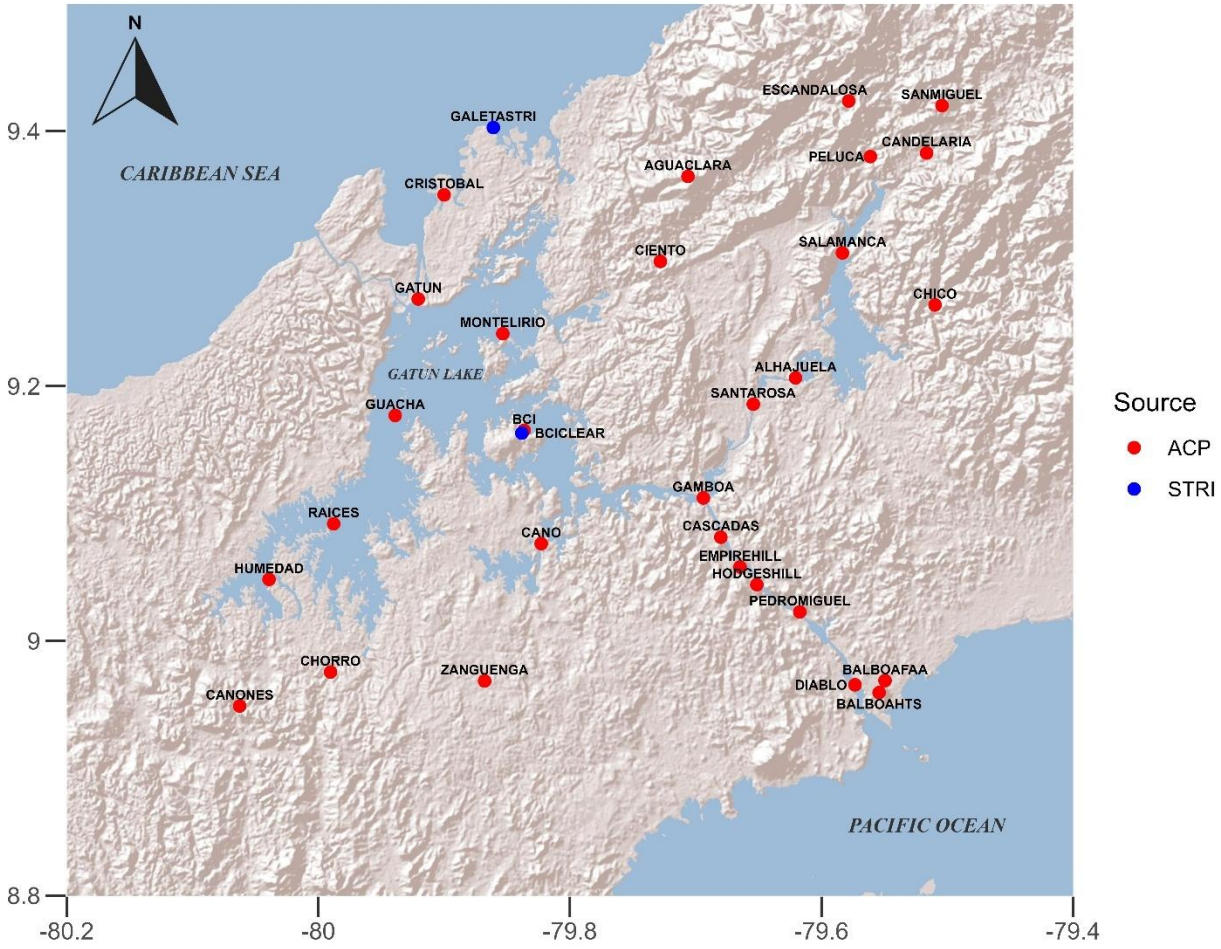


Figure 1. Topographic map of the focal region, indicating the location of in-situ measurement sites used in this analysis including ACP stations (red) and STRI stations (blue).

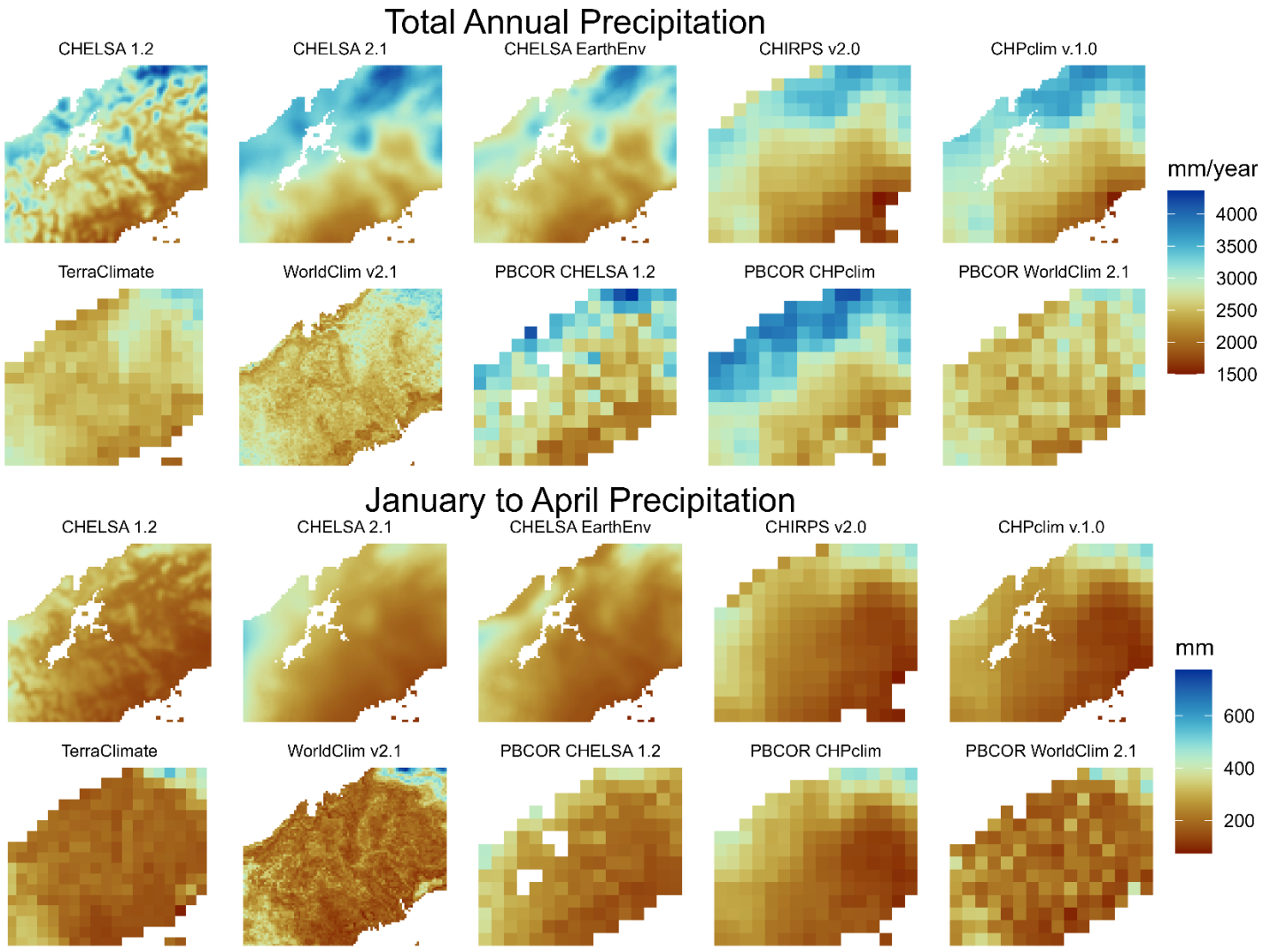


Figure 2. Spatial patterns in total annual precipitation (top) and January to April precipitation (bottom) for each gridded climate product. Note that the temporal range and the spatial resolution vary among datasets (Table 1).

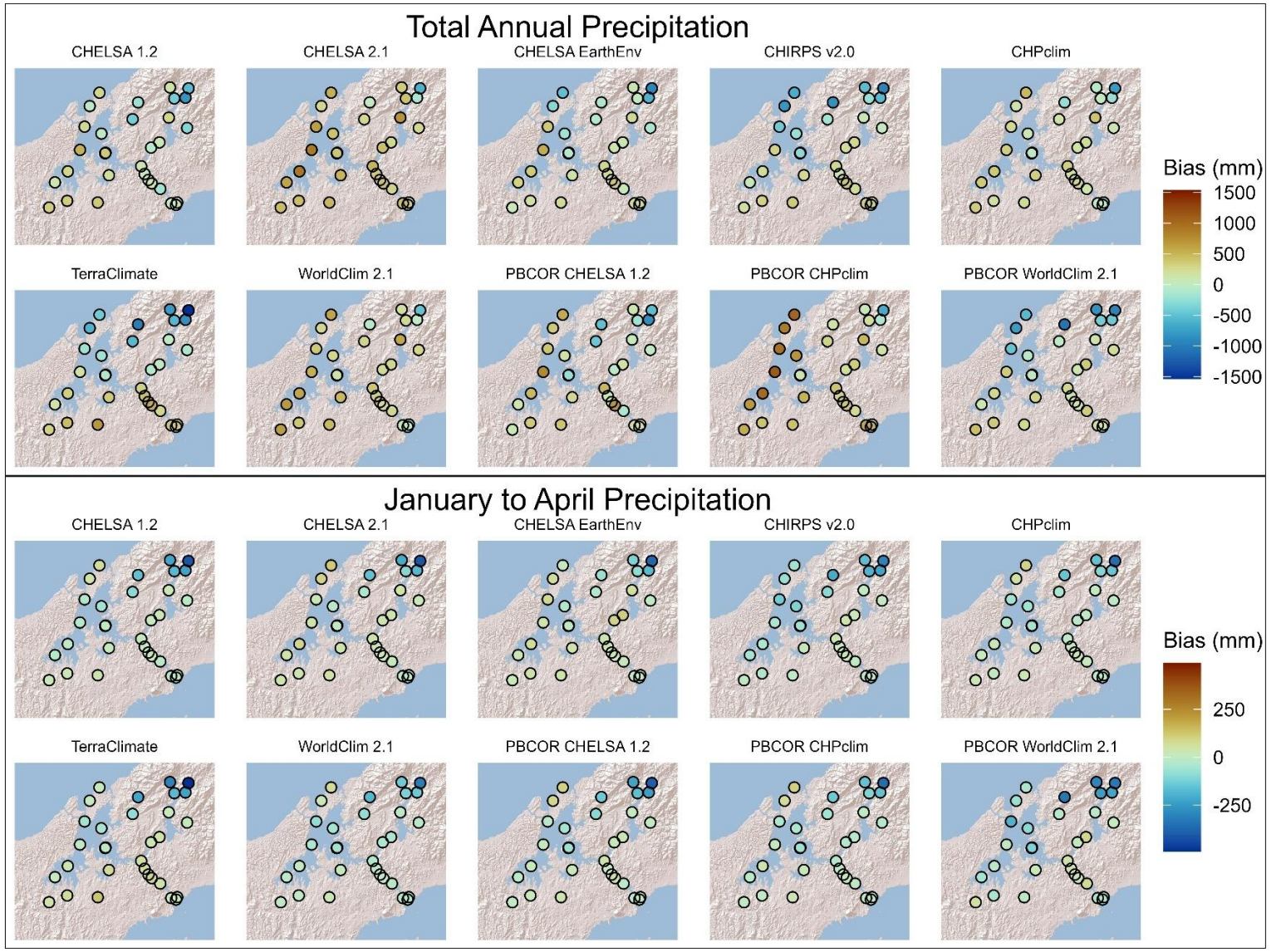
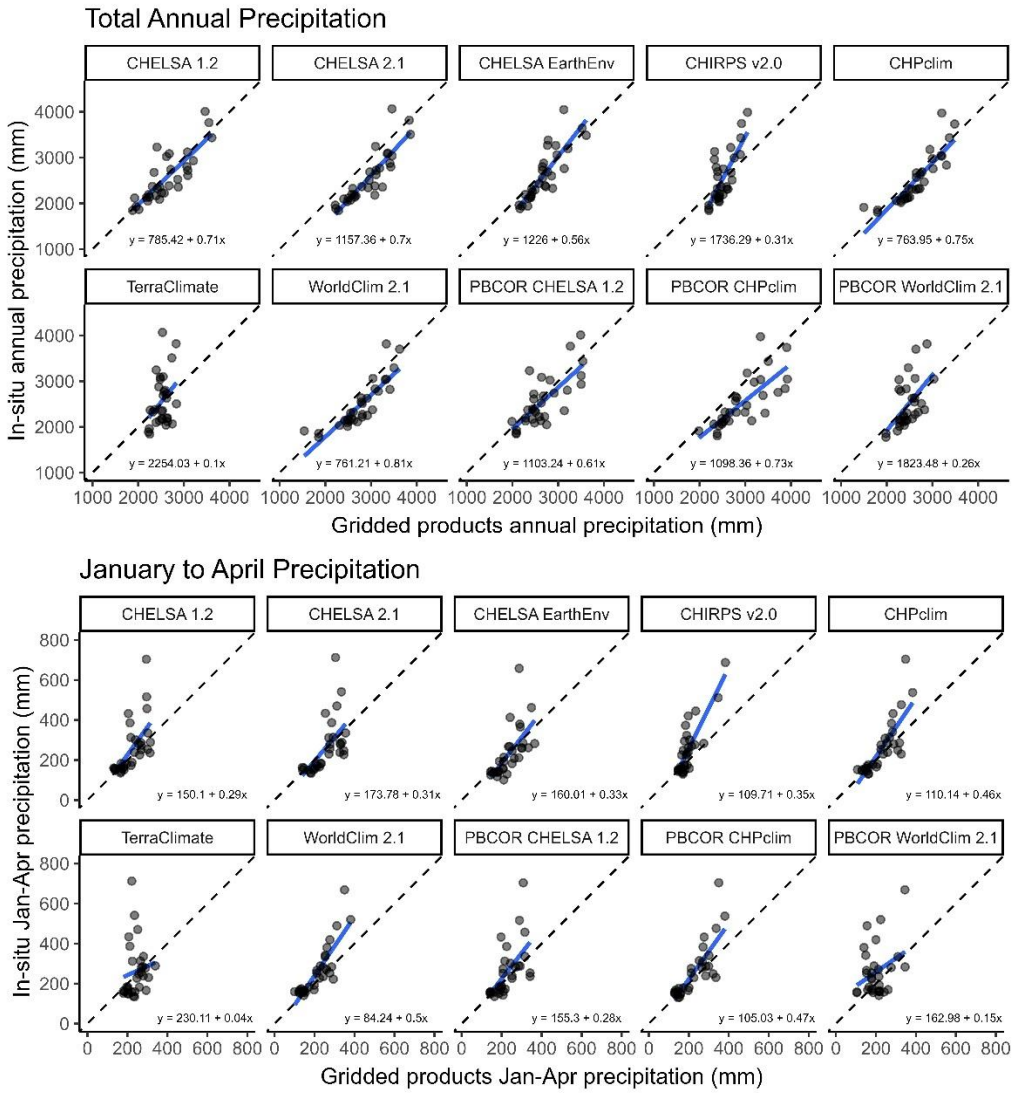


Figure 3. Spatial patterns of bias (in the gridded climate products in relation to in-situ measurements for total annual precipitation (top) and January-April precipitation (bottom).



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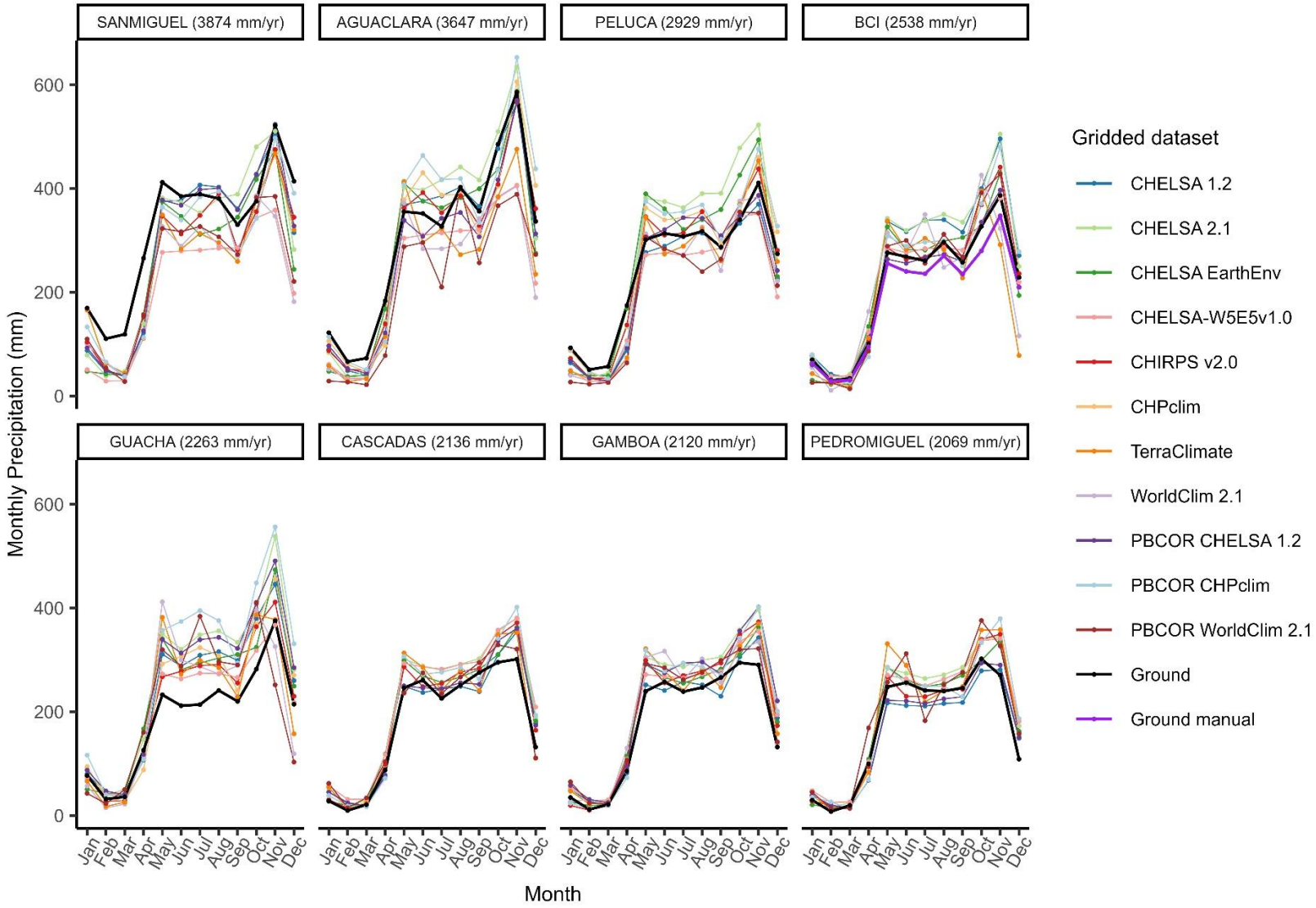
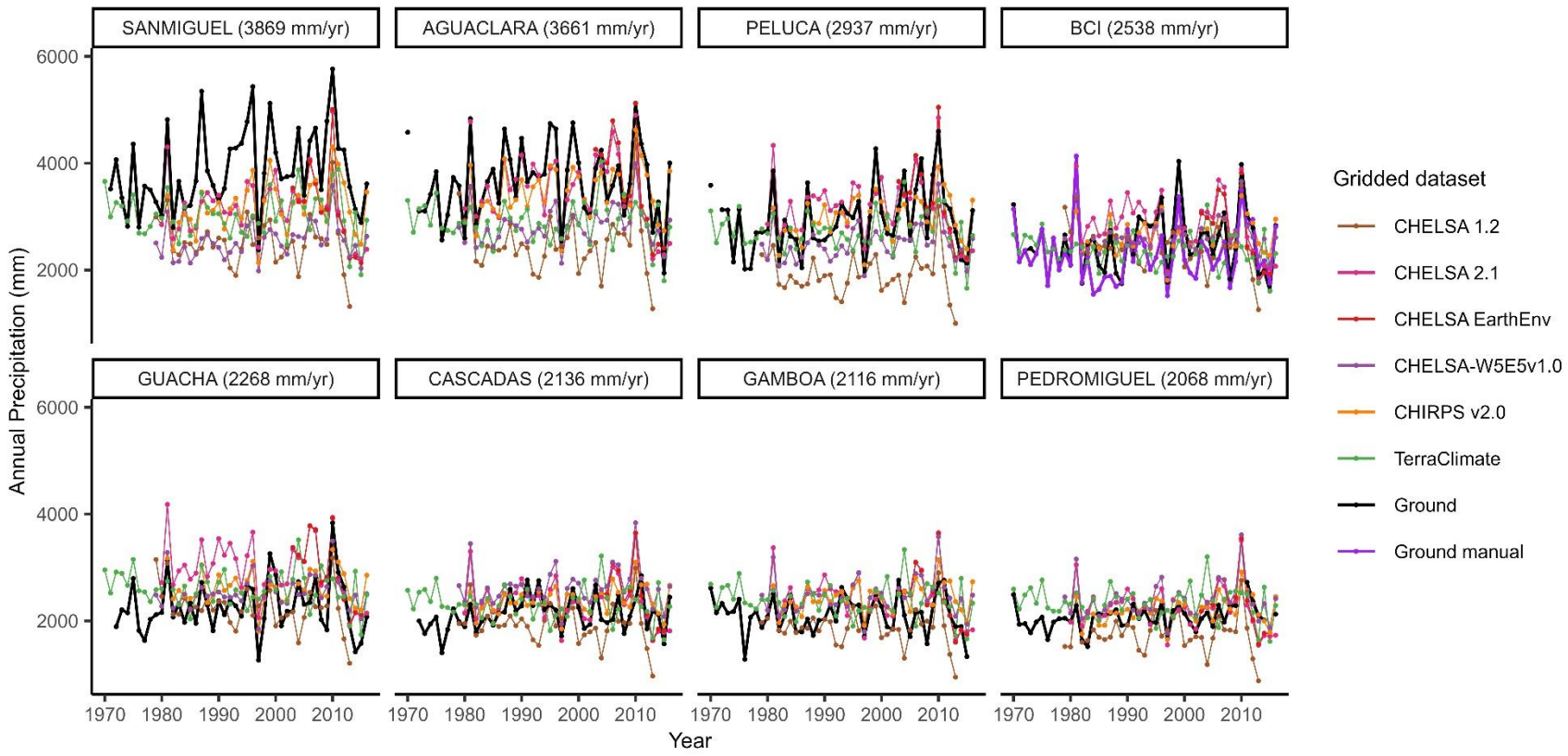
438 Figure 4. Comparison of the performance of different gridded climate products in predicting spatial variation in observed precipitation among
439 ground datasets in central Panama, for total annual precipitation (top) and January to April precipitation (bottom). Points show individual
440 ground stations, black dashed lines show 1:1 lines, and blue lines show type 1 regressions.



441

442 Figure 5. Seasonal patterns in the gridded climate products and in the in-situ observations for nine sites (note that BCI and BCICLEAR are in the
443 same grid cell and are graphed as “Ground” and “Ground manual”, respectively). Sites are ordered from highest to lowest rainfall.



444

445 Figure 6. Interannual variability in precipitation in the gridded climate products and in the in-situ observations for nine sites (note that BCI and
446 BCICLEAR are in the same grid cell and are graphed as “Ground” and “Ground manual”, respectively). Sites are ordered from highest to lowest
447 rainfall.

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