# Technical Note: Evaluation and bias correction of an observations-based global runoff dataset using ~~historical~~ streamflow observations from small tropical catchments in the Philippines

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## Abstract

~~The predictability of freshwater availability is one of the most important issues facing the world's population.~~ Even in relatively wet tropical regions, seasonal fluctuations in the water cycle complicate the consistent and reliable supply of water ~~to~~ urban, industrial and agricultural ~~demands,~~ Importantly, historic streamflow monitoring datasets are crucial in assessing our ability to model and subsequently plan for future hydrologic changes. In this technical note we evaluate a new global product of monthly runoff (GRUN; Ghiggi et al., 2019) ~~using~~ small tropical catchments in the Philippines. ~~This~~ observations-based monthly runoff product ~~is evaluated~~ using archived monthly streamflow data ~~presented in this study~~ from 55 catchments with at least 10 years of data, extending back to 1946 in some cases. Since GRUN didn't use discharge data ~~in~~ the Philippines to train/calibrate their models, data presented in this study provide ~~the opportunity to evaluate~~ independently ~~such~~ product. We demonstrate across all observations significant but weak correlation ($r^2$ = 0.372) ~~and skilful prediction (Volumetric Efficiency = 0.363 and log(Nash-Sutcliff Efficiency) = 0.453)~~ between the GRUN predicted values and observed river discharge. ~~At a regional scale we demonstrate that~~ GRUN performs best among catchments located in Climate Types III (no pronounced maximum rainfall with short dry season) and IV (evenly distributed rainfall, no dry season). We also ~~find~~ a weak negative correlation between volumetric efficiency and catchment area, and a positive correlation between volumetric efficiency and mean observed runoff. Further, analysis ~~of~~ individual rivers demonstrates systematic biases (over and under) in baseflow during the dry season, and under-prediction of peak flow during some wet months ~~among~~ most catchments. These results demonstrate the potential ~~utility~~ of GRUN and future data products of this nature ~~with due~~ consideration and correction of systematic biases at the individual basin level to: 1) assess trends in regional

scale runoff over the past century, 2) validate hydrologic models for un-monitored catchments in the Philippines, and 3) assess the impact of hydrometeorological phenomenon to seasonal water supply in this wet but drought prone archipelago. Finally, to correct for underprediction during wet months we perform a log-transform bias correction which greatly improves the nationwide Root Mean Square Error between GRUN and the observations by an order of magnitude (2.648 vs. 0.292 mm/day). This technical note demonstrates the importance of performing such corrections when accounting for the proportional contribution of ~~catchments from~~ smaller catchments in tropical land such as the Philippines to global tabulations of discharge.

## 1 Introduction

The global water crisis is considered ~~as~~ one of the three biggest global issues that we need to contend with~~, affecting~~ an estimated two-thirds of the world's population (Kummu et al., 2016; WEF, 2018). Among the sources of freshwater, the most important compartment in terms of ~~utility~~ is surface water ~~flow, which~~ is the primary resource for irrigation, industrial use and ~~for~~ bulk ~~domestic~~ water supply for many large cities. ~~Along with the purpose of flood mitigation during extreme weather events, monitoring streamflow is a vital activity that many nations conduct with various levels of coverage.~~ Long term streamflow datasets ~~prove~~ useful ~~in~~ resource management and infrastructure planning (e.g., Evaristo and McDonnell, 2019). Such data is even more critical in areas that rely on run-of-the-river supply and do not ~~utilize~~ storage structures such as dams and impoundments. Further, a robust, long term dataset is crucial in the face of increased variability in stream discharge due to land use change, increased occurrence of mesoscale disturbances and climate change (e.g., Abon et al., 2016; David, et al., 2017; Kumar et al., 2018).

There is a disparity in the availability of long-term gauged rivers datasets between continental areas and smaller island nations~~. This in the face of the latter having an invariably~~ more dynamic hydrometeorologic system owing to the size of their catchment and proximity to the ocean (e.g., Abon et al., 2011; Paronda et al., 2019). ~~Furthermore, in the case of~~ tropical island nations ~~these are where the impact of climate change in the hydrologic cycle could be observed the most~~ (Nurse et al., 2014). ~~Thus,~~ the Philippines offers a unique example where manual stream gauging programs have started in 1904 and, while spotty at times, have continued ~~on~~ to today. ~~In this work we analyse data since 1946.~~ This island nation on the western side of the Pacific Ocean ~~shows~~ a very dynamic hydrologic system ~~as~~ affected by tropical cyclones, seasonal monsoon rains, sub-decadal cycles such as the El Nino Southern Oscillation (ENSO) and ~~overlaid on top of all these are the hydrologic changes caused by~~ climate change (Abon et al., 2016; David, et al., 2017; Kumar et al., 2018).

In the absence of long-term streamflow datasets, several researchers have compiled datasets ~~worldwide which are used~~ to extrapolate streamflow in non-gauged areas (Maybeck et al., 2013, Gudmundsson et al., 2018, Do et al., 2018; Alfieri et al., 2020; Harrrigan et al., 2020). Several global hydrological models have also been created to project variations in streamflow and extend present-day measurements to the future (Hagemann et al., 2011; Davie et al., 2013; Winsemius et al., 2016). The latest contribution to modelled global runoff products is the Global Runoff Reconstruction (GRUN) (Ghiggi et

al., 2019). GRUN is a global gridded reconstruction of monthly runoff for the period 1902-2014 at 0.5 degree (~50km by 50km) spatial resolution. It uses global streamflow data from 7,264 river basins that to train a machine learning algorithm which learn the runoff generation processes from precipitation and temperature data.

This technical note evaluates the accuracy of the GRUN dataset (GRUN_v1) as applied to the ~~hydrodynamically-active~~ smaller river basins in the Philippines. Additionally, it explores the possible hydrologic parameters that may need to be considered and/or optimized such that global datasets ~~may be~~ able to ~~model~~ runoff in smaller, ungauged basins more accurately.

## 2 Dataset and Methods

### 2.1 GRUN observations-based global gridded (0.5°x0.5°) runoff dataset

GRUN is a recently published global reconstruction of monthly runoff time series ~~spanning~~ 1902 to 2014 created using a machine learning algorithm based on ~~training~~ temperature and precipitation ~~fields~~ from the Global Soil Wetness Project Phase 3 (GSWP3; Kim et al., 2017; http://hydro.iis.u-tokyo.ac.jp/GSWP3/index.html) using the Global Streamflow Indices and Metadata Archive (GISM) (Ghiggi et al., 2019). In this contribution we analyse GRUN v1 (https://figshare.com/articles/GRUN_Global_Runoff_Reconstruction/9228176; accessed September 9th 2019) which was trained on a selection of ~~small~~ catchments with area between 10 and 2500 km$^2$ GSIM (Do et al., 2018; Gudmundsson et al., 2018) and validated using 379 large (>50,000 km$^2$) monthly river discharge datasets from the Global Runoff Data Centre (GRDC) Reference Dataset (https://www.bafg.de/GRDC/EN/04_spcldtbss/43_GRfN/refDataset_node.html). ~~Additionally,~~ due to the ~~training~~ criteria GRUN's calibration is biased towards ~~an overrepresentation of~~ the northern hemisphere mid-latitudes ~~relative to the tropics with~~ few sites ~~available~~ in Africa and southeast Asia. Ghiggi et al. (2019) discuss that because of the dataset training techniques uncertainty scales with the magnitude of runoff ~~rates and~~ is likely to have high prediction uncertainty in regions with less dense runoff observations such as in tropical southeast Asia. ~~Further,~~ they show ~~in~~ southeast Asia an increase in runoff ~~rates~~ and a strong correlation of runoff with ENSO ~~over~~ the period of analysis (1902 to 2014). We refer the reader to Ghiggi et al. (2019) for more information but note that because of the catchment size filtering criteria, none of the GISM and GRDC data from the Philippines ~~was used~~ (*Personal Communications*, G. Ghiggi, 2019). As such, we view our analysis as a completely independent test of the GRUN runoff ~~reconstruction using~~ small tropical catchments.

### 2.2 Historical streamflow observations

In this contribution we analyse monthly observations of discharge from 55 manually observed streamflow stations from three Philippine datasets. The observations span 1946 to 2016, although only data through 2014 are ~~utilized~~ due to the time period included in GRUN.

### 2.2.1 Bureau of Research and Standards (BRS) Dataset

The ~~historical~~ discharge data was originally acquired from the Bureau of Research Standards (BRS) under Department of Public Works and Highways (DPWH). The records keeping was transferred to the Bureau of Design, also under DPWH, which continues to record gage data from some rivers up to this date. The degree of accuracy of records were categorized as "excellent", "good", "fair", or "poor" using the following convention: "Excellent" means about 95% of daily discharges are within ±5% difference of the actual gauge height vs height computed from the rating curve; "Good" is within ±10%; and "Fair" is within ±15%; while "Poor" means daily discharges are below the 15% "Fair" accuracy. This is the only basis of accuracy for this set of data. A majority of the reprocessed BRS data used in this analysis come from Tolentino et al. (2016), however, some of the datasets were subsequently updated using data available from the Department of Public Works and Highways.
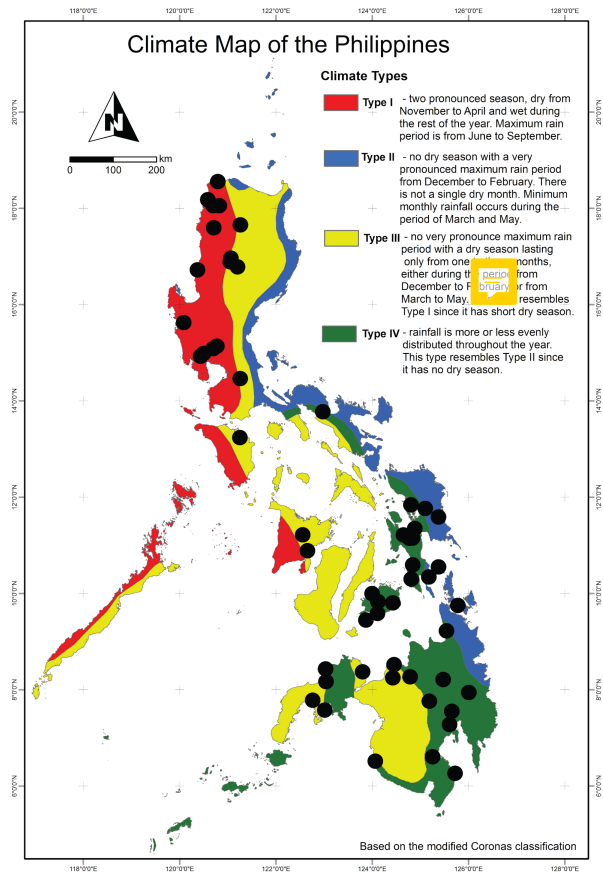


**Figure 1: Map of Philippines with location of streamflow stations** used in this analysis overlaid on climatic type (as in Tolentino et al., 2016; Kintanar, 1984; Jose and Cruz, 1999). Note that no publicly available long-term stations are available for Palawan.

### 2.2.2 Global Runoff Data Centre (GRDC) Reference Dataset

Ten catchments from the GRDC Reference Dataset ~~were~~ ~~compiled~~ (https://www.bafg.de/GRDC/EN/04_spcldtbss/43_GRfN/refDataset_node.html; requested July 2019) ~~and~~ analysed ~~in this contribution~~. Over 45 sites from the Philippines are available in the GRDC data; however, almost all do not fulfil our criteria of having over 10 years of ~~coverage.~~ Four of these catchments ~~also duplicated~~ or extended the BRS datasets, and one extends a GSIM dataset (see below). Notably four of the time series available from GRDC are available back to the 1940s (Table 1).

### 2.2.3 Global Runoff Data Centre (GSIM) Reference Dataset

Only two time series of the available five GSIM time series (Gudmundsson et al., 2016, Do et al., 2018) ~~cover~~ more than 10 years.

### 2.3 Criteria for Inclusion of Datasets

All catchment areas were verified using the digital elevation model from the 2013 Interferometric Synthetic Aperture Radar (IfSAR) data.  All ~~hydrologic~~ datasets were normalized ~~to runoff~~ (mm/yr), ~~sometimes also notated as~~ 'specific discharge' ~~in the literature~~. We only considered streamflow stations where the published and verified areas agreed ~~and coverage spanned 10 or more years. The location of all streamflow stations is shown on Figure 1 and listed in Table 1.~~ Catchment areas span 4 orders of magnitude (8.93 to 6487 km$^2$) and cover the majority of the Philippines excluding Palawan (see Figure 1). The location of catchments was paired to GRUN grid cells (0.5° by 0.5°) for the analysis. Instead of computing the weighted area runoff over the catchment, we employed nearest neighbour interpolation between the catchment outlet location and the GRUN gridded product (0.5° by 0.5° resolution). All but one catchment is smaller than the area of the GRUN grid cells (~2,500 km$^2$), thus, we view this pairing as sufficient for validation purposes. This assumption was tested by interpolating the GRUN grid to the gauging location as well as the watershed centroids, ~~and no~~ significant difference in correlation ~~to the observations that were observed~~.

### 2.4 Statistical Performance Metrics

To assess the performance of GRUN we use a suite of metrics commonly used to assess model performance in hydrologic studies. These metrics are calculated for each individual catchment (n=55) and for each climate type (n=4; see below) shown in Figure 1.

Firstly, we use the commonly used square ~~of~~ the ~~Pearson correlation coefficient~~ ($r^2$). This ~~metric for~~ bivariate correlation measures the linear correlation between two variables. In this case the predicted monthly values from GRUN ~~versus~~ the observed monthly values from the streamflow datasets. It varies from 0 (no linear correlation) to 1 (perfect correlation). The use of $r^2$ does not account for systematic over- or under-prediction in runoff because it only accounts for

145 correlation among the observed and predicted values (see Krause et al. (2005) for further discussion of the use of $r^2$ in hydrological model assessment).

Second~~ly, the primary~~ metric used here is Volumetric Efficiency (VE) (Criss and Winston, 2008), utilized previously by Tolentino et al. (2016) on a subset of the BRS catchments analysed here. VE is defined as:

$$VE = 1 - \frac{\Sigma Q_P - Q_O}{\Sigma Q_O} \qquad (1)$$

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where P is the modelled/predicted values and O is the observed runoff values. A value of 1 indicates a perfect score. Because we are interested in the performance of GRUN over the period of each streamflow record, ~~unlike Tolentino et al. (2016)~~, we calculate VE using all paired monthly observed and simulated values rather than the monthly medians. This results in lower
155 VE scores than those ~~previously~~ reported by Tolentino et al. (2016) ~~compared to hydrologic models~~.

Further, we use both the linear and logged Nash-Sutcliffe efficiency (NSE) ~~parameter. Proposed by Nash and Sutcliffe (1970) it is defined as~~:

$$NSE = 1 - \frac{\Sigma(Q_P - Q_O)^2}{\Sigma(Q_O - mean(Q_O))^2} \qquad (2)$$

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The ~~range of~~ NSE can ~~be~~ between -∞ and 1 (perfect fit). NSE values are useful ~~(compared to VE) in that~~ values less than zero indicate~~—~~that the model is no better than using the mean value of the observed data as a predictor. NSE is also calculated using logarithmic values ~~prior to calculation~~ to reduce the influence of peak flow and increase the influence of low flow values (see further discussion in Krause et al., 2005).
165 Finally, to evaluate a possible strategy for performing a bias correction of the GRUN simulated values at a countrywide scale we use the Root Mean Square Error (RMSE) in units of runoff (i.e., mm/day). The RMSE is applied to the raw GRUN simulated values and the observation based bias corrected GRUN values at the country, climate type (see below) and individual catchment level.


170 **2.5 Climate Types**

The Philippines has four Climate Types (see also Abon et al., 2016; Tolentino et al., 2017): Type I Climate on the western seaboard of the Philippines is characterized by distinct wet (May to October) and dry (November to April) seasons; Type II Climate on the eastern seaboard has no distinct dry period with maximum rains occurring from November to February; Type III inland climate experiences less annual rainfall with a short dry season (December to May) and a less
175 pronounced wet season (June to November); and, Type IV southeast inland climate experiencing depressed rainfall and characterized by an evenly distributed rainfall ~~pattern~~ throughout the year. ~~Further description is provided in Figure 1.~~
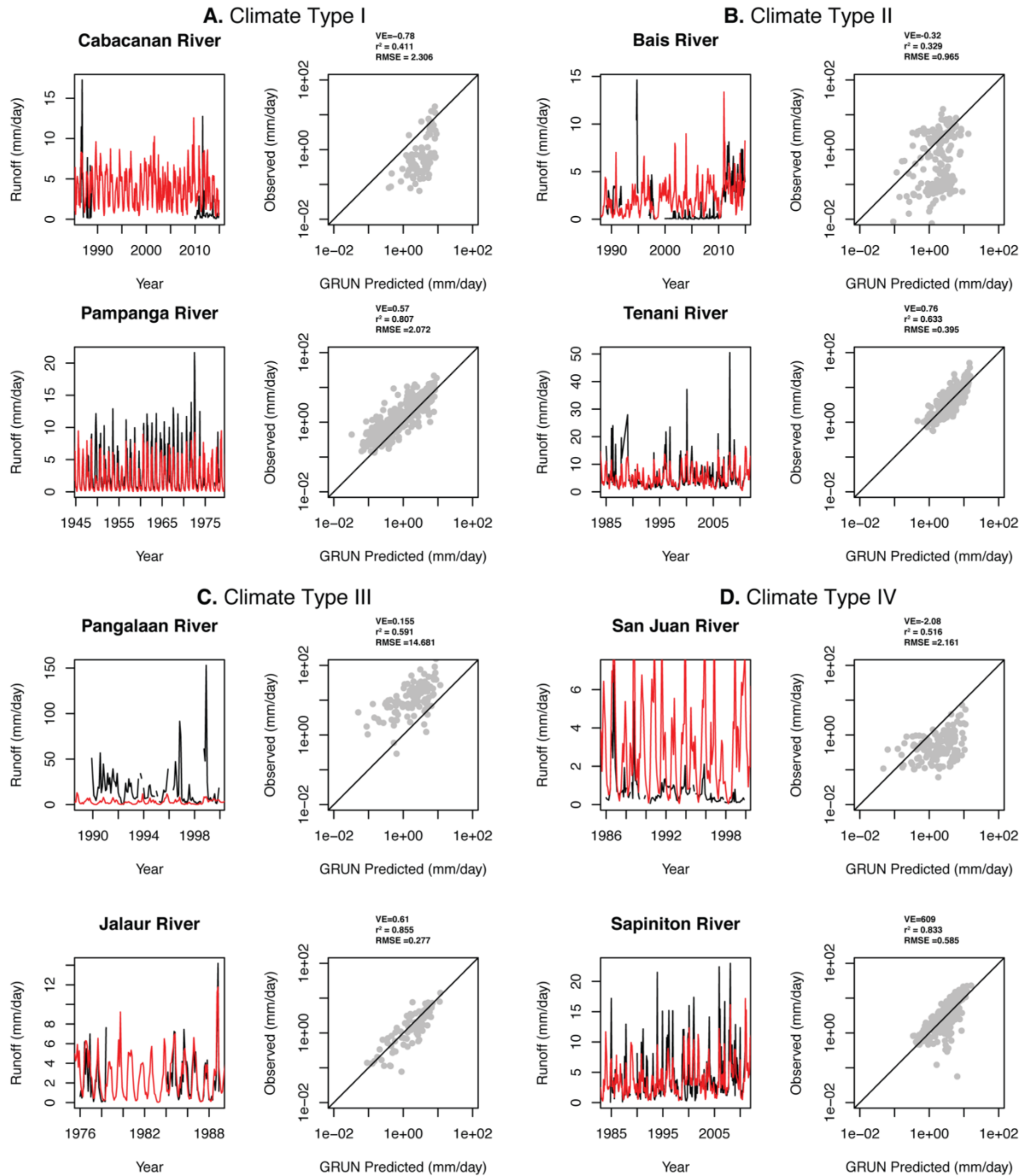
**Figure 2.** Example timeseries of GRUN predicted (red lines) and observed (black lines) runoff values, and cross-plots (log-scale) with VE, $r^2$ and RSME values for the worst (top) and best (bottom) performing river basins within Climate Types I, II, III and IV (panels **A-D**, respectively).

## 3 Results and Discussion

Statistical comparisons ~~described above~~ between ~~individual catchments~~ and the GRUN ~~dataset~~ are shown in the supplemental figures and tabulated in Table 1. ~~Shown as in examples in~~ Figure 2 and also ~~in~~ the supplemental figures (Figure A1) ~~are~~ time series comparisons between the GRUN runoff values and runoff (area normalized discharge). Statistics performance metrics across all data as well as by climate types I to IV are ~~also~~ listed in Table 1. Given the emphasis on a country scale evaluation of GRUN we primarily focus below on results in aggregate grouped by climate type or ~~among~~ all catchments.

Across all observations ~~GRUN has a~~ r-squared ~~of~~ 0.372 and ~~a~~ VE of 0.363 (Table 2). Using log(runoff) values (following Criss and Winston, 2008) this improves to an r-squared of 0.546 and a volumetric efficiency (VE) of 0.733, suggesting reasonable utility in the GRUN product at a country scale for the Philippines, despite no training data from the Philippines being used in the creation of GRUN. The ~~raw~~ RMSE across the dataset ~~is~~ 2.648 mm/day (Table 2). In the following we break down the comparison between the streamflow observations and GRUN by first comparing runoff distributions and extreme values at the individual basin level, then aggregating our results by Climate Type, and finally look at several correlations of VE to watershed characteristics.
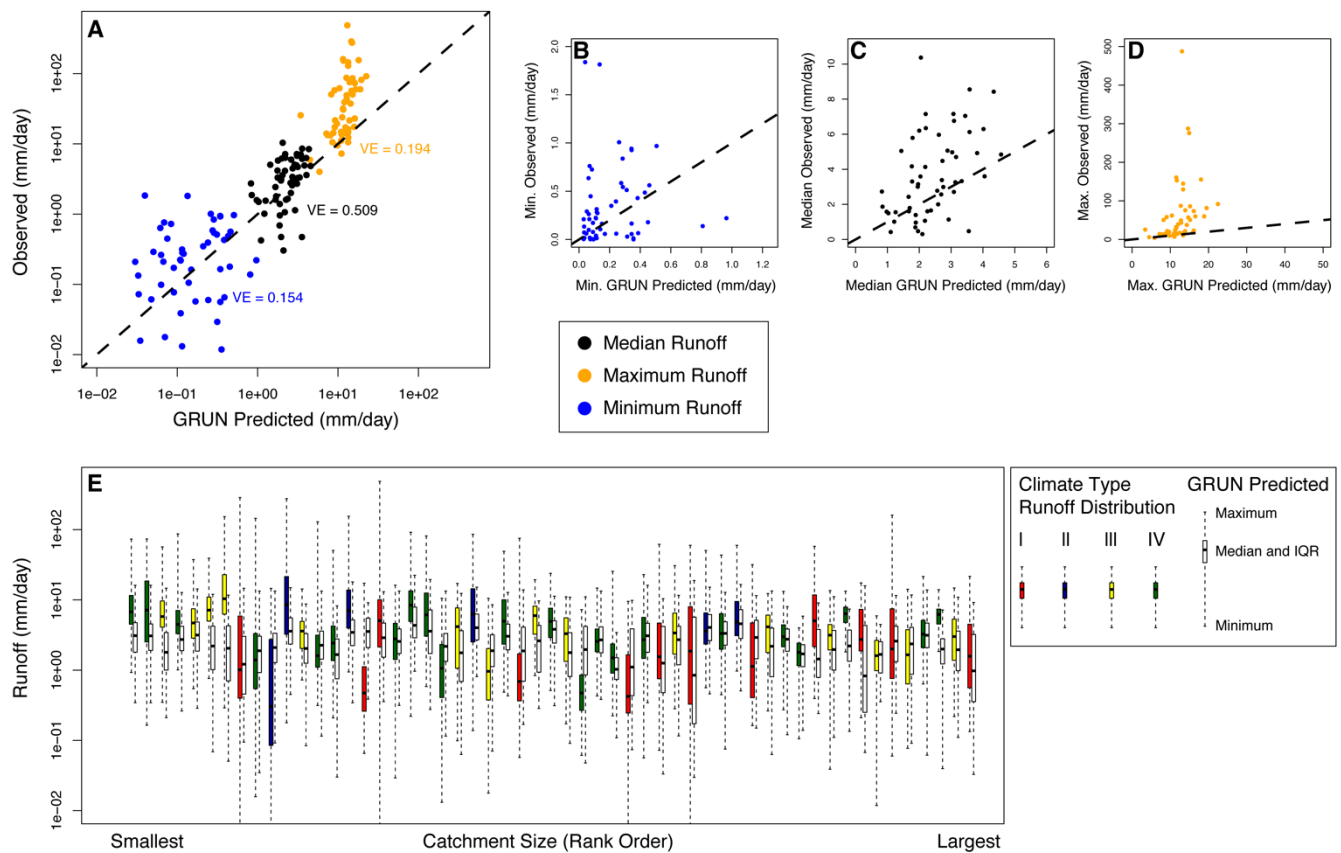
### 3.1 Comparison of runoff distributions

Average runoff values among all catchments ~~compared to~~ GRUN ~~show reasonably good predicted values~~. In Figure 3A median values of runoff (black dots) given a volumetric efficiency (VE) metric of 0.509 across all catchments, the average (mean) difference between median ~~observations~~ and simulated values is +16%. Looking at extreme monthly values (maximum and minimum) over the ~~months~~ of observation demonstrates significant underprediction in wettest conditions (orange dots in Figure 3A and 3D) with almost all catchments' maximum observations falling above the 1:1 line and a lower VE score of maximum values of 0.194. ~~For baseflow conditions spread~~ around the 1:1 line ~~for minimum values is~~ more evenly distributed, however the VE score of 0.154 is similarly low due to ~~a~~ greater spread than the median values.

This suggests two possibilities: first, that particularly for small catchments which may have steeper average slope, GRUN underpredicts monthly runoff values ~~associated with~~ the wet season; and second model-data agreement improves with catchment size. Bias is likely ~~inherited from~~ the high uncertainty in monsoonal precipitation ~~rates inputted~~ into GRUN. ~~However, we do find a~~ significant correlation (at p<0.01, r$^2$ =0.391) between log values of maximum runoff difference (observed minus predicted) ~~versus~~ catchment area (not shown)~~, with a negative relationship~~.

In general, the median and interquartile ranges (IQR, 25% to 75%) shown in Figure 2E overlap between GRUN and the observations. For five ~~catchments of~~ large (n=2) and relatively small ~~sizes~~ (n=3) the IQR of the observations does not overlap with the GRUN runoff IQR. The three small catchments are Climate Type III (yellow) and the two large catchments are Climate Type IV. ~~In~~ two catchments of moderate size the GRUN IQR is greater than the observed IQR runoff range.

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**Figure 3.** Comparison of runoff ranges and distributions. **(A)** Comparison of median and extreme (maximum and minimum) monthly values between the observations and GRUN in log space. **(B-D)** As in **(A)** for the minimum, median and maximum monthly values, respectively, in linear space. **(E)** Distribution of runoff between observations (coloured) and GRUN (white) using box and whisker plots. Plots show the median, interquartile range and maximum/minimum values. The GRUN distributions only include months where observations are present.

### 3.2 Comparison by climate type

In all basins regardless of Climate Type, a general underestimation of the model is seen for the highest runoff months, as noted above looking at the distributions by basin. This is especially evident in Climate Types I and II with pronounced wet seasons as also shown by their lower r-squared values (Figure 4) and lower VE values. Climate Type II also has the highest RMSE value of 4.554 mm/day. Climate Types III and IV have comparable r-squared and VE values though skewness towards underprediction during the highest runoff months is still evident, particularly for Climate Type IV.

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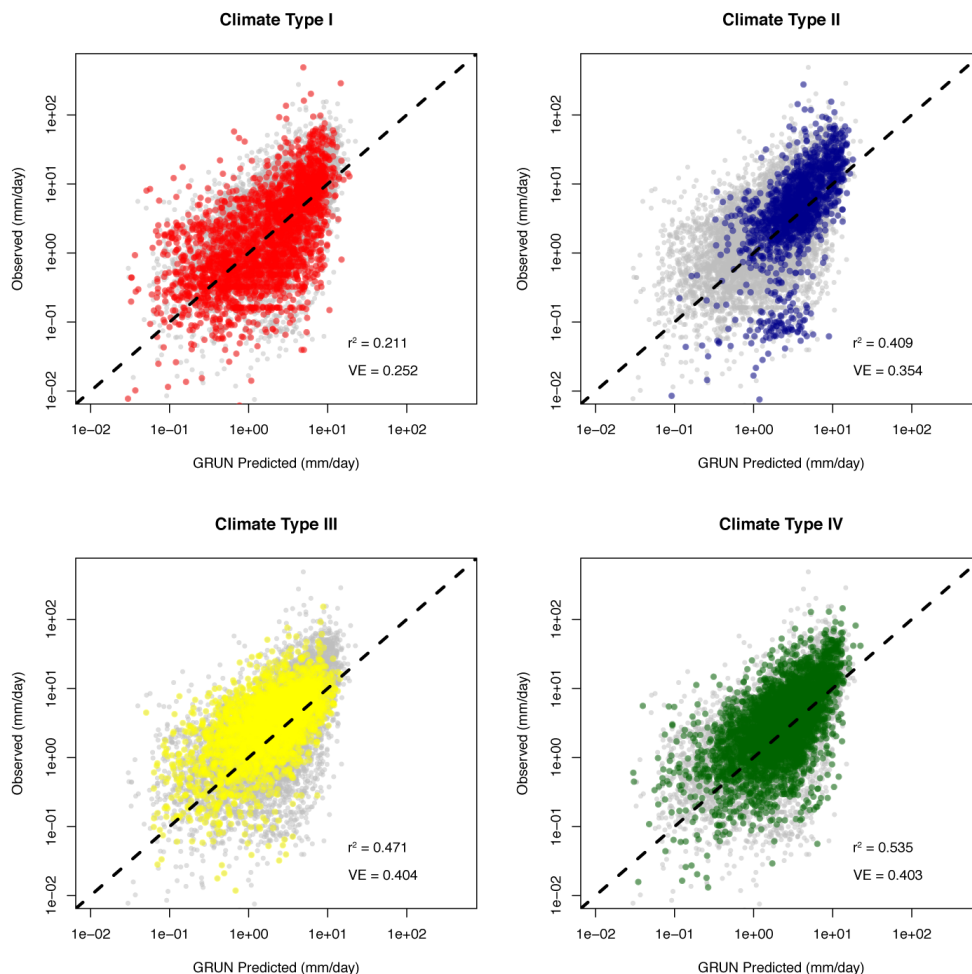
**Figure 4: Cross plots of GRUN predicted vs. observed monthly runoff by climate type (see Figure 1 for climate type distributions).** Grey dots represent all data, colored dots represent data points from that region. The squared pearson correlation coefficient ($r^2$) and volumetric efficiency (VE) metrics are listed on each panel.

### 3.3 Correlation and trends with watershed characteristics

~~In this section we analyse two potential correlations between watershed characteristics and VE scores. In Figure 5 we show~~ a weak positive correlation ($r^2 = 0.041$, $p = 0.137$) between VE and log(catchment size) (~~listed in Table 1~~) and a stronger negative correlation with mean runoff ($r^2 = 0.182$, $p < 0.01$). However, at low runoff there is significant spread in VE score, driven primarily by Climate Type I catchments (red box and whisker plot in Figure 5C). These catchments experience distinct wet and dry seasons ~~in~~ the northwest Philippines. The positive correlation with catchment size is likely primarily due to the extreme wet months ~~biasing results as described above~~. This is particularly evident from the Nash-

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Sutcliff Efficiency (NSE) and log(Nash-Sutcliff Efficiency) (NSE-log10) scores in Table 2 and Table A1. Since NSE puts more weight on large flow (Criss and Winston, 2008), it is not surprising that our NSE-log10 scores ~~are in most cases significantly more skilful among our catchments~~ because extremely wet months are weighted less than using the raw runoff

245 values compared to raw NSE scores. It is also notable that the VE scores using log10 values across the entire dataset ~~is significantly improved~~ (0.363 vs. 0.733; Table 2). The physical significance of these observations are that for large basins the time of concentration of any given flood event will be much longer, thus flood peaks will be wider and subdued due to abstractions and infiltration into the shallow aquifers. This phenomenon is likely less apparent in smaller basins where peak flows are expected to be higher because of less infiltration.

250      Previous studies have investigated the correlation between runoff and catchment size (Mayor et al., 2011), and the different hydrologic and geologic factors that cause non-linear relationships between these two variables (Rodriguez et al., 2014). Recently, Zhang et al. (2019) point out that runoff coefficients increase logarithmically as catchment size decreases. Moreover, the same paper reports ~~that~~ smaller catchments ~~are more sensitive to~~ vegetation cover, slope, and land use compared to larger catchments. This implies that predictability of basin runoff for smaller catchments are ~~increasingly~~ more

255 difficult due to variance in the compounding factors mentioned above. We hypothesize that these effects proposed by Zhang et al. (2019) ~~are~~ also influenc~~ing~~ the Philippines streamflow dataset ~~utilized~~ in this study. As such, we suggest that GRUN, is a useful new tool for studying trends, seasonality and average runoff from tropical catchments (such as in previous work: e.g., Merz et al., 2011; Wanders and Wada, 2015) ~~in the Philippines~~. However, we qualify this finding by noting that GRUN is not suitable for extreme value analyses associated with major tropical storms during the wet seasons unless suitable bias

260 corrections (see next section) can be effectively carried out.
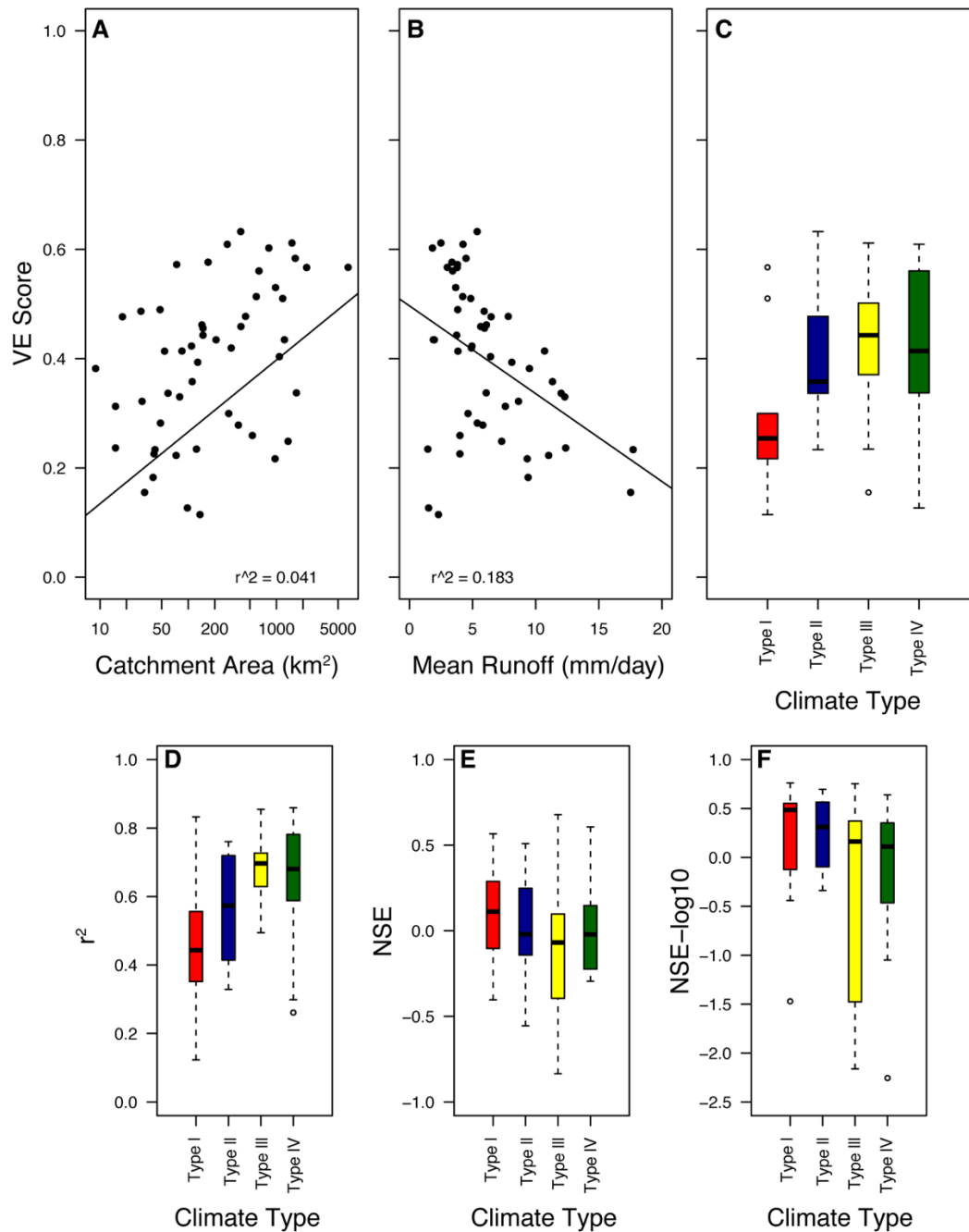
**Figure 5: Diagnostic plots of volumetric efficiency (VE) results.** Cross plots show the correlation of VE with **(A)** catchment area and **(B)** mean runoff. **(C)** Box and whisker plots show data from distribution of VE by climate type. Box and whisker plots show the median, interquartile range and 95% confidence intervals and outliers (dots). The regression in (A) is between the VE scores and ln(Catchment Area). **(D-F)** As in **(C)** for $r^2$, NSE and NSE-log10.

**3.4 Bias Correction and Outlook**

Overall, the GRUN ~~data~~ underestimates the actual observed runoff ~~from~~ Philippine basins. The GRUN dataset ~~shows~~ a range of 0 to 10mm/day for most basins and up to 20mm/day for larger basins ~~in the group~~. The observed maximum runoff values are on average higher ~~by~~ and exceed 50mm/day during extreme rain events (Figure 4). Furthermore, the GRUN dataset also appears to underestimate minimum flow in streams from highly seasonal catchments (e.g. Types I and II).

The underestimation of runoff values during extreme rain events may be a result of the fast saturation of the overlying soil and exceedance of rates of infiltration partly as a result of shallow aquifers filling up and consequently the conversion of excess rainfall into direct runoff (e.g., Tarasova et al., 2018). On the other hand, the underestimation of flow during low flow events may be a result of not accurately accounting for stream baseflow which is fed by shallow aquifers, as well as other effects such as land use and surface properties. These effects may be buffered ~~out~~ in larger catchments leading ~~to our observation described previously~~ that model-data agreement ~~improves~~ with catchment size (Figure 5B).

Given the biases ~~observed in our analysis~~ and in particular the clear underprediction of GRUN during the wettest months we perform a bias correction of the GRUN dataset at a nationwide level using all the available ~~filtered~~ data used in our analysis. We do so in a two-step process to both correct the mean offset and stretch the wettest months to higher values with all transformations occurring in log-transform space (i.e., as displayed in cross plots in Figures 2 and 4). Thus, we first add the mean log10(runoff) difference between the observations and the predicted values ($0.117 \pm 0.022$). Following this, using the *lm* function in R, we fit a linear regression between the observations and the GRUN predicted values (log10(runoff, observed) = m × log10(runoff, predicted) + b) and correct the predicted values using the slope (m=$0.774 \pm 0.025$) and intercept (b=$0.099 \pm 0.006$) derived from this regression. Uncertainties reported here are 68% confidence intervals and were assessed by bootstrap resampling 1,000 observation and prediction pairs without replacement 10,000 times. By carrying out these calculations in log-transform space the highest GRUN runoff values are the most ~~significantly~~ affected, which are the data points ~~we have observed to be~~ most underpredicted ~~in our above analysis~~ (Figures 3A and 4). Because these corrections ~~are being~~ carried out in log10 space statistical bias (underestimation) is possible (Ferguson, 1986). Following Ferguson (1986) we calculate the unbiased estimate of the variance (s) as 0.0686 mm/day which gives a correction factor (calculated as $\exp(2.65s^2)$) of 1.0126 may be applied uniformly as a correction factor (multiplier) to the bias corrected values to adjust for possible bias due to the log10 space regression we have implemented.

To assess this bias correction, we calculated RMSE values at a catchment, climate type and countrywide level (Figure 6 and Tables 2 and A1). The log-transform bias correction ~~greatly~~ improves the nationwide RMSE value by an order of magnitude (2.648 vs. 0.292) and most significantly improves catchments ~~from~~ Climate Types III and IV (Figure 6; 2.285 vs. 0.432 and 2.398 vs. 0.131, respectively; Table 2). Interestingly, the median RMSE value for Climate Type I and II catchments are not ~~significantly~~ improved, however, the RMSE range for both have been reduced (red and blue boxes in Figure 6, respectively).

300     This analysis and the improvement of RMSE values, as well as some of performance metrics such as NSE (see scores tabulated in Table 2), using a simple log-transform based bias correction demonstrates the importance of either: 1) including smaller catchments in future ~~iterations of~~ products such as GRUN, or 2) performing similar bias corrections on a country, region or even catchment scale as appropriate. This is particularly important ~~given that~~ taken at face value the proportional contribution of relatively small tropical land areas to global discharge ~~accounting~~ (e.g., Dai and Trenberth,

305     2002) would be underestimated without such corrections.
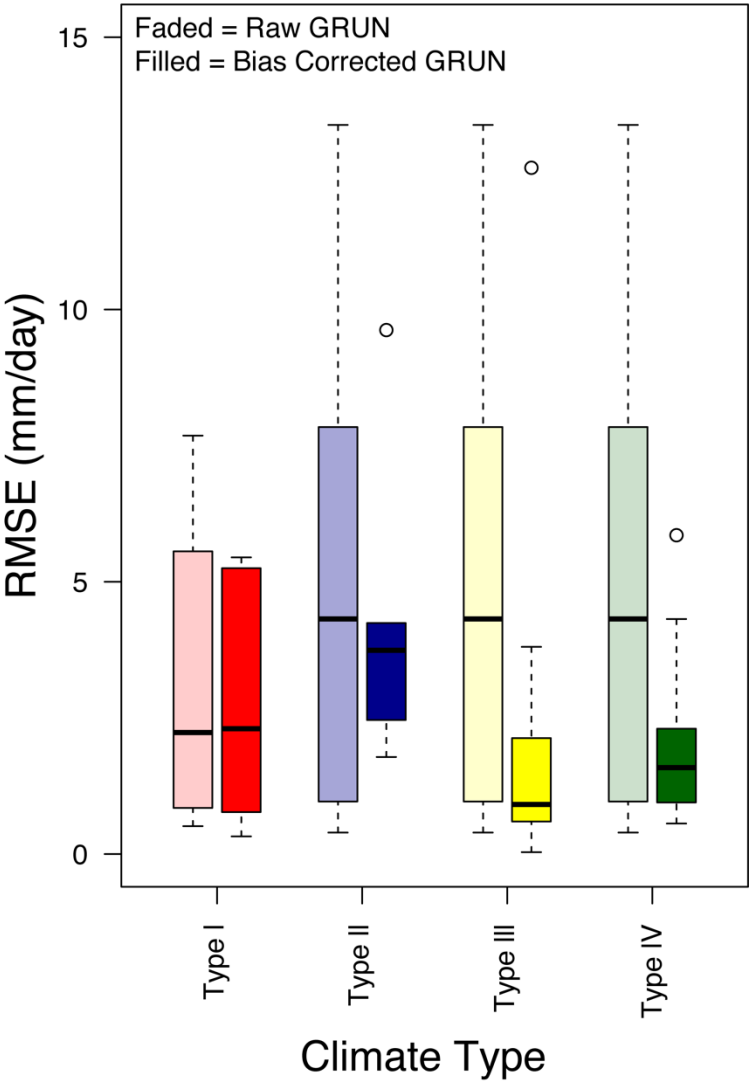


**Figure 6.** Root Mean Square Error (RMSE) ~~box and whisker plots~~ of catchments grouped by climate type of observed values versus raw GRUN values (light-coloured boxes) and bias-corrected GRUN values (bold-coloured boxes). For bias correction equation and country-wide results see Table 2.

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## 4 Conclusion

Using monthly runoff observations from catchments in the Philippines with more than 10 years of data between 1946 and 2014, we demonstrate~~d across all observations~~ significant but weak correlation ($r^2 = 0.372$) ~~and skillful prediction~~
315 ~~(Volumetric Efficiency = 0.363 and log(Nash-Sutcliff Efficiency) = 0.453)~~ between the GRUN-predicted values and actual observations. Looking at different hydrometeorological regimes, we demonstrate~~d~~ that GRUN performs best ~~among~~ low rainfall catchments located in climate types III and IV, ~~and showed~~ a weak negative positive correlation between volumetric efficiency and catchment area. Further, we found that particularly for smaller catchments, maximum wet season values are grossly underpredicted by GRUN. The application of a nationwide bias correction to stretch high runoff values using log-
320 transform runoff values greatly improved the RMSE of the predicted values. Global databases such as GRUN are applicable for aggregated stream discharge estimates and to investigate general trends in the hydrologic characteristics of a region. The recommended bias correction presented here will likely improve such estimates and analysis for the Philippines. While GRUN was never intended to be used for estimating single catchment ~~discharge~~ its applicability for such purposes can be extended provided that proper statistical comparison of modelled versus actual gauged data are initially performed. We thus
325 propose that the ~~utilization~~ of the GRUN dataset can be extended to other ungauged tropical regions with smaller catchments ~~upon~~ applying a similar correction as described in this study.

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**Data availability**

Data was compiled from the DPWH-BRS, GISM and GRDC datasets (see links in text) and is made available as a supplemental file.

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## Author contributions

345     DEI and CPCD designed the study, DEI and PLMT carried out the dataset compilation and screening, PLMT verified catchment areas, DEI and PLMT carried out the analysis, and DEI and CPCD prepared the manuscript with contributions from PLMT.

## Competing interests

350     The authors declare that they have no conflict of interest.

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**Table 1: List of stations** used in this analysis including full station names, updated catchment areas, years of coverage, division and climate type.

| River Name | Station Name | Latitude | Longitude | Coverage | Years of Coverage | Catchment Area (km$^2$) | Dataset | Climate Type |
|---|---|---|---|---|---|---|---|---|
| Sinalang River | Penarrubia, Abra | 17.622 | 120.715 | 1984-2015 | 32 | 136.128 | BRS | 1 |
| Antequera River | Sto. Rosario, Antequera, Bohol | 9.493 | 123.890 | 1984-2016 | 33 | 54 | BRS | 4 |
| Amparo River | Brgy. Mabini, Macrohon, So. Leyte | 10.042 | 124.018 | 1985-2007 | 23 | 74 | BRS | 4 |
| Hira-an River | Upper Hiraan, Rarigara, Leyte | 11.258 | 124.672 | 1986-2010 | 27 | 8.93 | BRS | 4 |
| Leyte River | San Joaquin, Capocan, Leyte | 11.880 | 124.829 | 1985-2007 | 23 | 29.15 | BRS | 3 |
| Surigao River | Surigao City | 9.796 | 125.808 | 1986-2010 | 25 | 85 | BRS | 4 |
| Bais River | Cabanlutan, Bais City, Negros Oriental | 9.876 | 124.140 | 1989-2015 | 27 | 41 | BRS | 2 |
| Lingayaon River | Lingayon, Alang-Alang, Leyte | 11.192 | 124.863 | 1957-1991 | 35 | 18 | BRS | 4 |
| Sapiniton River | Libton, San MIguel, Leyte | 11.188 | 124.795 | 1984-2010 | 27 | 277.3 | BRS | 4 |
| Laoag River | Poblacion, Laoag City, Ilocos Norte | 18.203 | 120.590 | 1984-2016 | 33 | 1355 | BRS; updated from Tolentino et al. (2016) | 1 |
| Pared River | Baybayog, Alcala, Cagayan | 17.682 | 121.270 | 1983-1996 | 14 | 966 | BRS; used in Tolentino et al. (2016) | 1 |
| Ganano River | Ipil, Echague, Isabela | 16.812 | 121.211 | 1986-2001 | 16 | 977 | BRS; used in Tolentino et al. (2016) | 3 |
| Magat River | Baretbet, Bagabag, Nueva Vizcaya | 16.992 | 121.073 | 1986-2002 | 17 | 2199 | BRS; used in Tolentino et al. (2016) | 3 |
| Camiling River | Poblacion, Mayantoc, Tarlac | 15.018 | 120.503 | 1985-2017 | 33 | 288 | BRS; updated from Tolentino et al. (2016) | 1 |
| Gumain River | Sta. Cruz, Lubao, Pampanga | 14.960 | 120.441 | 1985-2001 | 17 | 370 | BRS; used in Tolentino et al. (2016) | 1 |
| Rio Chico River | Sto. Rosario, Zaragosa, Nueva Ecija | 15.658 | 120.088 | 1985-2006 | 22 | 1177 | BRS; used in Tolentino et al. (2016) | 1 |
| San Juan River | Porac, Calamba, Laguna | 14.498 | 121.267 | 1986-1999 | 14 | 165 | BRS; used in Tolentino et al. (2016) | 4 |
| Pangalaan River | Pangalaan, Pinamalayan, Oriental Mindoro | 13.275 | 121.260 | 1989-1999 | 11 | 32 | BRS; used in Tolentino et al. (2016) | 3 |
| Das-ay River | Sto. Nino II, Hinungangan, Leyte | 10.385 | 125.202 | 1987-2007 | 21 | 59 | BRS; used in Tolentino et al. (2016) | 2 |
| Tukuran River | Tinotongan, Tukuran, Zamboanga del Sur | 7.627 | 123.030 | 1986-2009 | 24 | 147 | BRS; used in Tolentino et al. (2016) | 3 |
| Hijo River | Apokan, Tagum, Davao del Norte | 7.812 | 125.211 | 1986-2016 | 31 | 634 | BRS; updated from Tolentino et al. (2016) | 4 |
| Cagayan de Oro River | Cabula, Cagayan de Oro City, Misamis Oriental | 8.316 | 124.811 | 1991-2004 | 14 | 1079 | BRS; used in Tolentino et al. (2016) | 4 |
| Davao River | Tigatto, Davao City | 7.329 | 125.634 | 1984-1999 | 16 | 1683 | BRS; used in Tolentino et al. (2016) | 4 |
| Allah River | Impao, Isulan, Sultan Kudarat | 6.568 | 124.085 | 1980-1994 | 15 | 1231 | BRS; used in Tolentino et al. (2016) | 3 |
| Agusan Canyon River | Camp Philips, Manolo Fortich, Bukidnon | 8.296 | 124.450 | 1986-2004 | 19 | 48 | BRS; updated from Tolentino et al. (2016) | 3 |
| Wawa River | Wawa, Bayugan, Agusan del Sur | 8.261 | 125.501 | 1981-2010 | 30 | 396 | BRS; updated from Tolentino et al. (2016) | 4 |
| Buayan River | Malandag, Malungon, South Cotabato | 6.317 | 125.749 | 1986-2004 | 19 | 207 | BRS; used in Tolentino et al. (2016) | 4 |
| Gasgas River | Manalpac, Solsona | 18.080 | 120.830 | 1978-1988 | 11 | 73 | GISM | 1 |
| Jalaur River | Calyan, Pototan, Iloilo | 10.930 | 122.670 | 1976-1988 | 13 | 1499 | GISM and GRDC | 3 |
| Padsan River | Bangay | 18.080 | 120.700 | 1946-1979 | 34 | 534 | GRDC | 1 |
| Pampanga River | San Agustin | 15.170 | 120.780 | 1946-1977 | 32 | 6487 | GRDC | 1 |
| Sipocot River | Sabang | 13.810 | 122.990 | 1946-1970 | 25 | 447 | GRDC | 2 |
| Mambusao River | Tumalalud | 11.260 | 122.570 | 1950-1978 | 29 | 307 | GRDC | 3 |
| Padada River | Lapulabao | 6.660 | 125.280 | 1949-1978 | 30 | 821 | GRDC | 4 |
| Aloran River | Juan Bacay, Aloran, Misamis Occ. | 8.420 | 123.820 | 1978-2003 | 26 | 30 | GRDC + BRS | 3 |
| Cabacanan River | Baduang, Pagudpud | 18.580 | 120.800 | 1979-2017 | 39 | 60 | GRDC + BRS | 1 |
| Maragayap River | Sta. Rita, Bacnotan, La Union | 16.750 | 120.374 | 2004-2017 | 14 | 40 | BRS | 1 |
| Abacan River | San Juan, Mexico, Pampanga | 15.118 | 120.703 | 2004-2017 | 14 | 217 | BRS | 1 |
| Hibayog River | La Victoria, Carmen, Bohol | 9.876 | 124.141 | 2004-2017 | 14 | 41 | BRS | 4 |
| Manaba River | Calma, Garcia-Hernandez, Bohol | 9.631 | 124.131 | 2001-2016 | 16 | 98 | BRS | 4 |
| Gabayan River | Canawa, Candijay, Bohol | 9.848 | 124.450 | 2001-2017 | 17 | 48.5 | BRS | 4 |
| Bangkerohan River | Brgy. Tagaytay, Bato, Leyte | 10.342 | 124.834 | 1984-1990; 2000-2009 | 17 | 168 | BRS | 4 |
| Borongan River | Brgy. San Mateo, Borongan City | 11.628 | 125.403 | 1990-2008 | 19 | 111 | BRS | 2 |
| Loom River | Brgy. Calico-an, Borongan City | 10.594 | 125.404 | 1986-2004 | 19 | 42 | BRS | 2 |
| Pagbanganan River | Brgy. Makinhas, Baybay City | 10.637 | 124.865 | 1984-2008 | 25 | 128 | BRS | 4 |
| Rizal River | Brgy. Rizal, Babatngon, Leyte | 11.389 | 124.908 | 1990-2008 | 18 | 15 | BRS | 4 |
| Tenani River | Brgy. Tenani, Paranas (Wright), Samar | 11.806 | 125.127 | 1985-2001 | 17 | 394 | BRS | 2 |
| Disakan River | Disakan, Manukan, Zamboanga del Norte | 8.480 | 123.048 | 1985-1991; 1997-2000 | 11 | 109 | BRS | 3 |
| Kabasalan River | Banker, Kabasalan, Sibugay, Province | 7.831 | 122.778 | 2002-2011 | 10 | 143 | BRS | 3 |
| Sindangan River | Dicoyong, Sindangan, Zamboanga del Norte | 8.217 | 123.057 | 1990-2003 | 14 | 590.5 | BRS | 3 |
| Alubijid River | Alubijid, Misamis Oriental | 8.570 | 124.476 | 1991-2009 | 19 | 124 | BRS | 3 |
| Kipaliko River | Tiburcia, Kapalong, Davao del Norte | 7.602 | 125.681 | 2004-2016 | 13 | 147 | BRS | 4 |
| Banaue River | Poblacion, Banaue, Ifugao | 16.915 | 121.061 | 1987-1995; 2005-2010 | 15 | 15 | BRS | 3 |
| Aciga River | Santiago, Agusan del Norte | 9.269 | 125.570 | 2002-2015 | 14 | 80 | BRS | 4 |
| Agusan River | Sta. Josefa, Agusan del Sur | 7.993 | 126.036 | 1982; 1984-1987; 1989-2010 | 27 | 1633 | BRS | 4 |

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**Table 2: Results of statistical agreement** between GRUN aggregated by Climate Type and for the entire dataset (see Table A1 for individual catchments)

| | Pearsons Coeff ($r^2$)* | Volumetric Efficiency (VE) | Nash-Sutcliff Efficiency (NSE) | Nash-Sutcliff Efficiency (NSE-log10) | Root Mean Square Error | Root Mean Square Error Bias Corrected ** | Volumetric Efficiency (VE) Bias Corrected ** | Nash-Sutcliff Efficiency (NSE) Bias Corrected ** | Nash-Sutcliff Efficiency (NSE-log10) Bias Corrected ** |
|---|---|---|---|---|---|---|---|---|---|
| **Entire Dataset** | 0.372 | 0.363 | 0.091 | 0.453 | 2.648 | 0.292 | 0.323 | 0.182 | 0.385 |
| **Entire Dataset log10(runoff)** | 0.546 | 0.733 | n/a | n/a | n/a | n/a | 1.067 | n/a | n/a |
| | | | | | | | | | |
| **Climate Type 1 (n=12)** | 0.211 | 0.252 | 0.062 | 0.538 | 2.476 | 0.298 | 0.168 | 0.111 | 0.432 |
| **Climate Type 2 (n=6)** | 0.409 | 0.354 | 0.05 | 0.49 | 4.554 | 0.544 | 0.349 | 0.188 | 0.457 |
| **Climate Type 3 (n=15)** | 0.471 | 0.404 | 0.026 | 0.23 | 2.285 | 0.432 | 0.345 | 0.011 | 0.188 |
| **Climate Type 4 (n=22)** | 0.535 | 0.403 | 0.159 | 0.414 | 2.398 | 0.131 | 0.377 | 0.323 | 0.36 |

**Notes**
* For regressions forced through intercept of 0
** Two-step bias correction procedure where first mean offset is added to the predicted GRUN values and then a log-transform stretch correction is applied (see text for details)