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Key Points

- A countrywide process-based hydrological model was built for Panama using the Soil and Water Assessment Tool.
- Precipitation interpolation was used as an avenue for significant model improvement in the absence of global calibration.
- The resulting model will provide baseline precipitation and hydrology layers for an integrated sustainability platform.

Keywords

Hydrological modeling, Soil and Water Assessment Tool, Neotropical hydrology, Sustainability

Abstract

Water availability and extremes in river discharge associated with floods and droughts are critical determinants of human welfare and ecological function. Modeling the effects of climate scenarios and other social and environmental changes on waterways is thus a key component of effective planning and risk mitigation. Yet, the calibration of multiple-basin models, such as for a national planning framework, can be difficult due to limitations on quality and spatial

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coverage of available hydrological observations. In this manuscript, we build a process-based whole-country hydrological model for Panama using the Soil and Water Assessment Tool (SWAT). We also extend SWAT by deriving a precipitation interpolation model that incorporates regional climatic variability and spatial autocorrelation of precipitation, and we validate the model using data from 35 hydrological stations. Without calibration, the default application of SWAT reasonably predicted spatiotemporal variability in mean monthly discharge (NSE=0.70), but largely failed to predict variability (NSE=0.26) and maxima (NSE=0.22). However, with our relatively simply precipitation interpolation sub-model, we were able to strengthen predictions of discharge (NSE=0.87), but also able to more than double predictive ability for variance (NSE=0.62) and maxima (NSE=0.53). This moderate modification may allow process-based hydrological models such as SWAT to be much more broadly applied; crucially, even across regions with scarce hydrological data. The resulting precipitation and hydrology layers provide important baseline information for Panama.

1. Introduction

Changes in the hydrological cycle brought about by climate change and intensification of human activity pose significant risks to social and ecological well-being. These range from direct reductions in the availability of potable water or agricultural irrigation (FAO 2018, p. 31) to extreme events such as floods and droughts, which are anticipated to generally increase in frequency and magnitude with the changing climate (e.g., Hirabayashi et al. 2013; Cook et al. 2015). Indeed, access to clean water and resilience to climate-induced risks comprise two of the 17 UN Sustainable Development Goals (United Nations 2015). Changing patterns of precipitation and hydrology will also have ecological consequences, strongly influencing local vegetation and potentially affecting biodiversity (e.g., distance to water and precipitation were found to be two of the best predictors of species distributions, Bradie & Leung 2017). The capacity to predict hydrological patterns will be crucial for effective risk mitigation and building systemic resilience. Moreover, given the spatial heterogeneity in these dynamics, identifying critical regions at high risk for reductions in water availability and increases in extreme events must be an integral part of planning and management strategy. The need for this type of analysis is even more pronounced in the Global South, where the threat of climate change is compounded by economic and infrastructural inequality (e.g., Roberts 2010, Chapagain et al. 2020).

One method of carrying out such analysis is by using a spatially distributed, process-based hydrological model, such as the Soil and Water Assessment Tool (SWAT, Arnold et al. 1998). SWAT explicitly models spatial variation in the study area by splitting each watershed into units of non-branching stream segments and their drainage area, henceforth referred to as ‘subbasins’; and further splitting each subbasin into a set of Hydrological Response Units or HRUs which

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represent a particular combination of slope, land use, land management, and soil type that occurs within the subbasin.

In this manuscript, we use SWAT to build a countrywide hydrological model of Panama. Such a model, if it works, would be highly relevant for several reasons. Firstly, a national framework for water resource management already exists in the form of the Plan Nacional de Seguridad Hídrica or National Water Security Plan (Comité de Alto Nivel de Seguridad Hídrica, 2016), which predicts a rise in water insecurity as human consumption reaches 50% of freshwater availability in the country by 2050. Freshwater is also a key resource for the Panama Canal system, which requires 52 million gallons per ship transit. The Canal Authority came close to having to impose draft restrictions due to lack of water during the wet season in 2015, an El Niño year (Autoridad del Canal de Panamá, 2015). The canal is uniquely important not only to Panama's economy, representing 5.4% of national GDP in 2014 with $2.6 billion in revenue (OECD 2017), but also as a node in the global shipping trade. About 50% of the country's electrical capacity is accounted for by hydropower (Secretaria de Energia, 2012). Along with droughts like the one in 2015, floods and associated landslides are also problems faced by the country (e.g., Wohl and Ogden, 2013). Beyond human impacts, Panama is also at the center of one of the world's most biodiverse areas (Myers et al. 2000), with its enormously diverse tropical forests and aquatic ecosystems reliant on the health of its waterways.

It is standard procedure to calibrate a predictive model before validating it, and the utility of SWAT in simulating single watersheds with model parameters calibrated to local conditions, at least at the monthly timestep, is well established (e.g., Perez-Valdivia et al., 2017). The calibration of SWAT models is an especially complex issue due to factors such as the large number of potentially sensitive parameters in the model, the variety of fitting algorithms available (e.g., SUFI-2, GLUE, ParaSol), the variety of possible objective functions, and parameter non-uniqueness or the possibility of multiple combinations of parameter values that yield similar results. General protocols have as a result been developed for the process of calibration and uncertainty quantification (Abbaspour et al. 2018), but these are most applicable to SWAT models that are (i) of limited geographical scope and (ii) calibrated on long time series of observed hydrological data.

The geographical extent and heterogeneity of our model system – the whole country of Panama – makes such protocols designed for single watersheds difficult to implement. Nor can we calibrate each watershed individually and then aggregate them into a global model, as there are several small, ungauged waterways that would still require a more generalized model. Parameter interpolation techniques addressing the issue of spatial gaps in hydrological data are an active area of investigation (e.g., Asurza-Véliz and Lavado-Casimiro, 2020). Another solution could be to use much simpler rainfall-runoff models based on a much smaller set of equations, without explicit modeling of spatial variation (e.g., Dos Santos et al. 2018). This approach can be suited to the description of

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runoff and related phenomena (e.g., flash floods, Rozalis et al., 2010) but would have to be extended if we desire to explicitly simulate changes in other physical processes such as groundwater infiltration, nutrient pollution, and land use change using a single model architecture. As an alternative, spatially explicit first-principles watershed models such as SWAT could be used, but without calibration of each of the model's parameters. However, the utility and predictive power of such models have not been examined in depth and we propose to do so in this manuscript.

Panama provides a high bar to test the effectiveness of uncalibrated hydrological models. Hydrological observations are lacking for many smaller rivers, and watersheds across the country have a wide range of physical characteristics. Due to its location on an isthmus, Panama is composed of several watersheds with marked differences in precipitation regimes, ecology, and human use. For example, the rain shadow effect caused by the central spine of mountains in Western Panama leads to a wet, tropical climate on the Caribbean coast and a more seasonally variable, drier climate on the Pacific coast (Kusunoki et al. 2019).

As the modeling of spatial variation is our central concern, we explore a relevant avenue for improving the predictive power of SWAT: interpolation of the precipitation input. Given that precipitation data is often more readily available than stream discharge and precipitation gauges are more numerous than hydrological measurement stations, we propose and test modifications to the precipitation submodel of SWAT that could make it more robust in contexts where hydrological data is a limitation or sophisticated calibration techniques are otherwise difficult. For both an "out-of-the-box" SWAT model and one with our modified precipitation algorithm, we first examine the predictive accuracy to estimate water availability (mean monthly streamflow) as well as variability (standard deviation and maxima of discharge) across space and time, i.e., by location and calendar month.

A physical hydrology model of the country built from first principles would be an indispensable part of a central water resource management framework both in terms of providing baseline hydrological information on ungauged watersheds and for simulating the effects of changes in climate on the interlocking systems integral to the economy and ecology of the country. Furthermore, having such a broad-based model provides a baseline for motivating more focused area research, which could in turn feed back into and strengthen the global model. To this end, the model will also serve as a key building block in the ongoing larger initiative to develop a countrywide platform for sustainability science (the Panama Research and Integrated Sustainability Model (PRISM); http://prism.research.mcgill.ca).

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2. Methods

2.1 SWAT Model Setup

The SWAT model requires a set of spatially explicit inputs for the study area: a digital elevation model (DEM), a soil map, a land use map, and a set of weather station locations. The weather stations further must be provided with precipitation, solar radiation, relative humidity, and wind data in the form of either (i) records for each day of the simulation or (ii) parameters for a rainfall distribution that the model samples from on each simulated day. The data sources used for each of the above in the current study are summarized in Table 1. Publicly available data on river discharge from the ETESA (Empresa de Transmisión Eléctrica, S.A; https://www.etesa.com.pa/) hydrological monitoring network from the period 2005 – 2015 was used for model validation, while ETESA precipitation data from the periods 1990 – 2000 and 2005 – 2015 were used for fitting the precipitation submodel parameters and running the validation simulation respectively.

Watershed delineation was carried out in ArcSWAT. A threshold of 5000 cells was chosen as the minimum inflow into an outlet for which a subbasin would be defined, which amounts to a drainage area of about 40.5 km^2 given the DEM cell size at the equator. Areas smaller than this which drain directly into the sea or either neighboring country were not part of the model, resulting in a model delineation covering roughly 65,000 km^2 or 86% of the total land area of Panama. SWAT further assigns each non-branching segment of stream its own subbasin and calculates Hydrological Response Units (HRUs) within each subbasin based on existing combinations of soils, land use, and slope. SWAT generates daily mean discharge output (m^{3}s^{-1}) at the outlet of each subbasin, so additional outlets were manually defined at the location of each hydrological measurement station (65 in total) to provide direct comparison points. This resulted in a delineation of 980 subbasins in total.

2.2 Precipitation interpolation

Daily precipitation data from ETESA was downloaded for 249 rain gauge locations across Panama, of which 120 were active during the simulation period of 2005 - 2015, though many had temporal gaps in their records. SWAT requires daily precipitation values for each subbasin (980 in total in the current model) and thus some method of interpolation is required to fill both spatial and temporal gaps in the data coverage. For spatial gaps, the method used by default is a nearest neighbor (or Thiessen polygon) interpolation from each subbasin centroid to the nearest rain gauge. For temporal gaps, the default method is sampling from an empirically determined rainfall distribution at rain gauge locations using a skew-normal distribution following Ficks (1974). Means, standard deviations, skew, and wet-dry transition probability values were calculated at all gauge locations using the observations spanning the period of 1990 - 2000. Henceforth this default method will be referred to as the nearest neighbor ('NN')

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model.

In our modified method, interpolation of precipitation at each location was carried out for each day, and separately for each of six regions that the country was split into to account for climatic differences (Fig 2). The interpolation method at each location incorporated two-steps: (1) we interpolated the probability of a wet or dry day (occurrence) using a logistic regression with the inverse distance weighted mean of observations in the region as the predictor (using a threshold observation < 0.5 mm, dry gauges were given a value of 0 and wet gauges a value of 1); (2) given the probability of a wet day, we performed a binomial trial; and if a wet day was generated, we interpolated the quantity of rain, again using an inverse distance weighted mean of all observed quantities of precipitation within the region for that day. Dry days were assigned a quantity of 0 mm. Each of the two steps involved a single parameter each, $_1$ and $_2$, which controlled the decay of the relative weighting with distance.

$$p_{\text{ikt}} = \frac{\sum p_{\text{jkt}} e^{-\alpha_{\text{kt}} d_{\text{ijkt}}}}{\sum e^{-\alpha_{\text{kt}} d_{\text{ijkt}}}} \text{ Eq 1}$$

Where p_{ikt} was the precipitation value of interest (i.e., either wet/dry or quantity of rain), p_{jkt} denoted all measured precipitation values, d_{ijkt} was the distance between points i and j, and $_{\text{kt}}$ was a shape parameter.

These $_{\text{kt}}$ values were fit separately to each monthly time interval (t), and each of 6 regions (k) in Panama based on regional variation in climate, to capture expected differences in spatial and seasonal autocorrelation patterns. In addition, this prevented the influence of gages that may be physically close to a point but across a microclimatic boundary – most notably, areas on either face of the central ridge of mountains in the Western half of the country are separated from each other by this regional delineation.

Each fitted parameter ( ) represented the average daily degree of spatial autocorrelation within that region on that month. This fitting process was run using the gauge data from 1990 - 2000, and the fitted algorithm was then used to interpolate daily values at the 980 subbasin centroids using the measured data from 2005 - 2015 for the validation run. This model will be referred to in this manuscript as the regional distance-weighted or RDW model.

2.3 Model evaluation

As the objective was to gain insight into patterns of water distribution and extreme flood events, the hydrological model results were compared against river discharge data from ETESA, which was not used to calibrate or parameterize any part of the models. R^2 and Nash-Sutcliffe Efficiency (NSE) of mean model predictions against mean observed daily discharge values were calculated for each month and station across the entire simulation period and these metrics were used to gauge the ability to predict average flow. The Nash-Sutcliffe Efficiency or NSE is a metric often used to test hydrological models where NSE $= 0$ indicates that the model is no better than using the mean of the observed

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values as the prediction, and NSE = 1 indicates that the simulation perfectly corresponds to the observed values. Models with negative NSE values predict worse than the mean value of the observations.

We also used NSE and R^2 to examine the ability of the hydrological model to estimate the variation in water flow at a given location by comparing both standard deviations of discharge by month as well the magnitudes of the 3 highest discharge events across the simulation period in each location-month combination, which we chose as representative of the extreme highs of the discharge distribution at that location for that month, and as an indicator of flood risk.

Finally, we used NSE and R^2 to examine the model's ability to simulate the observed monthly time series of mean discharge within each basin from 2005 – 2015. Instead of spatial variation across locations, this procedure tested the ability of the model to capture temporal variation within each location. We posited several variables across observation locations (hydrological stations) that could explain variation in model predictiveness, namely: (i) elevation of the observation, as we did not account for orographic effects explicitly, (ii) existence of a precipitation gauge within the same subbasin as the observation and (iii) number of precipitation gauges in the region, as measures of the relevance and quantity of precipitation information respectively, (iv) number of subbasins in the watershed, as larger watersheds can have more complex behaviour, (v) number of subbasins downstream from the observation, as interior locations could be subject to terrestrial climate processes not explicitly modeled, and (vi) simulated standard deviation of mean monthly discharge at the location, as the model may be over- or underestimating variation in general. We used a stepwise forward selection algorithm in R to arrive at the linear combination of these variables and their pairwise combinations with the lowest AIC value.

3. Results

3.1 Precipitation interpolation

In the regional distance weighted (RDW) model, there was a strong seasonal signal in the autocorrelation patterns (Figure 5). Maximum values of the interpolation parameters $_1$ and $_2$ correspond to the greatest weighting of the closest stations and, correspondingly, the fastest decay in weighting with distance. These maxima consistently occurred for both precipitation occurrence and quantity in April and October, and these months represent precisely the two transitions between the wet (generally May to November) and dry seasons. During these transitions, the immediate neighborhood of a point was reliably much more predictive than areas that are further away. Over the remainder of each season, the parameter value declined, indicating the opposite: that precipitation stayed more consistent over an entire region, leading to stations in the region being more generally predictive of one another regardless of distance. Parameter values for interpolating the occurrence of rain were also remarkably

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similar across regions for a given month, suggesting a countrywide seasonal effect. Variation across region was comparatively higher for the interpolation of quantity, suggesting that there were regional differences in the spatial patterns of rainfall intensity, given occurrence.

3.2 Model evaluation

Even without hydrological calibration, the standard SWAT model using nearest neighbor precipitation interpolation (NN) performed well for mean discharge across locations with an NSE and R2 of 0.7. Despite this strong performance, improving the precipitation interpolation approach yielded even better predictions, yielding NSE = 0.87 and R^2 = 0.88 using the RDW model (Table 2).

While the NN model worked well for mean discharge, it was less able to capture different metrics of variability. For standard deviation, the RDW model achieved NSE = 0.62, R^2 = 0.65, which compared very favorably with the NN model (NSE = 0.26, R^2 = 0.35). For predicting the 3 highest values of daily discharge at each location-month combination, we found again that the NN model performed poorly, with NSE = 0.22, R^2 = 0.32, while the RDW model achieved an NSE of 0.53, R^2 = 0.56 (Table 2).

We examined the predictiveness of temporal patterns within each watershed for the NN and RDW models across the ten-year period. We found that, in contrast to the country-wide analysis, the NN model performed generally poorly, with 24 out of 35 sites performing worse than the mean of the observations (NSE $<$ 0), indicating that the NN model was less predictive at the median site than the mean of observations. The RDW model performed significantly better: while 8 sites still performed poorly (NSE $<$ 0), 18 sites had good performance at NSE $>$ 0.5 (Figure 4), and the median NSE was 0.4 across locations. Thus, the RDW showed substantial improvements over the standard SWAT model using NN, although the predictions were still imperfect. However, the performance of RDW was largely predictable. We identified areas of failure in the RDW model (NSE $<$ 0) largely occurring in one region (the Pacific Northwest), as well as in the Panama City area and Comarca Emberá. Further, 71% of the variation in NSE across locations was explained by a linear combination of six variables (and three interaction terms), namely: (i) elevation, (ii) proximity to a precipitation gauge, (iii) number of gauges in the region, (iv) standard deviation of discharge at the location, (v) number of downstream subbasins, and (vi) total watershed size in number of subbasins (Table 3). Of these, (ii), (v), (vi), and the interaction terms (iv)*(vi) and (v)*(vi) were found to be significant ($p < 0.05$).

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4. Discussion

4.1 Model performance

Process-based hydrological models could be useful in predicting changes to water availability and extreme discharge events. However, it was unclear the extent to which such models would be predictive without calibration − without this capability, their utility would be reduced at larger scales and in countries where many waterways remain ungauged. Our results suggest that concerns about running detailed hydrological models without calibration are warranted (e.g. Dos Santos et al. 2018) - the uncalibrated standard SWAT model failed to predict variability and maxima of discharge across locations and temporal fluctuations within most watersheds at a monthly timestep. However, modifying the precipitation interpolation to incorporate spatial autocorrelation greatly improved predictions of hydrological patterns. Our RDW model yielded substantial improvements across all metrics examined, most notably more than doubling the variation explained for standard deviations and maxima of discharge across locations and calendar months. While it also significantly improved prediction of mean monthly discharge, standard deviations and maxima represent additional information about the hydrological distributions that are crucially important in the predictive modeling of flood risk (e.g. van der Wiel et al. 2019). Intra-annual variability in water availability is furthermore a critical indicator of water scarcity, despite often being overlooked in favour of annual means (Damkjaer & Taylor, 2016).

In addition to performing well in predicting the spatial variation of these statistics, the RDW model dramatically improved predictions of temporal variability within watersheds (median NSE = 0.4 across locations, NSE > 0.5 at 50% of locations), compared to the uncalibrated standard SWAT model (median NSE < 0, all locations NSE < 0.5). Furthermore, we could largely identify where failures in the RDW model should occur (explaining 71% of the variation in NSEs). The most significant predictors of better performance at a given hydrological station were (i) the presence of a precipitation gauge within the subbasin itself, (ii) the number of subbasins downstream of the one of interest, (iii) the total number of subbasins in the entire watershed, and two interaction terms: between the simulated standard deviation of discharge at a point and the total number of subbasins in its watershed, and between the number of subbasins downstream of a point and the total number of subbasins in its watershed. While all three single variables had a positive effect on NSE, and thus on model performance, the two interaction terms notably had negative effects. The negative effect of the interaction between number of downstream subbasins and total watershed size suggests that the positive effect of a large watershed is reduced by being further upstream in that watershed, i.e., that interior subbasins in large watersheds tend to do poorly. The presence of a precipitation gauge very close to the location has a positive effect as predicted, pointing to the importance of relevant precipitation input.

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The single-basin NSE values produced by the RDW model tend on the whole to be lower than those reported in calibrated single-basin studies, which is to be expected. In addition to being a significant improvement on the default NN model, the RDW model has clearly-defined areas of failure that could benefit from more specific study. Furthermore, the improvement of the precipitation model does not aim to replace the role of traditional hydrological calibration in finer-scale analyses of individual watersheds. The modular nature of a SWAT model makes it possible to run parameter calibration procedures for specific areas of interest pending data availability, while the interpolation of precipitation serves as an improved baseline for the entire country.

4.3 Caveats and limitations

While our focus was on improving the precipitation sub-model, models such as SWAT also incorporate several other input data layers such as maps of soils and land use, which may be avenues for further improvement of model performance. Nonetheless, our analyses provide evidence that even without calibration of model parameters or modification of the other input layers, it is possible to generate useful large-scale predictions of variation in hydrology by capturing patterns of spatial autocorrelation in precipitation.

The interpolated model showed good predictive power across a range of metrics, but it was not a panacea. As expected, predicting maxima of discharge was more difficult than predicting mean discharge across locations (i.e, NSE 0.54 versus 0.87, respectively). Further, the model's predictive ability across different areas of Panama was spatially heterogeneous. We argue that it is equally important to know where models should fail, and the linear model assessing hypothesized predictors of failure captured 71% of spatial variation in model performance as measured by NSE at each location.

While hydrological models take into account non-stationarity in terms of environmental conditions (e.g., precipitation), the underlying fitted parameter values representing rainfall spatial autocorrelation may not be constant. However, parameter values for the interpolation algorithm were fitted using precipitation data from 1990 – 2000 and validated on hydrological data from 2005 – 2015, providing evidence of some temporal stability. Moreover, the peaks in parameter values in the months of April and October (indicating the unreliability of close neighbors in predicting precipitation values at a given gauge) coincide with the periods of change in variation patterns of observed rainfall in several locations across the country (Fabrega et al., 2013) as well as periods of strongest increase and decrease in average rainfall respectively (Kusunoki et al., 2019). Further elucidation of the processes that lead to the variation captured by the current model may aid in the development of a dynamical procedure that can account for nonstationarity. Process-based model improvements can match or outperform calibrated models (e.g., Qi et al., 2020 found this to be the case for a soil process extension of SWAT). While seasonal and regional patterns of spatial autocorrelation in precipitation are being studied in several arid and semi-arid

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areas in places such as China (Xu et al., 2021) and Iran (Darand et al., 2017), to our knowledge it is a relatively understudied phenomenon in the tropics. The existence of seasonal signals in the parameter values as well as the marked improvement of the model by accounting for these patterns both point to the need for further study.

Conclusions

Our findings indicate that even uncalibrated hydrological models such as SWAT can be highly predictive, and that a key limitation had been the simple nearest-neighbor accounting of spatial autocorrelation in the precipitation sub-model. As precipitation gauges tend to be common and relatively simple to set up, the application of hydrological models across large spatial contexts becomes much more feasible, even in regions without long time-series of hydrological data.

Data availability

All data of simulation results used in the current analysis are available at https://doi.org/10.5281/zenodo.5498323.

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Tables and figures

Table 1. Data sources for building the SWAT model.

@ >p(- 2) * >p(- 2) * @ **Data layer** & **Source**
DEM (Digital Elevation Model) & USGS Earth Resources Observation And Science (EROS) Center. (2017). Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global [Data set]. U.S. Geological Survey. https://doi.org/10.5066/F7PR7TFT
Soil map & FAO-UNESCO Soil Map of the World, accessible at https://data.apps.fao.org/map/catalog/srv/eng
8383-11db-b9b2-000d939bc5d8
Land use map &

1. For fitting the precipitation submodel, simulation period 1990 − 2000;

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2. For the validation simulation, 2005 – 2015; ”Panama 2012 Forest Cover and Land Use”, STRI GIS Data Portal, accessible at https://stridata-si.opendata.arcgis.com/maps/SI::panama-2012-forest-cover-and-land-use-tile-layer/about

Precipitation & discharge & ETESA hydrological and meteorological stations, STRI meteorological stations
&
Other climate variables (Solar radiation, wind, relative humidity, temperature) & National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) data, available at https://globalweather.tamu.edu/

Table 2. Summary of simulation results; all statistics calculated per location per month.

Model	Summary statistics (monthly discharge, m^3/s)		
	Mean	Standard deviation	Maxima
	R^2	NSE	R^2
Nearest neighbour	0.70	0.70	0.35
Regional distance-weighted	0.88	0.87	0.65

Table 3. Linear regression model summary for predictors of within-basin NSE value. AIC = 5.74, R^2 of prediction = 0.71.

Variable	Estimate	Std. Error	Significance ($p < 0.05$)
Intercept	-0.49319	0.40089	
1. Elevation	0.00067	0.00222	
2. Presence of gauge in subbasin	0.23928	0.10765	*
3. Total number of gauges in region	-0.00027	0.00640	
4. SD of discharge (simulated)	0.00760	0.00847	
5. Number of downstream subbasins	0.15142	0.03346	*
6. Size of watershed (# subbasins)	0.01755	0.00440	*
Interaction term 5:6	-0.00204	0.00047	*
Interaction term 4:6	-0.00037	0.00011	*
Interaction term 1:5	-0.00036	0.00025	
Interaction term 3:4	0.00017	0.00014	

Figure 1: Map of meteorological and hydrological stations used in simulation. Basin area upstream of gauge locations used for validation highlighted in blue (30 basins), all other regions were ungauged for the period of 2005 – 2015. Not all meteorological stations are necessarily active at any given point.

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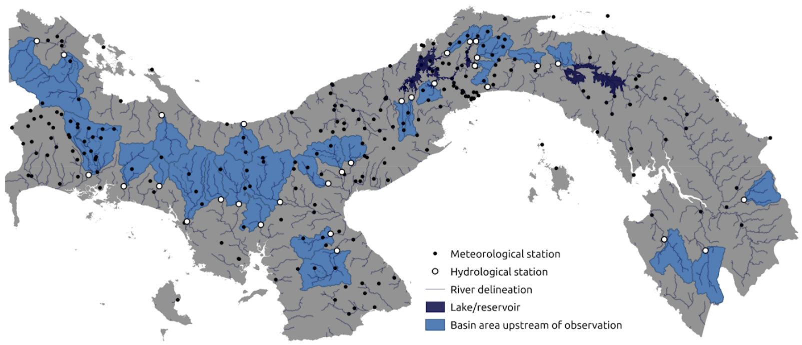

Figure 2: Climatic regions as delineated on the area covered by the SWAT model. 1 – Caribbean side of the Tabasará mountains, 2 – Pacific side of the Tabasará mountains, 3 – Azuero peninsula, 4 – Central Panama, 5 – East-Central Panama, 6 – Darien region

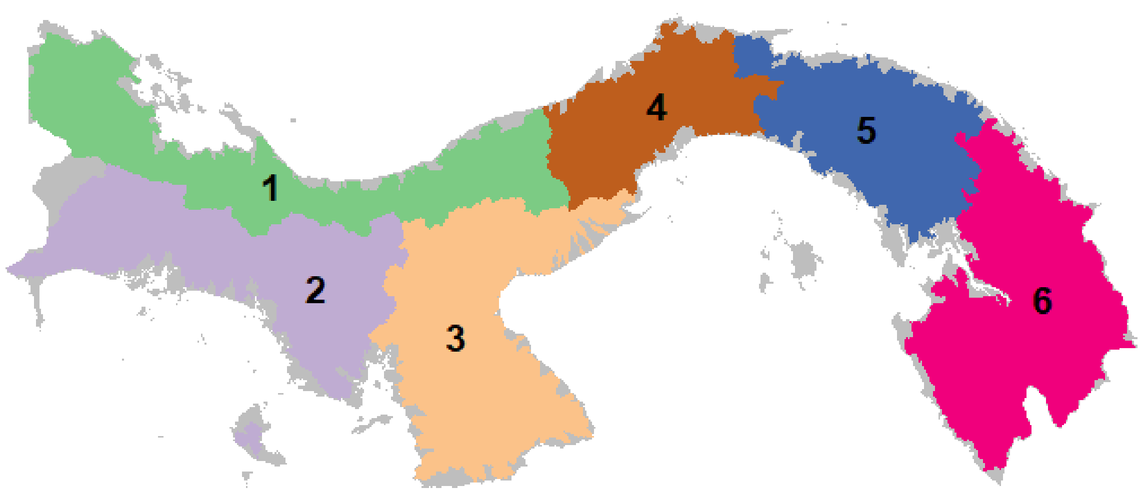

Figure 3: Scatterplots of different models – nearest neighbour and regional

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distance-weighted; mean monthly discharge, standard deviations, and maximum monthly discharge by location

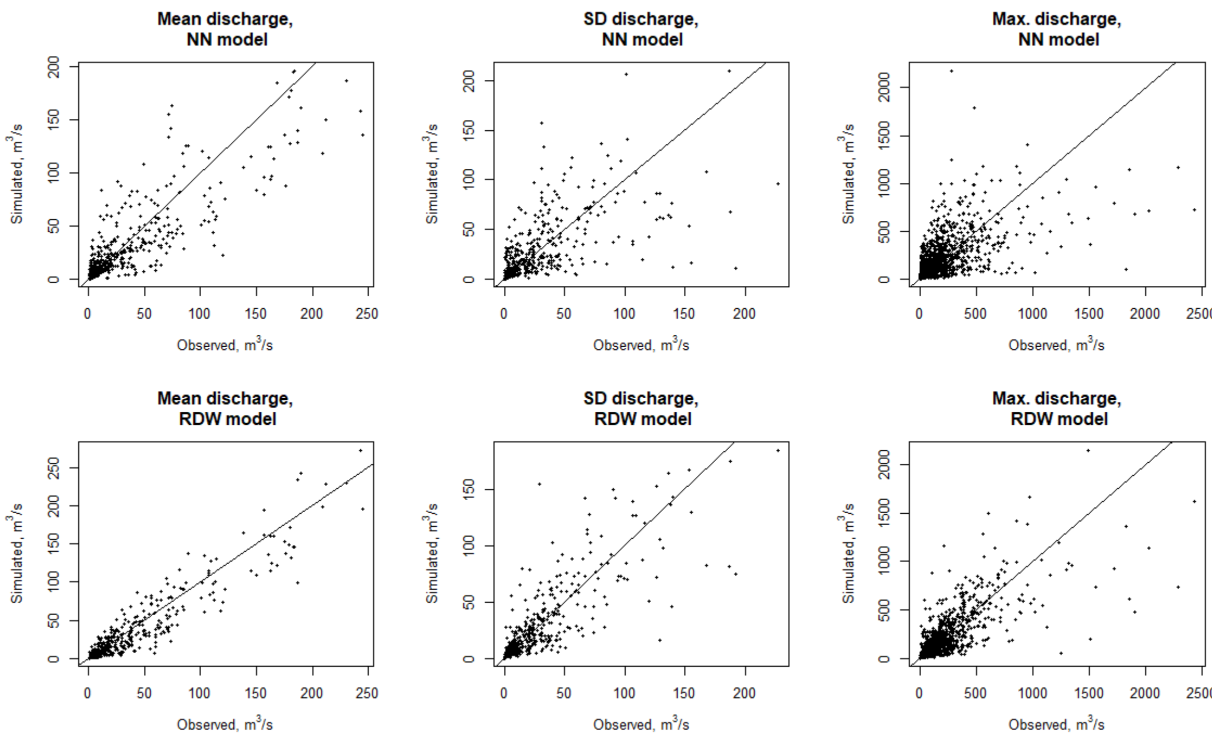

Figure 4: NSE for monthly mean prediction by basin for (a) final regional distance weighted model and (b) nearest neighbor model. Basins with NSE < 0 are not labeled.

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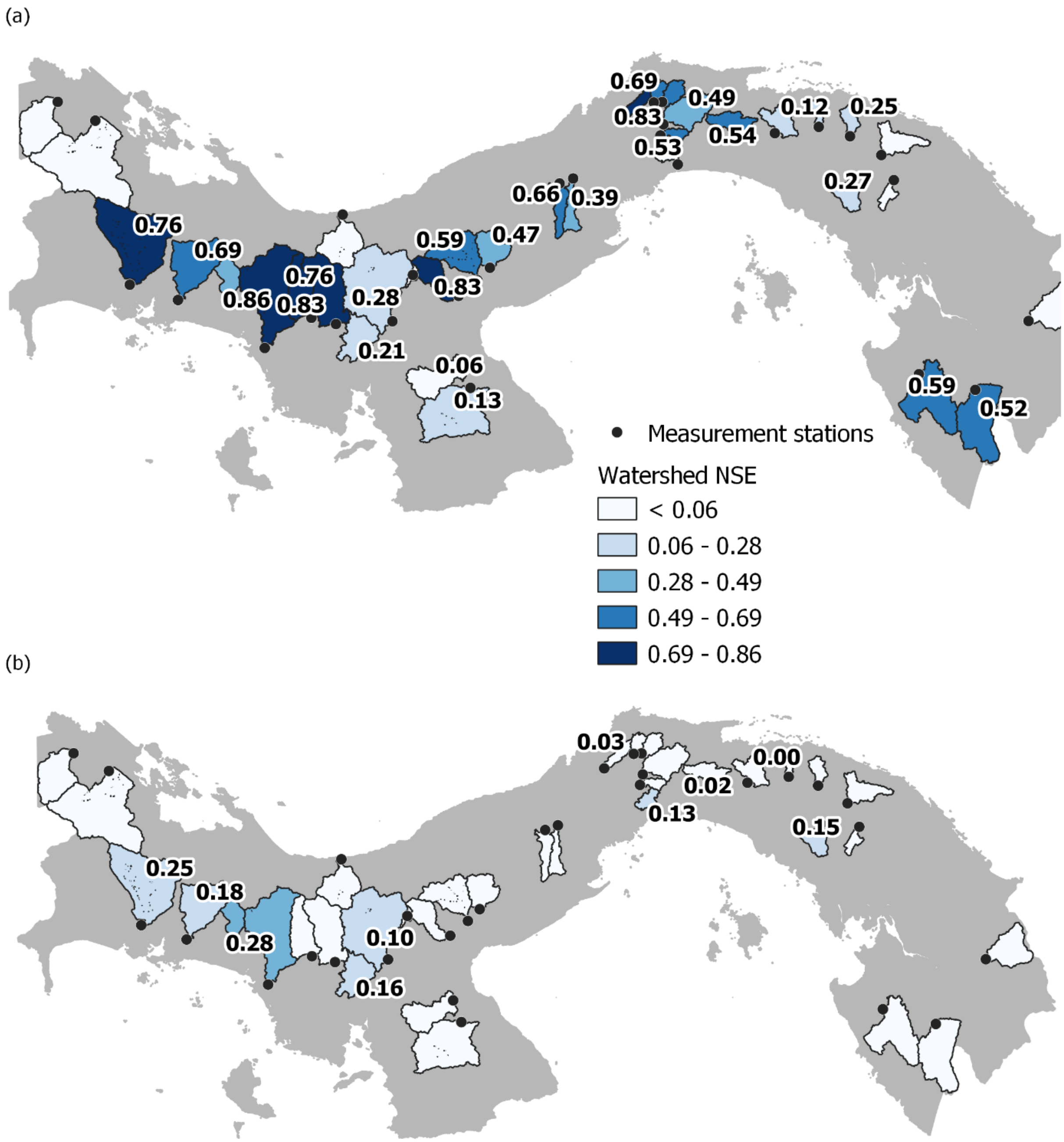

Figure 5: Interpolation parameter values for the RDW model. A higher value of the parameter indicates that closer neighbours are weighted much higher than

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ones further away, and a lower value indicates a slower distance-decay function and thus a more even distribution of weights across the region.