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COMBINED USE OF REANALYSIS INFORMATION AND HYDROLOGICAL MODELLING FOR SUPPORTING WATER PLANNING AND MANAGEMENT IN THE MAGDALENA-CAUCA MACROBASIN - COLOMBIA

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ABSTRACT

In Colombia water resources planning and management is supported mainly by technical instruments such as the National Water Assessment Study, which are based on the calculation of several different management indices, estimated solely with in-situ data. In this study we explore the complementarity of two global reanalysis datasets coming from the EartH2Observe project (WFDEI and MSWEP) and the use of rigorous regional and local hydrological modelling for deriving two water management indices, the Aridity Index and the Water Regulation Index in the Magdalena-Cauca macrobasin. Results show that the conjunctive use of in-situ data, global reanalysis, and hydrological modelling allows updating the indices calculation more often and that the results are consistent compared to the indices values estimated only with in-situ data. Besides, the methodology implemented has capabilities for being used in scarce data regions and can contribute to assessing uncertainty in the indices estimations.

Keywords: EartH2Observe reanalysis, Hydrological modelling, Magdalena-Cauca macrobasin

1 INTRODUCTION

Integrated water resources management requires a proper assessment of the state and fluxes of the hydrological variables in a basin. Gauging these variables allows to evaluate the state and evolution of a hydrosystem, but is cumbersome for decision-making processes related to water management and planning, which need rapid and very easy data interpretation. In these cases, water indices are an asset which can contribute to the identification of trends and changes in the state of water resources in a watershed. Besides, water indices can be easily integrated into technical instruments or decision support systems at different spatial scales.

In Colombia for example, the technical instrument that supports, at a country level, water management and planning is the National Water Assessment Study (ENA, for its acronym in Spanish) which evaluates, approximately every four years, the state of the national water resources. The ENA is mainly based on the estimation of several water indices associated with natural water supply, hydrometeorological regime, water demand, water quality, and others. Among the indices related to the natural regime of a basin, the widely known Aridity Index (AI) and the Water Regulation Index (WRI) (IDEAM, 2010) are included. Although in-situ measurements are essential to determine the state of the water resources through the indices estimations, the limitations and lack of hydrometeorological information in some regions can translate into weaknesses in the analysis that derive into problematic and not that well-informed decisions.

Related to this is the fact that since the 1980s, the number of gauges that directly acquire hydroclimatological information started to decline in several parts of the world (UN-WWAP 2015; Lorenz and Kunstmann 2012; Vörösmarty et al. 2001). For example, in the Magdalena-Cauca macrobasin, the most monitored watershed in Colombia, the number of rain gauges reduced from around 1,500 in the 1980s to nearly 1,000 in the 2010s.

Complementary sources of information such as Earth Observations (EO) (Cruz-Roa et al. 2017; Garcia et al. 2016) and reanalysis simulations (Schellekens et al. 2017; Weedon et al. 2014) are useful for coping with the reduction of in-situ measurements (García et al. 2016; Enrique and Estrada 2016; UN-WWAP 2015). Although these modern sources of information have not been widely used in the calculation of water indices around the globe, the conjunctive use of in-situ, EO and reanalysis data, has produced improvements in the quantification of water resources in Colombia (Elgamal et al. 2017).

In this sense, the aim of the research here reported was to assess the usefulness of complementary datasets to the in-situ data in the calculation of the AI and WRI water indices in the Magdalena-Cauca macrobasin in Colombia.

2 CASE OF STUDY: THE MAGDALENA-CAUCA MACROBASIN

The Magdalena-Cauca macrobasin (MCMB) is the main hydrographic system in Colombia, in socio-cultural and economic terms. With 30 million people, and 257.000 km^2 (Restrepo et al. 2016), it concentrates 80% of the GDP, and 80% of the Colombian population. Its terrain presents high complexity, mainly due to the Andes Cordillera that crosses from south to north, creating two alluvial valleys (Cauca and Magdalena valleys), where these two main rivers flow, as depicted in Figure 1.

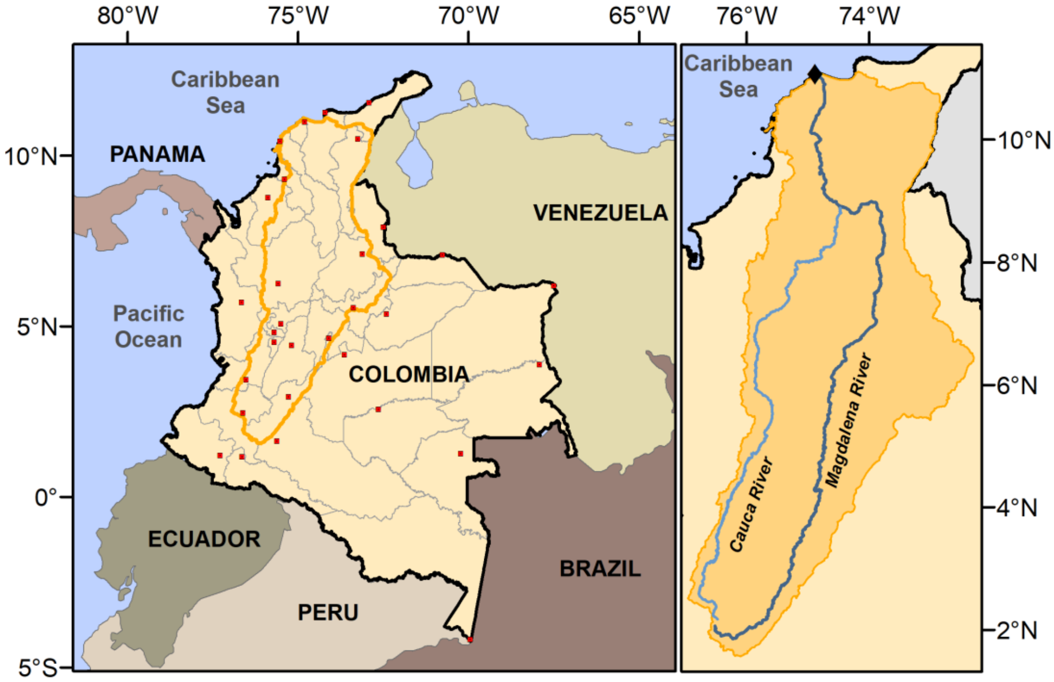

Figure 1. Location of the Magdalena - Cauca macrobasin in Colombia.

The Magdalena River flows through around 1,600 km before reaching the Caribbean Sea. Its main tributary, the Cauca river, flows through 1,015 km. The mean annual discharge at Calamar, the gauging station closest to the mouth, is around 7,200 m^3/s, with maximum discharges happening in November, and minimum in March, with a range between 4050 and 10,200 m^3/s (Camacho et al., 2008). Both rivers start at the south, and flow through the inter - Andean valleys that form the three mountain ranges, before reaching the Caribbean plains, where the Cauca river pours its waters into the Magdalena river (Cormagdalena, IDEAM, 2001).

The MCMB is under the influence of the Intertropical Convergence Zone (ITCZ), and due to its movement along the year, the upper and mid parts of the basin present a bimodal precipitation regime, with two peaks in April-May and October-November, and two dry periods between them, while the lower parts of the basin experience a single rainfall season from May to November (Poveda 2004).

3 DATA AND METHODS

3.1 Meteorological datasets

Three different meteorological datasets were considered in this research. Two of them have global coverage, whereas the third one is a local product based on in-situ data interpolations. The three products correspond to distributed daily time series at a scale of 0.1° (approximately 10 km at tropical latitudes) for the period 1980-2012. These datasets were used to force the hydrological models, which outputs were considered in the water indices calculations.

The so-called quasi-observed dataset is a local product obtained from the records of precipitation and temperature for the climatological stations operated by the Institute of Hydrology, Meteorology and Environmental Studies in Colombia (IDEAM) in the MCMB. Daily data for precipitation, maximum and minimum temperature (for approximately 2,200, and 500 stations, respectively), was interpolated using different geostatistical methods (Rodriguez et al., 2019). Due to the incompleteness of the wind speed in-situ time series, this variable was retrieved from the WFDEI dataset (Weedon et al., 2014), and downscaled to 0.1° using a geographical correspondence method. Daily evapotranspiration was estimated using the interpolated maps of temperature and the Hargreaves equation. In spite of having other ET datasets available, such as GLEAM and ET calculated from reanalysis information, we decided to use local information as much as possible, as a benchmark to evaluate the global products.

The second meteorological dataset, stemming from the ERA-Interim reanalysis (Dee et al. 2011), is the WFDEI dataset that provides sufficient information to force hydrological and land surface models. It is a benchmark meteorological product that seeks to promote the comparison between hydrological and earth system simulations. Its spatial resolution is 0.5° (nearly 50 km), and it was downscaled also with the geographical correspondence method to 0.1°.

MSWEP is the third dataset investigated. It is a precipitation product that has been widely used, which main feature is the optimal merging of the diverse gamut of precipitation products (Beck et al., 2017). It is based on the climatology values given by CHPclim, bias-corrected with local datasets and also includes correction using streamflow observations through inverse water balance calculations. In this product, rainfall time series at different scales are derived from precipitation anomalies of the different satellite, reanalysis and interpolated gauge products that were chosen to create it. Its spatial resolution is 0.25° (nearly 25 km), and in this project, it was also downscaled to 0.1°.

3.2 Regional hydrological models

Three regional hydrological models were implemented in the MCMB, using a split-sample approach, and the quasi-observed dataset. The period 1982-2000 was used for calibration, and 2001-2011 for validation. Daily observed streamflow data on 88 control points throughout the MCMB were used to compare and evaluate different performance metrics. After calibration, the three models were forced using the optimal parameter sets obtained from the quasi-observed data calibration, and the two meteorological forcings (MSWEP and WFDEI). The general structure of each of the models is presented below.

3.2.1 Dynamic Water Balance - Budyko Model

The Dynamic Water Balance (DWB) (Zhang et al. 2008) model is based on the concept of limits, as stated by Budyko regarding real evapotranspiration respect to potential evapotranspiration and precipitation. This concept was used into a dynamic water balance model, with four parameters and two conceptual tanks, that represent the main hydrologic processes on the surface.

The model implemented uses regular cells with 0.1° x 0.1° size. The calibration methodology followed GLUE, and runoff results were converted into discharge values, using an areal relation, with results at monthly time resolution.

3.2.2 Variable Infiltration Capacity Model

The regional Variable Infiltration Capacity (VIC) model (Liang et al. 1994, Zhao & Liu 1995) is a physical based model which uses a water balance equation and calculates runoff from three soil layers. To represent the infiltration, it uses the Xinanjiang model, while the Penman-Monteith equation is used to estimate evapotranspiration.

The model was implemented in a 0.1° x 0.1° regular cell, using a mosaic approach (it means that every single cell is split into multiple land cover types), and a daily time step. The calibration followed the GLUE methodology. Likewise the DWB model, runoff was converted to discharge based on drainage areas.

3.2.3 OpenStreams wflow-hbv

The OpenStreams wflow-hbv model (Schellekens, 2014) is based on the conceptual HBV-96 model (Saelthun, 1996) in a distributed grid-based way. Inside each cell, the water balance is calculated considering three components: precipitation - snow, soil moisture, and runoff. Daily runoff is the result of direct runoff, interflow from upper soil layer, and baseflow from the lower soil layer. The model uses a kinematic wave function for routing the total runoff obtained for every single cell, to get the river discharge.

The model was implemented at 1 km x 1 km cell size. The difference in spatial resolution for this model is due to a prior application of the model on sub basins of the MCMB, that showed that the 1 km grid size was adequate for the modelling purposes. The calibration process used a PSO search algorithm on the 88 control points across the MCMB.

3.3 Water management indices

Two water indices were calculated in the MCMB to better understand fluxes of water between the atmosphere and the land surface, and over the land surface.

First is the Aridity Index - AI (UNEP, 1997), which relates meteorological inputs (precipitation, or water available on the surface) and land surface responses to those inputs (evapotranspiration, or energy available on the surface), and so, allows understanding the fluxes and their constraints. The relationship could take several different forms, but here we used the following expression:

$$AI = P/PET \qquad [1]$$

Where *AI* is the Aridity Index, *P* is the mean annual multiyear precipitation, and *PET* is the mean annual multiyear potential evapotranspiration.

Second is the Water Regulation Index - *WRI* (IDEAM 2010). This index connects flow regime and basin conditions through a relationship between values from the flow duration curve. The formula used to calculate the *WRI* is:

$$WRI = Vp / Vt \qquad [2]$$

Where *Vp* is the volume under the mean discharge in the flow duration curve, and *Vt* is the total volume under the flow duration curve.

This expression is commonly used in Colombia, especially in the ENA, as a proxy for the general basin conditions, including flow regulation and drainage characteristics, and general land cover and soil features. Values of 1 mean a basin with large regulation which maintains a constant flow throughout the year (even for low precipitation periods), while lower values mean that the basin presents a high flow variability.

WRI is commonly computed from a daily flow duration curve, but a flow duration curve with another time aggregation can also be used (for example, monthly time-step data). However, a daily time-step is adequate to capture basin scale fluxes and hydrologic variability on the flow regime. For this reason, the daily flow duration curves were used to calculate WRI values, except for the DWB model, due to its time-scale limitations.

3.4 Methodology

A general representation of the methodology is depicted in Figure 2. In order to calculate and compare the values of AI, the three above mentioned meteorological datasets were combined with the equation [1] and then the percent bias (PBias), with respect to the quasi-observed AI results, was calculated.

Simultaneously, the three hydrological models were forced with the three meteorological datasets in order to obtain simulated streamflow values, that were later used to calculate the WRI, using equation [2]. Consequently, we compared the percent bias between the estimates of the WRI made by the hydrological models, with the WRI values calculated from observed streamflow data.

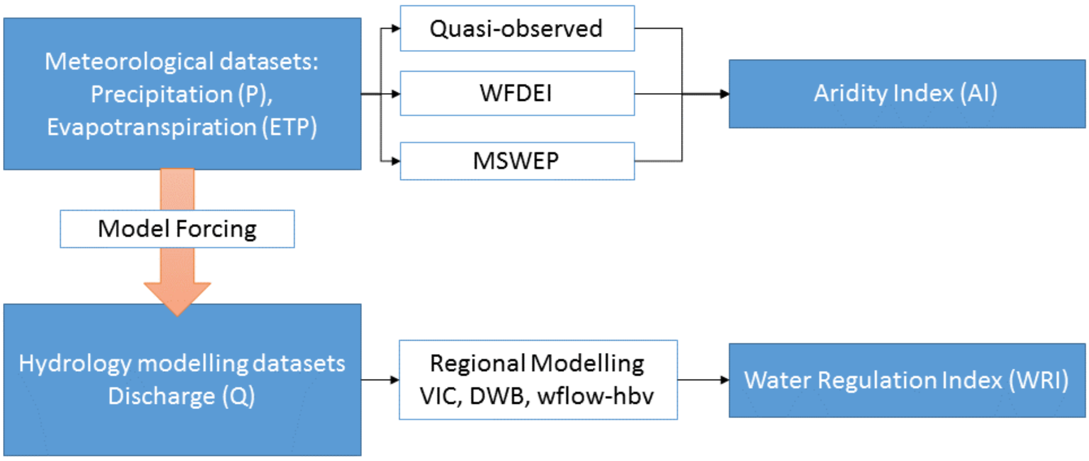

Figure 2. General framework of the procedures followed to calculate the water management indices, from the meteorological datasets and the regional hydrological model outputs.

4 RESULTS

Results are split according to the calculated index. This order permits to analyze the results from the precipitation datasets, through the AI index, and the results from the hydrological modelling, through the WRI index.

4.1 AI results

As depicted in Figure 3, the MCMB is mainly an area with water surplus, with around 60% of the MCMB classified as “humid”. There are also some “sub humid” areas on the southwest (on the Valle del Cauca province, near the city of Cali) and on the southeast (on the Magdalena Valley and the Altiplano Cundiboyacense, a high plateau where Colombia's capital, Bogotá, is located).

To the north, near the Magdalena river outlet, there is a drier region, which in general is classified as “dry subhumid” by the quasi-observed dataset, but that could be classified as “semi arid” by the WFDEI and MSWEP datasets. This area presents lower precipitation and higher evapotranspiration rates, due to its flat geography and different precipitation patterns, which results in a higher AI value.

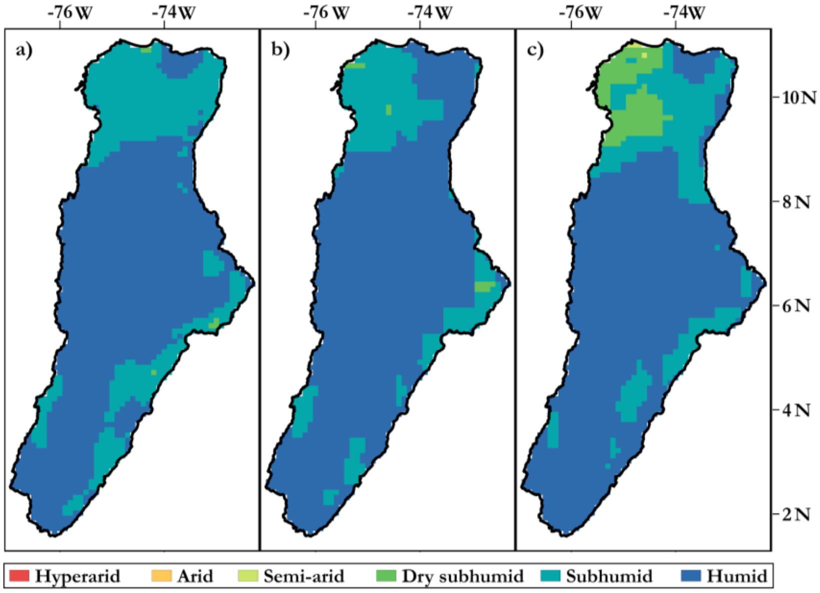

Figure 3. Distributed AI as calculated using (a) the quasi-observed, (b) WFDEI, and (c) MSWEP precipitation data. AI < 0.05, Hyper-arid; 0.05 < AI < 0.20, Arid; 0.20 < AI < 0.50, Semiarid; 0.50 < AI < 0.65, Dry subhumid; 0.65 < AI < 1.00, Moist subhumid; and AI >1.00, Humid. Source: Rodriguez et al. (2019)

When comparing, through the PBias, the quantitative differences in AI values, between the three datasets (Figure 4), the differences in the datasets values arise. For example, MSWEP overestimates on the southern areas, where the Andes mountains are located, and over a small area to the north, on the Sierra Nevada de Santa Marta mountains, while in general, it underestimates on the northern areas, where flatter and warmer areas are located. WFDEI, on the other hand, does not present this separation between the mountainous and flatter zones, but it seems to give mixed results: areas located at the south can show underestimations or overestimations, which seems to happen also at the north.

Despite these differences, it is evident that the AI derived from these two datasets show the same trends that the quasi- observed data, for both qualitative and quantitative analysis, and could provide an easy way to complement the evaluation solely based on in-situ data, which is especially important in areas with information limitations or when there is a need to update the index estimation in a faster and more complete way.

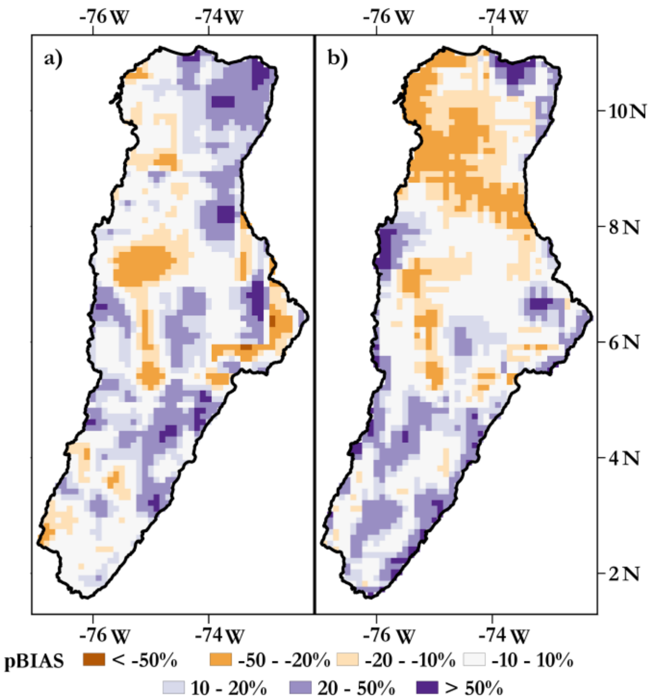

Figure 4. Distributed PBIAS differences between the quasi-observed AI values and AI values calculated from (a) WFDEI, and (b) MSWEP

4.2 WRI results

Each forcing dataset was used to run each of the regional hydrological models, obtaining three results by model, and in total 9 different outputs. For comparison purposes, these outputs were used to compute WRI point values, located where there is a streamflow gauge station.

Figure 5 presents the qualitative values of the WRI index calculated with the observed streamflow values. It can be seen that the moderate and low WRI categories are mainly located in mountainous subbasins, whilst the high and very high regulation categories are along the two main streams (the Magdalena and the Cauca rivers) and in the northern savannas.

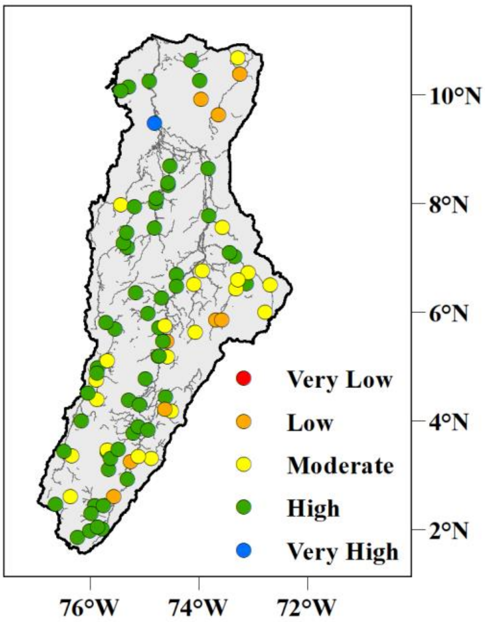

Figure 5. Water Regulation Index (WRI) calculated with observed data

Figure 6 depicts WRI values from modelling experiments, for each forcing dataset. The first row displays the quasi-observed forcing results, the second row displays MSWEP outputs, and the third row displays WFDEI results. It is clear that the forcing dataset impacts the results of the index values, yet the results are mainly driven by the model structure. WFDEI and MSWEP produce an increase in the WRI classification in most of the streamflow gauges for VIC model, meanwhile, wflow-hbv results using the same datasets show a reduction on the WRI category.

On the other hand, DWB model tends to decrease the WRI values, but these results are linked to the model time scale, the monthly seasonality of the precipitation datasets, and the over and underestimations from MSWEP and WFDEI, when compared to the quasi-observed data.

Figure 7 shows the percent bias of the WRI values for all models and precipitation datasets, with respect to values derived from point streamflow observations. It is noticeable that the wflow-hbv and DWB WRI values have mixed tendencies, while the VIC model has a clear trend to underestimate WRI values.

DWB displays an overestimation trend in the southern part of the basin that is reproduced in the other two forcings (WFDEI and MSWEP) but is less strong for WFDEI. In the north of the basin, there is a clear trend to underestimate when using WFDEI, but it is less clear for MSWEP, and it is not clear at all for the quasi-observed data.

Wflow-hbv shows a clear overestimation of the WRI values in the Sogamoso river basin (middle east zone) for the three datasets. This trend is visible in the southern regions for the quasi-observed and the MSWEP datasets but is less clear for WFDEI (in this case, there are mixed tendencies). The northern zones present a tendency to underestimate, which is stronger for the WFDEI, and weaker for the MSWEP and the quasi-observed datasets.

These results make clear the difficulties to compute WRI values based on regional hydrological modelling experiments. Regional hydrological modelling needs to use innovative techniques, in order to derive the uncertainty from sources like model structures, and inputs (precipitation forcings in this case). The use of hydrologic ensembles could improve the results while investigating the different uncertainty sources.

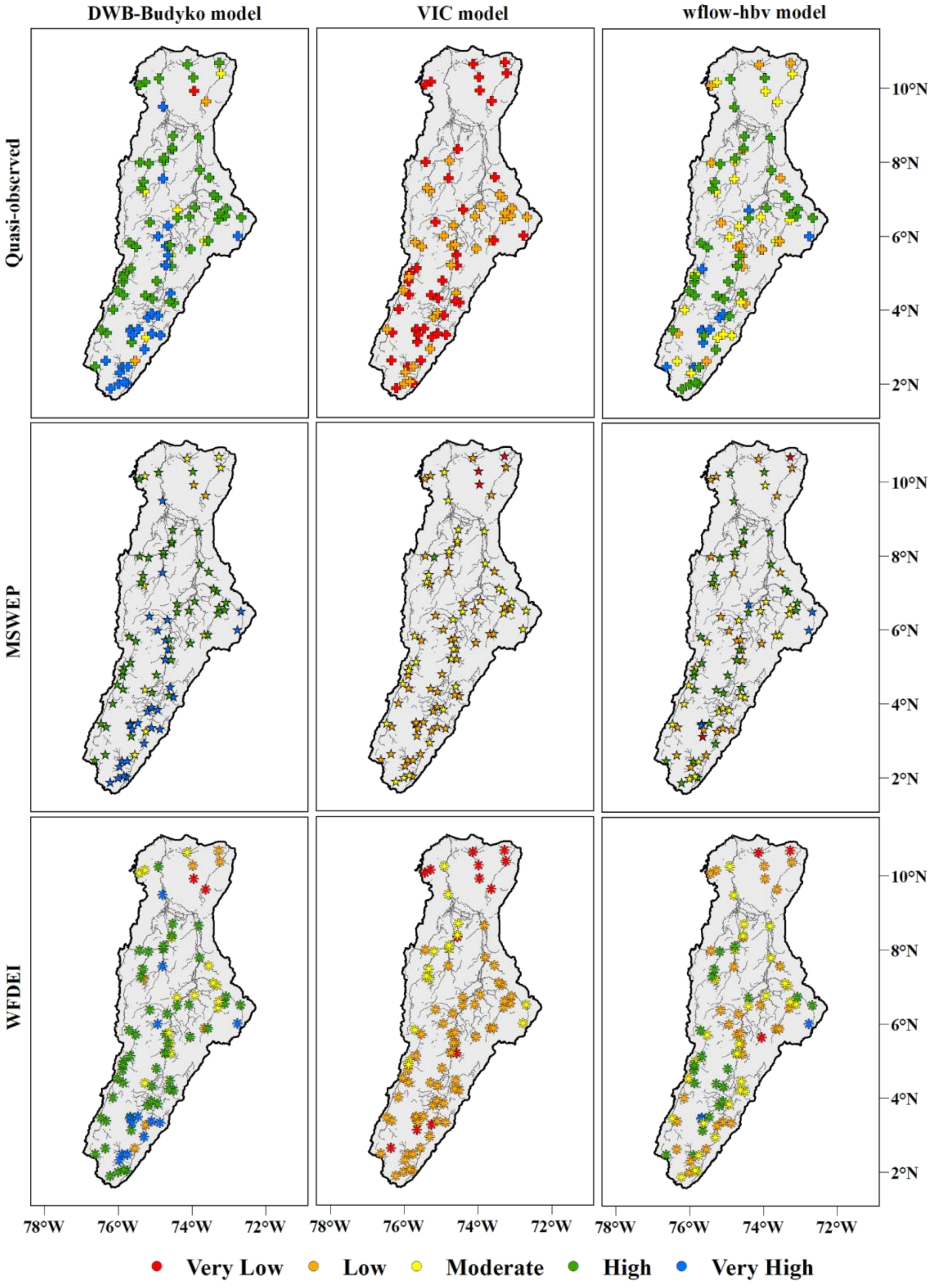

Figure 6. Water Regulation Index (WRI) calculated with the simulated runoff of the three hydrological models using the three different forcings.

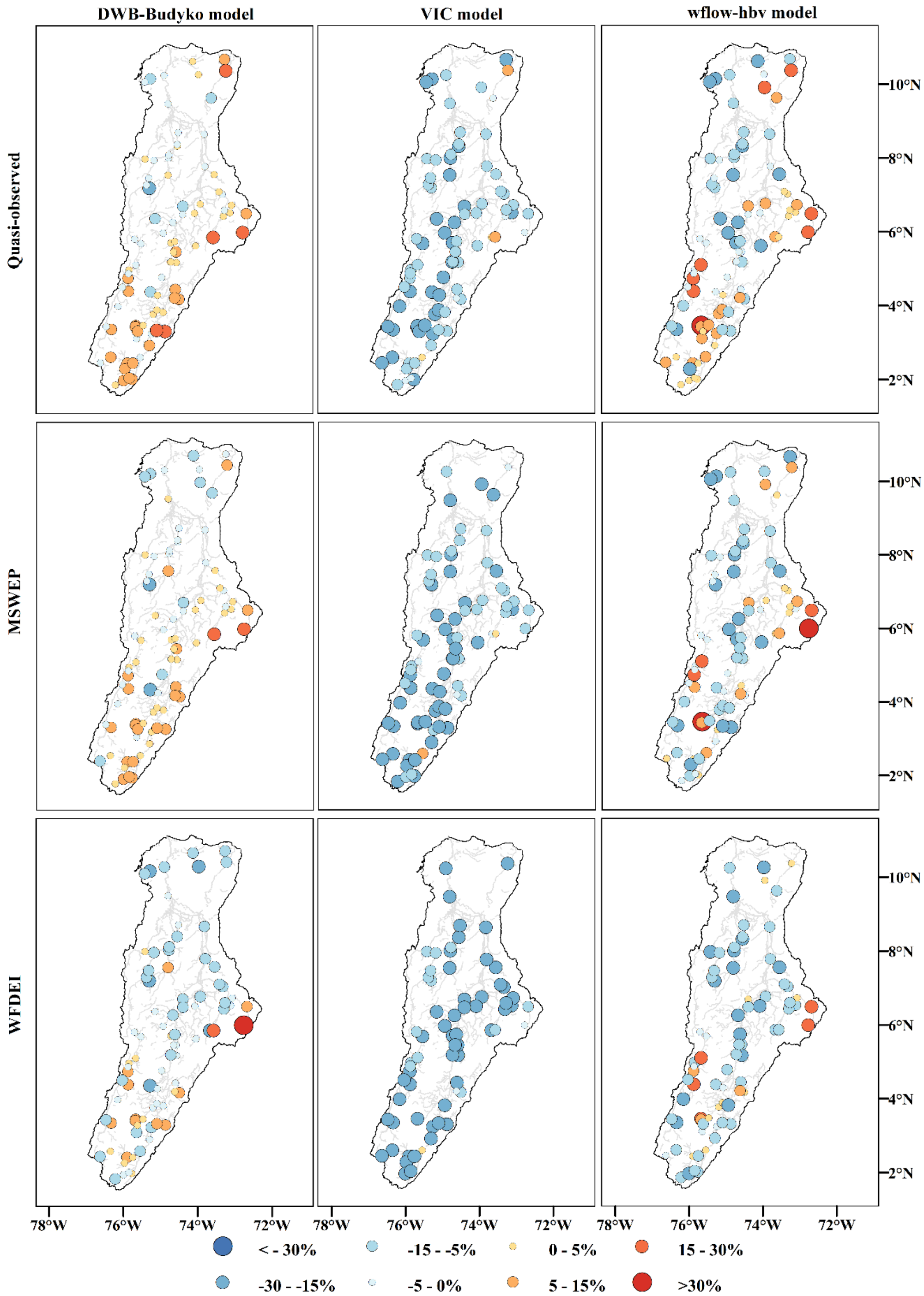

Figure 7. Percent Bias of WRI point estimations obtained between model simulations using the three datasets against WRI derived from observed streamflow data.

5 CONCLUSIONS

Hydroclimatological data combination from different sources provides a helpful and low-cost way to calculate water management indices like the Aridity Index (AI) and the Water Regulation Index (WRI), which are currently used in Colombia to support the National Water Assessment Study, which is the basis for water planning and management at the national scale. In the study here reported, the combined use of global meteorological datasets, with observed data, and hydrological modelling results, has allowed the assessment of these two water management indices in the Magdalena-Cauca macrobasin.

The two global meteorological datasets analyzed (WFDEI and MSWEP) showed good results for deriving the AI index, which is a proxy for water availability, when compared to calculations made using the in-situ data (quasi-observed dataset). Although there are differences between the results, the two global datasets capture the regional trends of the AI index that are observed from the results with the quasi-observed data. This is very useful for complementing indices estimations based solely on observed data. Moreover, the results give insights into the probable use of these two global meteorological datasets in scarce information areas, like the

Orinoco and the Amazon macrobasins in Colombia. This suggests the importance of establishing water indices comparisons in those areas, using multiple data sources, as a strategy to better assess water resources. Improvements on the global datasets can be performed using downscaling techniques based on topography or vegetation features, or by merging the meteorological products with in-situ time series coming from meteorological stations.

On the hydrological modelling side, there are limitations in the estimation of the WRI index from the different models and forcing datasets investigated. DWB performs reasonably well, but its time scale does not allow to compute daily-based WRI values, and so, WRI values cannot be compared to observed data. VIC model presents an underestimation of the WRI values all along the basin, probably due to the model´s structure limitations. Wflow-hbv presents a good agreement in the WRI values compared to the observed data but presents limitations in the highland basins. In spite of these results, one of the main advantages of using distributed hydrological modelling is the possibility of estimating the WRI index in ungauged locations, yet the estimates should be treated with caution.

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