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Combined Use of Local and Global Hydro Meteorological Data with Hydrological Models for Water Resources Management in the Magdalena - Cauca Macro Basin – Colombia

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Abstract

Reanalysis and earth observation data have enormous potential to support water resources management, particularly in river basins where data availability is poor or where available stations are unequally distributed. Despite this potential, these datasets continue to be under-used around the world. In this article, we combine a recently established global water resources reanalysis that was developed within the EartH2Observe research project, and in-situ data in the Magdalena Cauca Macrobasin in Colombia. Through rigorous hydrological modelling we evaluate the contribution of this new information to the derivation of water availability indices used to support water policy and management. Results confirm the complementarity of the reanalysis, with water management indices derived from the reanalysis data showing good comparison to values obtained using in-situ data only. Indeed, the estimation of simple indices such as an Aridity Index and a Water Regulation Index show to be a suitable method for assessing and comparing the different reanalysis datasets. We also explore the value of the reanalysis and earth observations datasets in the study of climate and land use change scenarios in the basin. While considering the associated uncertainties, results show that on average rainfall is projected to increase in the basin and thus available water resources. Deforestation will increase the water balance due to lower evapotranspiration. However, reduced fog deposition in deforested cloud forest areas will lead to a decrease in the water balance. The promising results of the comparison have bolstered the confidence of the national hydro-meteorological agency to include the evaluated reanalysis datasets in the national water resources evaluation, complementing available in-situ datasets.

Keywords eartH2Observe project · Magdalena-Cauca Macrobasin (MCMB) · Hydrological modelling · Colombia · Aridity index (AI) · Water regulation index (WRI)

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1 Introduction

Hydrometeorological information is critical for water resources assessment and management, extreme events prediction and for studying climate variability and change. Despite its importance, several authors have reported a global decline in the number of in situ hydrometeorological monitoring gauges since the 1980's (UN-WWAP 2015; Lorenz and Kunstmann 2012; Vörösmarty et al. 2001). For instance, in the Magdalena-Cauca Macrobasin (MCMB), the most monitored hydrosystem in Colombia, the number of rain gauges with good quality data has reduced from about 1500 in the 1980's to around 1000 in the 2010's.

With the availability of in situ data declining, or lacking, the use of Earth Observations (EO) (Cruz-Roa et al. 2017; Garcia et al. 2016) and reanalysis datasets (Schellekens et al. 2017; Weedon et al. 2014), has been identified as a useful complementary alternative (García et al. 2016; Herrera-Estrada 2016; UN-WWAP 2015). But, the use of EO and reanalysis data for water resources studies is not common around the globe. Nevertheless, in Colombia, the combination of in situ data, EO and reanalysis data has shown improvements in the quantification of water resources (Elgamal et al. 2017).

In the implementation of water policies in Colombia, a set of technical instruments has been formulated by different governmental institutions, which are used to identify the current state, trends, and changes in water resources; and to support decision making in water management and planning in the country at diverse scales. The most important one, formulated at the national level, is the so-called National Water Assessment Study (ENA, according to its initials in Spanish), in which an integrated assessment of the current state of water resources is made and updated approximately every 4 years. The main purpose of the ENA is identifying regions that need to be prioritized, regarding environmental and management policies.

The formulation of the ENA is based on a set of indices that characterise the hydrometeorological regime, including an aridity index (AI) and a water regulation index (WRI) (IDEAM 2010), as well as other indices that evaluate the water quality state of the resource and the level of anthropic intervention. Notwithstanding its relevance, weaknesses in the estimation of these tools have been identified due to asymmetrically distributed in-situ data across the country, and because the available in-situ data only partially provide the variables necessary to establish the required indicators. The decision-making process may be compromised as a result of the representativeness of the indicators when established using in-situ data alone.

In order to improve the assessment of the indices contained in the ENA, we included data from the eartH2Observe project (Schellekens et al. 2017) in the calculation of the indices that characterise the natural regime of the MCMB and compared the results obtained with those established using in situ observed data. The eartH2Observe project is a collaborative project that aims to use global EO, in situ datasets and models with innovative techniques in order to assist in global water resources assessment.

To also test the utility of EO, we then applied the global WaterWorld Policy Support System to the MCMB catchment using downscaled global data to calculate indices at the 1 km resolution as a baseline run, and then applied climate change and deforestation scenarios to test the impact on the indices. WaterWorld is a hydrological model designed for water policy makers to test the impact of policy decisions on water resources under conditions of land use change, land management and climate change using global data on the likelihood of water hazards such as flood and drought.

In this regard, there are three main objectives to this research:

1. To evaluate the applicability of eartH2Observe global datasets to monitoring the regional hydrometeorological state (or analysis) of key variables of the hydrological cycle, through computation of the AI as a representation of the interaction between the atmosphere and the surface.
2. To evaluate the applicability of global and regional hydrological models to water resources planning through calculation of the WRI, to assess the interaction between basin conditions (e.g. soil type, canopy, landscape) and discharge fluxes.
3. To assess the impact of spatial climate and deforestation scenarios in the MCMB and its population on AI, using the WaterWorld Policy Support System.

2 The Magdalena Cauca Macrobasin

The MCMB is the primary river basin system in Colombia, draining an area of around 257,000 km^2, which is about 25% of the total territory of the country. It has its headwaters high up in the Colombian Andes at the Magdalena Lagoon at an elevation of about 3700 m.a.s.l. which is located in the south (Restrepo et al. 2016). As depicted in Fig. 1a, the Magdalena River flows northward for about 1600 km through the western part of the country before reaching the Atlantic Ocean. The mean annual river discharge at Calamar, which is the gauging station closest to the mouth before the diversion of the Canal del Dique, is approximately 7200 m3 s-1, with mean maximum discharges occurring in November (10,200 m3 s-1), and minimum average flows in March (4050 m3 s-1) (Camacho et al. 2008). Due to the movement of the Intertropical Convergence Zone (ITCZ), the upper and mid MCMB experience a bimodal annual precipitation cycle with two wet periods (April – May, and October – November) and two interspersed dry periods, while the lower MCMB has a unimodal cycle (May–November). Terrain model, soils and land use maps for the MCMB are shown in the supplementary material SM Figure 1.

Several meteorological and climatological phenomena impact the MCMB at different spatial and temporal scales, such as El Niño - Southern Oscillation (ENSO) (Poveda et al. 2006). The MCMB experienced extensive flooding caused by the strong La Niña event of 2010–2011 that affected four million Colombians (Hoyos et al. 2013; Ricaurte et al. 2017). Severe droughts occurred recently as a result of the El Niño event of 2015–2016, which caused a significant amount of fires that impacted several regions of the basin (Hoyos et al. 2017). Additionally, the very complex terrain of this predominantly Andean basin makes the hydrological study of the water resources in the MCMB and its variability not only challenging but also quite complicated (Poveda 2004).

3 Data Used

3.1 Hydrometeorological In Situ Information

The Institute of Hydrology, Meteorology and Environmental Studies in Colombia (IDEAM) provided all in situ hydrometeorological information for the MCMB, corresponding to daily time series of precipitation (2256 stations), maximum and minimum temperature (467 and 481 stations), wind speed (137 stations) and streamflow (752 gauges), available for the reference period 1981–2012 (see Fig. 1b).

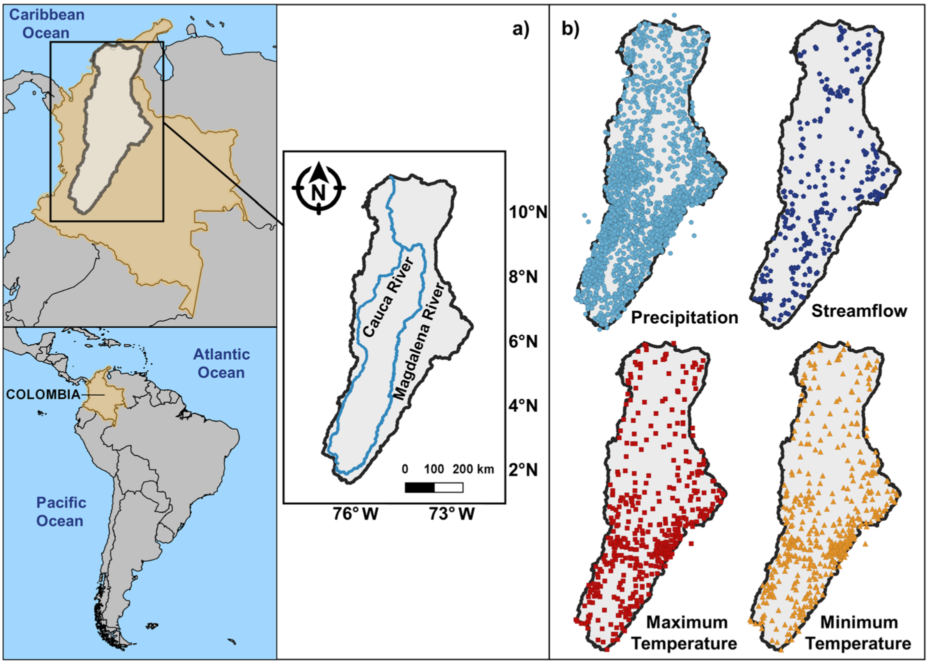

Fig. 1 **a** Location of the Magdalena-Cauca Macrobasin in Colombia. **b** Location of gauging stations for precipitation, streamflow, maximum and minimum temperature

Although the number of available stations seems comprehensive, the records of observed data were found to be incomplete at many stations. We applied rigorous techniques for pre-processing data and the detection of outliers (see supplementary material). Data gaps were not filled in, and spatial interpolations in the MCMB were implemented for each day using the stations with data available for that day. Due to the few stations with records for wind speed and a large number of days without data, we used the information contained in the WATCH Forcing Data ERA-Interim (WFDEI) meteorological dataset (Weedon et al. 2014), which is based on the ERA-Interim reanalysis (Dee et al. 2011). In this way, we created a quasi-observed forcing dataset for the implementation of regional hydrological models.

Daily maps for precipitation, maximum and minimum temperature were produced at a spatial resolution of 0.1° (around 10×10 km) using interpolation methods and evaluated through cross-validation. As there is a clear link between altitude, and rainfall and temperature in the MCMB (Poveda et al. 2006), we used Kriging with External Drift (KED) for interpolating precipitation, and Cokrigring (CK) for air temperature; in both cases, we used the Digital Elevation Model (DEM) information as a covariate. We also tested interpolated precipitation using Splines and Inverse Distance Weighting but found the KED method gave better results overall. KED has been shown to provide reliable results in interpolating precipitation in a small sub-basin of the MCMB (Rogelis and Werner 2013).

Evapotranspiration (ET) measurements in the MCMB are lacking. The Hargreaves method (Hargreaves and Samani 1982) was selected to derive daily potential evapotranspiration from maximum and minimum daily temperature information. Several studies have shown that the Hargreaves equation provides reliable estimations of daily potential evapotranspiration in different climates, including the tropics (Hargreaves and Allen 2003; Allen et al. 2006). We produced daily and monthly maps of potential evapotranspiration at a spatial scale of 10 × 10 km. The GLEAM (Global Land Evaporation Amsterdam Model, Martens et al. 2017, Miralles et al. 2011) evapotranspiration estimates were evaluated using an evapotranspiration dataset derived from temperature and the Hargreaves method as a benchmark. Considering the spatial scale of the two datasets (GLEAM is a global product unable to simulate local phenomena, due to its original scale of 0.25°, around 25 × 25 km) we chose to use the estimations based on Hargreaves for the regional and local ET calculations. This was done mainly because of the low performance of GLEAM in forested zones (Yang et al. 2017).

3.2 Global Meteorological Datasets

The use of Earth Observations (EO, mainly of precipitation) and meteorological reanalysis in hydrological modelling can support integrated water resources management (Serrat-Capdevila et al. 2014). Hence, the eartH2Observe project takes advantage of various global reanalysis and derived datasets, the WATCH Forcing Data applied to ERA-Interim (WFDEI; Weedon et al. 2014) and the Multi-Source Weighted Ensemble Precipitation (MSWEP; Beck et al. 2017b).

WFDEI was generated using the WATCH Forcing Data methodology and the ERA-Interim reanalysis data for the 1979–2012 period and is a 0.5° (about 50 km) resolution meteorological product. It was specially designed to "compare hydrological and Earth System models outputs with hydrologically and phenologically relevant satellite products" (Weedon et al. 2014). On the other hand, MSWEP (available from 1979 to 2015 in the version used) was specially designed for hydrological modelling, it is a 0.25° (about 25 km) resolution precipitation product based on rain gauges, streamflow gauges, EO of precipitation and reanalysis data.

The evaluation of these two products against the interpolated raingauge data is presented in the supplementary material (see SM Figure 2 and SM Figure 3), using the percent bias (PBIAS) and the root-mean-square error (RMSE) as performance metrics (Dawson et al. 2007).

These precipitation datasets (obtained from WFDEI and MSWEP) were used in conjunction with other meteorological variables obtained from the WFDEI reanalysis (these were first downscaled to a 0.25° resolution when used in conjunction with the MSWEP data), to create two versions of the water resources reanalysis using global hydrological models, which are mentioned in section 4.1. In the results, these are referred to as the Tier I and Tier II reanalysis datasets (Schellekens et al. 2017). In addition, these meteorological datasets were also used to force the regional hydrological models (DWB & VIC and WFLOW) as described in section 4.2, using the same reference period as for the observed data.

For long term (multi-year monthly means) water management planning, a long term precipitation dataset is needed, so downscaled precipitation data from WorldClim (1950–2000, Hijmans et al. 2005) and MODIS PET (2000–2012, Mu et al. 2011) data was used for the analysis of the impact of climate and deforestation using the WaterWorld Policy Support System (Mulligan 2013), both with a spatial resolution of about 1 km2.

3.3 WaterWorld Land Use and Climate Change Scenarios

Deforestation has had severe impacts in the MCMB, resulting in floods and sedimentation downstream (Hoyos et al. 2013; Restrepo et al. 2015, Restrepo and Escobar 2016). A deforestation scenario was constructed using the QuickLUC model (V2, Mulligan 2015) considering actual deforestation rates and patterns derived from past MODIS satellite data provided by Terra-i (Reymondin et al. 2012). The deforestation scenario assumed the same past deforestation rate per administrative region for 50 years and assumed that 80% is taken from the tree cover in a deforested pixel (i.e. reduces to zero tree cover if the present day tree cover is 80% or less) and converted to herbaceous cover and bare soil in the same proportions as the most common agriculture locally, if terrain is suitable for agriculture. Existing Protected Areas (UNEP-WCMC and IUCN 2016) were not deforested. As a result, in this scenario the average percentage of tree cover in the catchment reduced from 29% to 20%, thus reducing the canopy storage. The deforestation took place in areas where previous deforestation had occurred, which is mainly to the north of the catchment, and around cities as Medellin and Cali.

Climate change scenarios were developed using an average of 19 General Circulation Model (GCM) for rcp4.5 (2040–60) (see Supplementary Material, SM Table 1). To assess uncertainty in GCMs, the average plus and minus one standard deviation of the 19 GCMs was also run using WaterWorld Policy Support System (see section 4.2.4).

4 Hydrological Models

In this section, we briefly describe the main characteristics of the hydrological models used in this research to simulate runoff in the MCMB. The models are divided into global hydrological models; with no calibration, and regional models; calibrated in the MCMB domain.

4.1 Global Hydrological Models

To reduce errors and uncertainty stemming from the simplifications that models make of the real world, within the eartH2Observe project framework a large set of Global Hydrological Models (GHM) and Land Surface Schemes (LSS) were forced with the WFDEI data (Schellekens et al. 2017). This is referred to as the Tier I reanalysis and ensemble. All models included were forced for the 1979–2012 period, and the LSS were not run coupled with an atmospheric model (when LSS are applied to a regional scale, normally they receive and give feedbacks to atmospheric models to solve the energetic balance). In general, GHM and LSS were not strictly calibrated against observed streamflow data and they were warmed-up using different procedures. Four of the global models were subjected to a calibration process, but there was not a unique calibration methodology (calibrated models were LISFLOOD, SWBM, WaterGAP3, and HBV-SIMREG; Beck et al. 2017a). A summary of the models that comprise the Tier I water resources reanalysis, their features and structure can be consulted in Table 1 of Schellekens et al. 2017. A second phase of the water resources reanalysis, called Tier II, was developed using the WFDEI dataset at a resolution of 0.25° and the MSWEP product as the precipitation forcing. In the case of the Tier II data, models were run for the 1980–2014 period.

The GHM and LSS have different structures, and consequently, they simulate different variables. A common strategy to validate them was implemented through streamflow results. The flow validation was done through the use of runoff or river discharge (runoff that has been routed). Unfortunately, not all of the global models have a routing scheme; in the Tier I reanalysis, seven out of ten models routed the generated runoff (Table 1 of Schellekens et al. (2017) and Table 2 of Beck et al. (2017a)), whereas in Tier II just the LISFLOOD, WaterGAP3, and HTESSEL-CaMa models included a routing procedure. Therefore, here we validated the river discharge simulations produced by the seven global models of the Tier I reanalysis, their ensemble mean, and the three models in the Tier II reanalysis. We used the Nash-Sutcliffe Efficiency (NSE) coefficient to compare simulated discharges to observed daily discharges (and also the NSE was calculated with streamflow data aggregated on a monthly basis) at the 88 streamflow gauges in the MCMB, for the period 1981–2011. This was done prior to the application of the modelled streamflow estimates for calculation of the WRI. The results of the model validation are presented in the supplementary material. Based on the validation results, we choose the SURFEX-TRIP and the Tier-I ensemble to provide the streamflow estimates used in this research. Detailed results for the global models and the Tier I ensemble are included in the supplementary material (SM Figures 4 and 5).

4.2 Regional Hydrological Models

In this section, we briefly describe the model structures of the regional hydrological models considered. We have used a split-sample approach for model calibration and validation. For all the regional models the period 1982–2000 is used for calibration and the remaining period 2001–2011 was used for validation. The calibration and validation of the simulated discharges, obtained with these models, were performed following the same criteria used for the GHM and LSS; the results are included in the supplementary material.

4.2.1 Dynamic Water Balance-Budyko Model

The Budyko framework (Budyko 1974) was developed to evaluate the relationship between precipitation, actual evapotranspiration and potential evapotranspiration for river basins. This approach assumes either an energy or a water limit at multiannual time scale. Zhang et al. (2008) extended the Budyko framework, developing the Dynamic Water Balance model (DWB), a lumped conceptual hydrological model for annual and sub-annual time scales. The DWB model has a simple structure without routing, trying to explain the hydrological processes in a basin with a reduced number of parameters. The model parameters include the basin rainfall retention efficiency ($\alpha 1$), the evapotranspiration efficiency ($\alpha 2$), the recession constant (d), and the maximum soil moisture storage capacity (Smax). This hydrological model has been applied in several basins around the world (Kaune et al. 2015; Tekleab et al. 2011) showing promising runoff simulations at the monthly temporal scale. In Colombia, the DWB model has been used for evaluating the surface water availability (runoff and soil water storage) in selected basins (Londoño et al. 2010; Kaune et al. 2015). Moreover, the Budyko postulate is currently applied in the ENA for determining the aridity index. In this study, the DWB model was applied at a monthly time step and its calibration against the 88 streamflow gauge time series was performed using the GLUE methodology (Beven and Binley 1992).

4.2.2 Variable Infiltration Capacity Model

The three-layer macro-scale hydrological model of soil and semi-distributed Variable Infiltration Capacity (VIC; Liang et al. 1994, Zhao et al. 1995) is a physically based model that simultaneously solves the water and energy balances in a watershed. Three runoff components, coming from the three soil layers, represent the runoff generated by each grid, which can be routed along the streams using the scheme proposed by Lohmann et al.

(1998). The VIC model is recognized for its adequate representation of infiltration and evapotranspiration; the first estimated based on the scheme proposed in the Xinanjiang model (Zhao et al. 1980), and the second through the use of the Penman-Monteith equation (Allen et al. 2006). A mosaic type of approach allows the user to represent sub grid-scale variability in land cover, soil moisture, and soil texture. In this study, we implemented the standard version of the VIC model in water balance mode using a 1-day time step and a spatial resolution of 10 × 10 km. The VIC model has a large number of parameters (many of them initially derived from soil and land cover conditions). For water balance applications, as reported here, seven model parameters are generally calibrated, including the infiltration curve parameter, the fraction of the maximum base flow rate, at which a non-linear base flow begins, the maximum base flow speed, the exponent in Campbell's equation for hydraulic conductivity, the hydraulic conductivity in saturation, the depth in meters of each layer and the fraction of maximum soil moisture at which non-linear base flow occurs. The model was calibrated against the 88 streamflow gauges using the GLUE methodology.

4.2.3 OpenStreams wflow-hbv Model

The OpenStreams wflow-hbv model (Schellekens 2014) was implemented in the MCMB on a 1 km × 1 km spatial resolution using a 1-day time step. The reason behind the selection of this model was the previous application of the model in the MCMB for estimating discharge at different locations along the Magdalena River and its main tributaries (Ramirez et al. 2015). The model is based on the conceptual HBV-96 model (Saelthun 1995), and it is programmed in the PCRaster-Python environment (Karssenberg et al. 2010), providing a grid-based representation of the hydrological processes. For each grid cell, the model determines the water balance considering three components: precipitation-snow (including interception), soil moisture and runoff. Daily total runoff of every grid cell results from adding direct runoff and interflow from the upper soil zone and baseflow from the lower soil zone. The total runoff is accumulated from all grid cells and routed using the kinematic wave function to obtain river discharge. Its calibration against the 88 streamflow gauge time series was performed using the PSO algorithm (Kennedy and Eberhart 1995). The model has 19 parameters, and based on the HBV-96 model, 11 of them were calibrated in this research.

4.2.4 WaterWorld Policy Support System

WaterWorld (www.policysupport.org/waterworld) is a detailed process-based model for water quantity, quality and regulation ecosystem services (Mulligan 2013; Mulligan and Burke 2005). It includes scenario tools for climate change and land use change and policy option/intervention tools for land management. It uses global data at 10 km, 1 km and 1 ha resolutions. For anywhere in the world, this produces a hydrological baseline based on evapotranspiration and runoff for 1950–2000 at a monthly resolution using over 140 input maps and a sophisticated spatial physically based model. This baseline can be compared to modelled scenario runs for testing outcomes of water resource policies under land use, land management and climate change. WaterWorld was used to evaluate the impact of climate change (2040–2060) and 50 year deforestation (a "Business As Usual" scenario based on recent past deforestation spatial patterns and rates in the basin) on water management indices at 1 km spatial resolution.

5 Water Management Indices

Nine key indices of water stress, quantity, quality, and vulnerability are used in the National Water Assessment Study in Colombia (ENA) to analyse water availability in the MCMB (IDEAM 2015). Of these nine indices, two are used to characterise the hydro-climatology, while the remaining seven incorporate factors such as the exploitation pressure of water resources, water use efficiency and water quality. One of these indices (the aridity index), is related to runoff through the balance of energy and precipitation (Arora 2002), while the other (water regulation index) is used to understand the relationship between basin conditions and the discharge regime. Both are to some extent related to catchment conditions, land use and water management practices. Both indices have continuous numerical values but are classified in six qualitative categories for the AI, and in five classes for the WRI. In this research, results for both indices are used to evaluate the performance of EO, global reanalysis and results of the regional hydrological models on capturing the hydroclimatological and basin conditions. Additionally, WaterWorld is used to spatially model the impact of deforestation and climate change on the AI and runoff in regulated catchments.

5.1 Aridity Index

There are several definitions of the AI. In general, this index is used to indicate areas of water deficit, and mapping the AI allows water managers to track changes in local water availability. The AI defined in the ENA 2014 (IDEAM 2015) considers the in-balance between actual and potential evaporation, scaled by the potential evaporation. In this study, we use the more general relation between potential evapotranspiration and precipitation, as defined by UNEP (1997):

$$\mathrm{AI} = \mathrm{P}/\mathrm{PET} \tag{1}$$

Where AI is Aridity Index (dimensionless), P is precipitation, and PET is Potential Evapotranspiration.

This aridity index shows the relationship between meteorological inputs (precipitation) and the response of the land surface to those inputs (potential evapotranspiration, or available energy on the land surface) on a multi-year basis. Even if this index does not represent water availability, it can be used as a proxy (Pérez-Foguet and Giné Garriga 2011). The aridity index has shown to be useful in assessing the influence of climate change on runoff (Arora 2002). Its simplicity and easiness for spatialization allow comparing results from different sources, across large basins.

5.2 Water Regulation Index

In Colombia, and according to the ENA (IDEAM 2010), the Water Regulation Index (WRI) accounts for the basin regulation capacity as a system, based on the percentage of time a discharge is exceeded on an average year, represented on the flow duration curve. The WRI is calculated as shown in Eq. (2):

$$\mathrm{WRI} = \mathrm{Vp}/\mathrm{Vt} \tag{2}$$

Where WRI is the Water Regulation Index, Vp is the volume represented by the area under the mean discharge in the flow duration curve, and Vt is the total volume represented by the area under the flow duration curve.

This indicator characterizes the variability of the discharge regime and is commonly used in Colombia as a proxy for the conditions inside the basin (regulation, vegetation, soil and drainage characteristics). Values of WRI close to 1 reveal better conditions for sustaining a constant flow regime throughout the year, even under low precipitation circumstances (IDEAM 2010, 2015), while lower values indicate high variability of flows.

WRI is calculated using daily data, as this time scale is considered sufficient for capturing basin-scale fluxes. However, other timescales can also be used, although they are not so common. Due to the temporal resolution of the DWB model, monthly data were used to compute WRI values, while for all the other hydrological models, daily data was considered. Assessment will take into account the temporal difference.

6 Methodology

The selected meteorological datasets were used for the calculations of the AI, as shown in Fig. 2. To compare results, we used the percentage bias against the index calculated using observed values. Also, WaterWorld was used to investigate the effects of climate change and deforestation on regional hydrology and thus the AI.

For estimations of the WRI the meteorological datasets were used to run the different hydrological models (see Fig. 2), using the following approach:

1. The quasi-observed, MSWEP and WFDEI information was used to force the regional hydrological models VIC, DWB, and OpenStreams wflow-hbv.
2. WFDEI was used as the forcing of the global hydrological models in the earthH2Observe project to create the Tier 1 water resources reanalysis.

With discharge as the main output from the modelling strategy, the WRI was computed. As WaterWorld calculates river discharge on a monthly timestep, and so does not produce flow duration curves in the same way as the other models used here. So it is not possible to use this monthly timestep model for this particular WRI equation, for the climate change

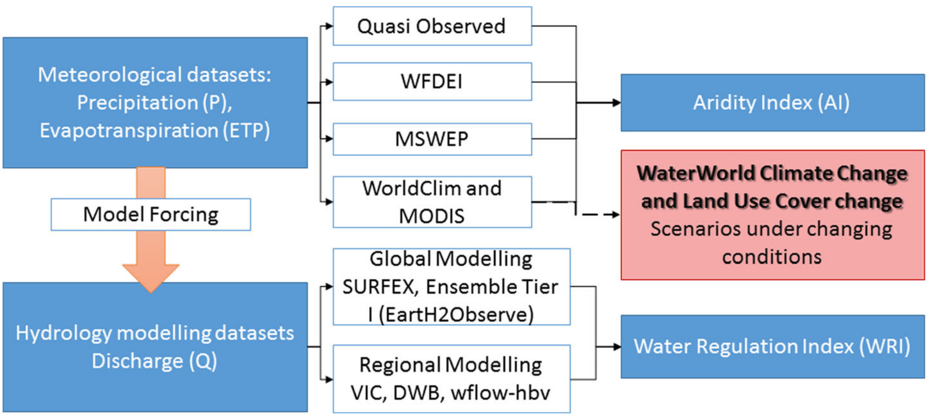

Fig. 2 General use of meteorological datasets and modelling outputs for calculations of the two water management indices selected

and deforestation impacts analysis. WaterWorld has its own water resources indices based on monthly data and is used for the long term analyses.

7 Results

7.1 Aridity Index Results

The AI was calculated using the four precipitation forcing datasets described in sections 3.1 and 3.2 (quasi-observed, WFDEI, MSWEP, and WorldClim). We compared AI results obtained with these precipitation products with the AI results calculated using the quasi-observed dataset as a benchmark. Figure 3 shows that in general there are no water deficits in the MCMB. Around 60% of the MCMB, mainly located in the central region, presents a humid category for the AI, meaning that there is a surplus of water in this part of the basin.

In the flat northern area, there are some regions in the subhumid category, near the outlet of the Magdalena River into the Caribbean Sea. Some of the forcings (MSWEP and WorldClim) even classify this region as dry and semi-arid. These results are explained by a lower precipitation amount from these products in this part of the watershed, and a larger evapotranspiration rate in the lower northern part of the MCMB. For the WorldClim dataset, there are hotspots of semi-arid areas around several main cities (such as Bogota - central part) indicating potential areas of local water stress and communities vulnerable to drought. As can be seen in panel d of Fig. 3, the downscaling procedure used for WorldClim analysis allows identifying some of the features of the index with more detail. This explains the importance of using EO precipitation or reanalysis data for this variable, in conjunction with post-processing procedures (downscaling), in order to achieve improved local datasets and therefore better water deficit analysis. It is necessary to note that Water World does not take into account the connection with the Ciénaga Grande de Santa Marta (largest marsh in Colombia), therefore some cells at the north of the basin have no value (in black).

Even though there are qualitative similarities between the distributed AI values in the MCMB, this does not mean that the differences are not important when comparing the numerical values of the AI. As part of the assessment, the differences in the AI index were evaluated using the percent Bias between forcings and observed data, resulting in the maps shown in Fig. 4. Computation of mean values for the MCMB show good agreement with the quasi-observed results; WFDEI presents a mean percentage bias of 7.4%, MSWEP presents a value of 2.9% and WorldClim of 3.0%.

When comparing the AI values of the three precipitation datasets with the observed baseline dataset (quasi-observed), lower AI values are observed in the north of the basin, due to the underestimation of precipitation, while in the southern area, where the Andes mountains are located, the different products tend to overestimate precipitation. In spite of these differences, it is evident that the use of reanalysis data for both, qualitative and quantitative analysis of the AI index, is consistent with the observed results, providing an opportunity to complement the evaluations made solely with in-situ data and to update estimations of the index more often in a faster way.

7.2 Water Regulation Index Results

Each precipitation forcing dataset (quasi-observed, WFDEI, and MSWEP) was used to run each of the regional models (DWB, VIC, and OpenStreams wflow-hbv). We obtained point estimates of the WRI using Eq. (2).

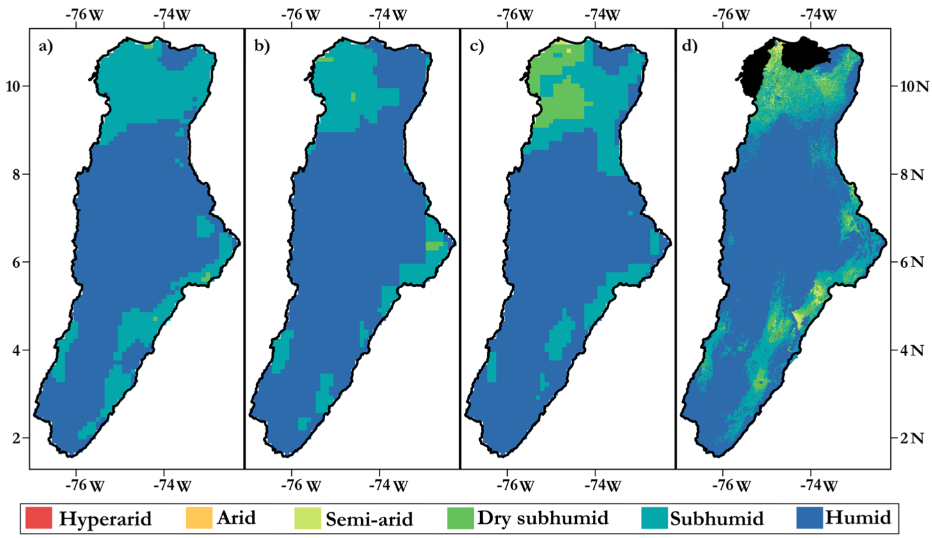

Fig. 3 Distributed AI as calculated using (**a**) the quasi-observed, (**b**) WFDEI, (**c**) MSWEP and (**d**) WorldClim precipitation data. AI <0.05, Hyper-arid; 0.05 < AI <0.20, Arid; 0.20 < AI <0.50, Semiarid; 0.50 < AI <0.65, Dry subhumid; 0.65 < AI <1.00, Moist subhumid; and AI >1.00, Humid

Figure 5 depicts the WRI estimates using the in situ hydrological information, the regional models, and the two global models as selected in section 4.1. As the in situ hydrological information is the basis for the WRI calculations reported in ENA-2010, the gauge station WRI estimates were used to assess the performance of each of the models in the estimation of this index. Moreover, the WRI reported by the regional models were also computed using each of the three forcing datasets; this is shown in the supplementary material (SM Figure 6) with its respective analysis.

When comparing model-based WRI with the classification obtained using the streamflow gauge, using the quasi-observed dataset, the OpenStreams wflow-hbv model was found to successfully reproduce the behaviour of the index at half of the stations (panel d), most of them with high degree of flow regulation. For the other half, the model underestimates WRI values, with the exception of some points in the highlands. The wflow-hbv model is the model with the finest spatial resolution as well as with the best performance at daily timescale. On the other hand, the WRI values derived from the VIC simulations have a mixed tendency with the majority of points having lower WRI values (i.e. Low and Very Low regulation) than those obtained from the gauge streamflow data (see panel c). Due to the monthly-time step used for the DWB model, the WRI estimates are not exactly comparable with those reported by the gauges and the other two models, which are derived using daily information (panel b). However, we also compared results for this model against the values depicted by the streamflow gauges, obtaining close values to the WRI reported by gauges in the Cauca river and in the lowlands. The former indicates that even with the difference in time scales, the DWB model can represent, to a degree, the highly regulated flow pattern in the MCMB. The results using the other two forcings reported similar WRI values as obtained using the quasi-observed forcing, meaning that the WFDEI and the MSWEP capture the main precipitation patterns in the basin quite well (see SM Figure 6).

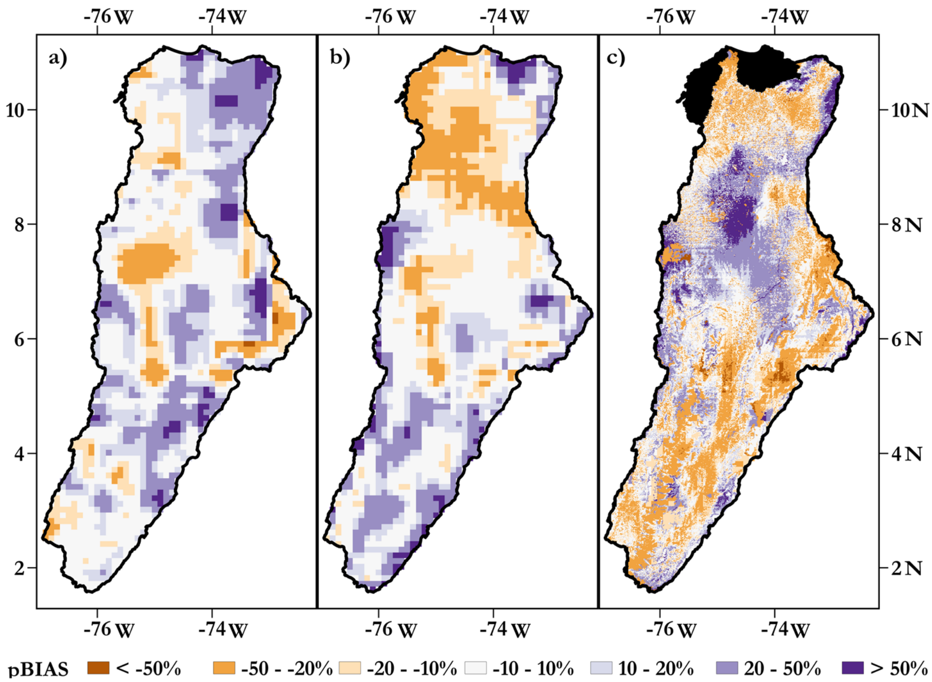

Fig. 4 Distributed PBIAS between the quasi-observed AI values and AI values calculated from (**a**) WFDEI, (**b**) MSWEP, and (**c**) WorldClim precipitation data.

Also, in panels e) and f) of Fig. 5, the estimates of the WRI obtained from the SURFEX-TRIP and the Tier-I ensemble streamflow simulations show an overall agreement with respect to the values calculated with local information. There is not a clear locational trend of the differences and both estimates report a moderate regulation in the upstream regions of the watershed. They also show a low regulation in the streamflow gauges located in the North-East, near the Sierra Nevada mountains. SURFEX-TRIP shows a moderate regulation in the highlands and a high degree of regulation in the lowlands. The Tier-I simulations also display in general moderate and high regulation throughout the watershed, though it shows some points with high regulation in the southern regions, results that are more similar to the values obtained with the observed streamflow time series than for the SURFEX-TRIP. The other global models of the eartH2Observe datasets show different behaviour of the WRI when compared to the values calculated using observed streamflow. The coarse estimates of the index made by global models might be related to the spatial resolution of 0.5°, and the impossibility of the routing function to represent the physiographic features of the lowlands. Although the results are coarse, the overall estimates of the ensemble are similar to the observed ones and can be used in big watersheds that are poorly instrumented.

We also calculated the percentage error in the estimation of the WRI for the three precipitation products and the different hydrological models considered (see Fig. 6 and in the supplementary material SM Figure 7). Once again, for all the precipitation forcings, the behavior obtained from the wflow-hbv model seems to fit the observed index behavior (panel a), and the change in the performance under different forcing datasets does not seem to affect the robustness of the index calculation. In general, for the wflow-hbv, the error

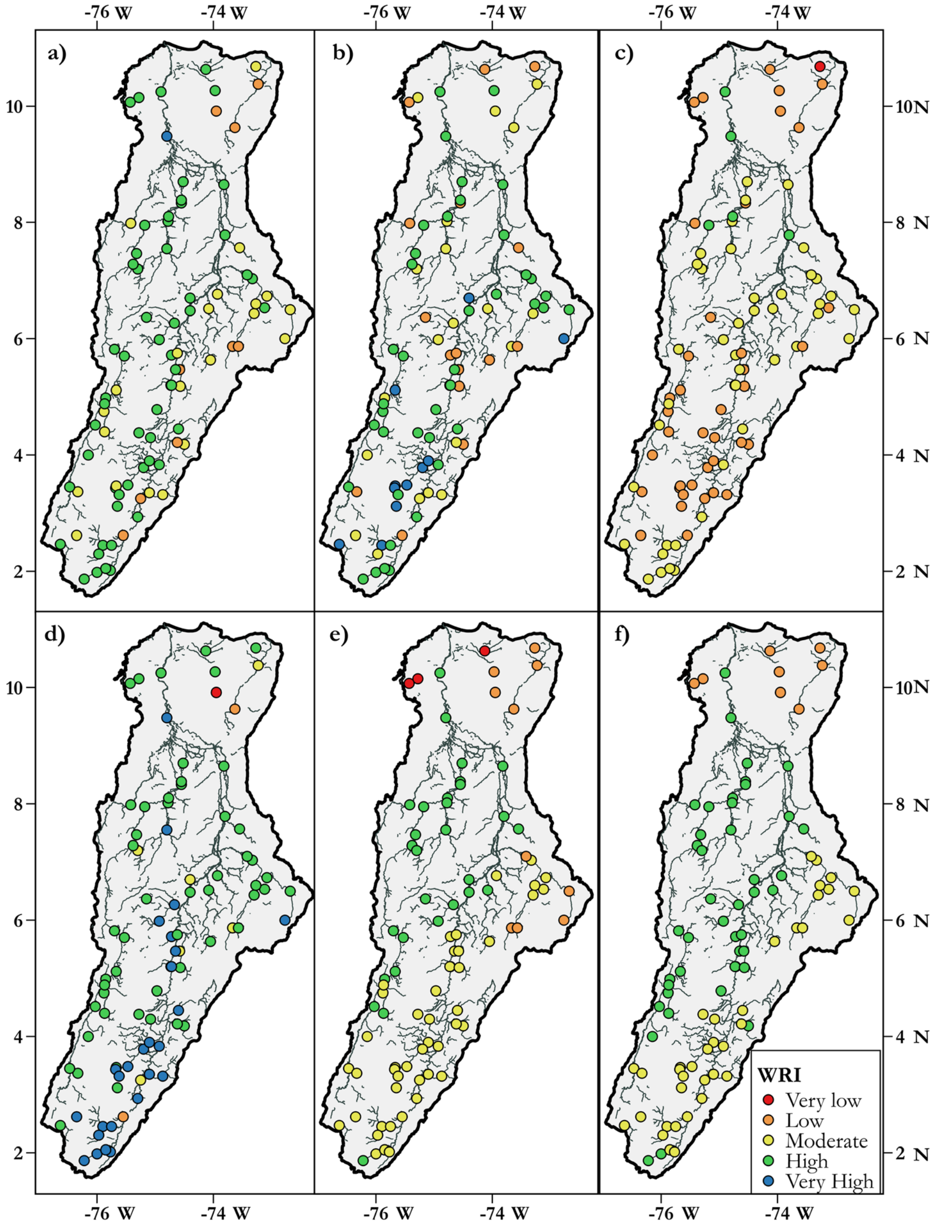

Fig. 5 Water Regulation Index calculated using **a**) In situ data, and simulations from the quasi-observed forcing and models **b**) wflow-hbv, **c**) VIC, **d**) DWB, **e**) SURFEX-TRIP and **f**) Tier-I ensemble. WRI < 0.05, Very low; 0.5 < WRI < 0.65, Low; 0.65 < WRI < 0.75, Moderate; 0.75 < WRI < 0.85, High; and WRI > 0.85, Very high

tends to be spatially located in the southern areas. WRI estimates with the VIC model show errors between −10% to −20%, with some up to −50%, with no specific area or input dataset giving better or worse results (panel b). The DWB model, on the other hand, mostly overestimates the WRI values when compared to monthly indices. The overall estimates of SURFEX-TRIP result in biases between −10% and 10%, a feature that probably may be

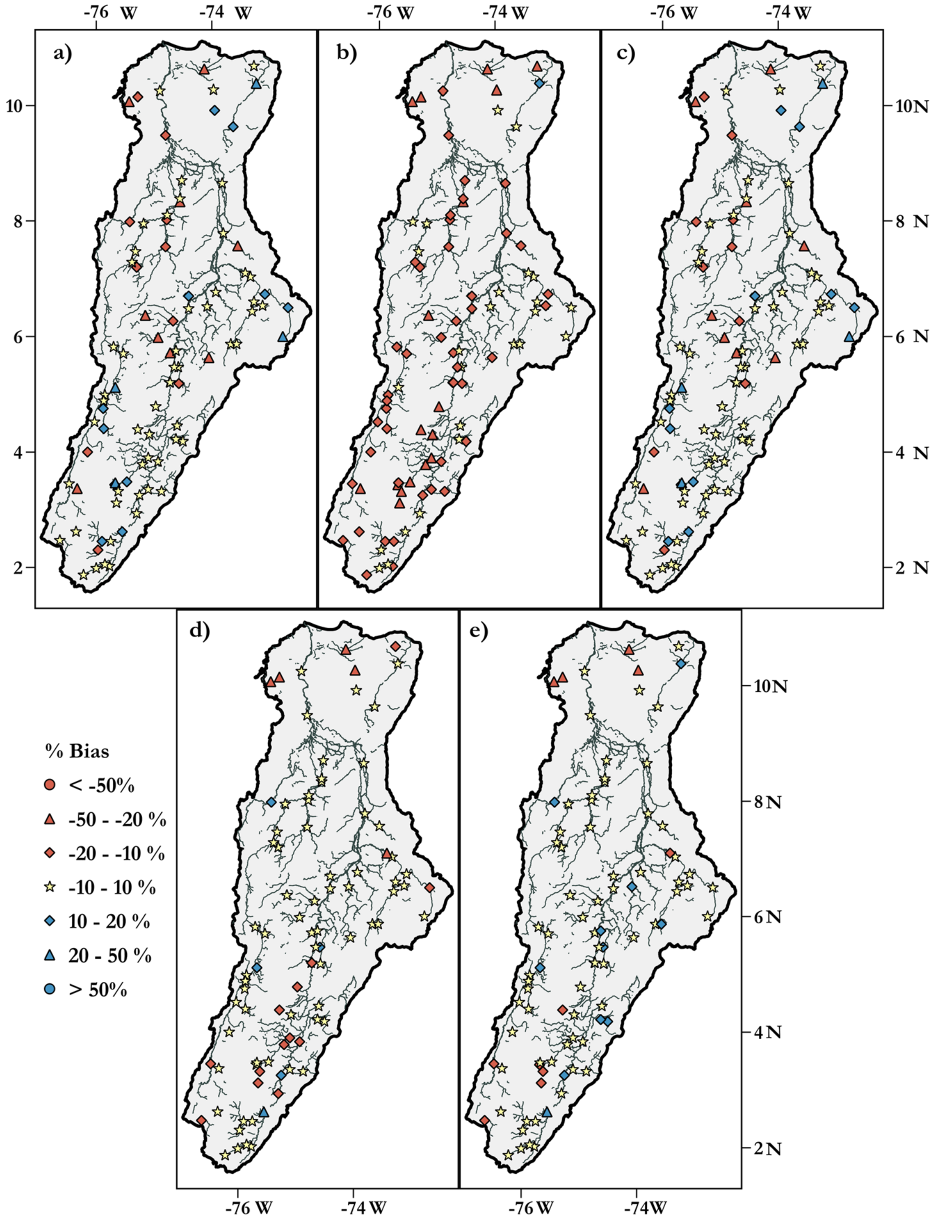

Fig. 6 Percentage bias as calculated using observed discharge values and and modelling outputs from **a**) wflow-hbv, **b**) VIC, **c**) DWB, **d**) SURFEX-TRIP and **e**) Tier-I ensemble values of the WRI. Every modelling exercise used quasi - observed dataset as forcing

due to the complex routing routine included in this LSS (see panel d). The ensemble of global models also performs well in terms of the WRI; the majority of the biases in WRI values are between −10% and 10% (see panel e). Although all the models included in this ensemble have a routing routine, the good results of the ensemble might also come from the complementary information that is gathered together in the ensemble.

7.3 WaterWorld Assessment of Climate Change and Deforestation Impacts

7.3.1 Climate Change

The spatial average of the projected changes in rainfall according to 19 GCMs for rcp4.5 (2040–60) is shown in Table 1 below, along with the population affected by these changes according to the LandScanTM Global Population (2011) population dataset. It is important that GCM uncertainty is taken into account when taking policy decisions that factor in climate change scenario results. Projections of rainfall can vary substantially depending on which General Circulation Model is chosen. The areas that are expected to become wetter using the mean of all 19 GCMs +1 Standard Deviation, the wet central highlands and the Sierra Nevada de Santa Marta in the north, are the same areas that show the greatest drying for the drier GCMs (mean − 1 Standard Deviation), so even the direction of rainfall change is dependent on the GCM.

Table 1 shows the average spatial results of the impacts of climate change on rainfall and the water indices. The left column shows the results of the mean of all GCM models minus one standard deviation (representing the drier GCMs), in the right column the average of all models plus one standard deviation (representing wetter GCMs), and the differences between them shows the uncertainty. Projected rainfall changes under CMIP5 rcp4.5 vary from −290 mm/ year to +470 mm/ year, an important consideration for taking policy decisions. It is also important to consider how the catchment population of 30.5 million LandScanTM Global Population (2011) is affected by these changes. Craven et al. (2017) estimate the population to be 32.5 million. Table 1 shows that the drier GCMs will affect over 30 million people in the catchment with lower AI, but conversely, over 30 million people will be affected by higher AI from the wetter GCMs. Therefore any water resources policies based on GCMs using these indices will be very sensitive to which GCM is chosen.

7.3.2 Deforestation

Using the "Business as Usual" deforestation scenario described in section 3.3 using WaterWorld v3, the catchment average water balance increased slightly by 0.3%. The greatest increases are in the downstream lowland areas in the North. Some of the higher altitude cloud forest areas show decreases in water balance due to the loss of fog deposition in deforested areas. Total evapotranspiration reduced by a catchment average of 2.7% from the baseline run (in which present day tree cover was used), due to lower evapotranspiration in the deforested areas. We analysed the impact of the deforestation scenario on total runoff in six catchments

Table 1 Climate change in the MCMB: impacts on rainfall, AI and population

	Mean-1 SD GCMs (drier)	Mean of all GCMs	Mean + 1 SD GCMs (wetter)
Change in rainfall	−290 mm/y	+90 mm/y	+470 mm/y
Population affected by increase in rainfall	200,000	29,900,000	30,500,000
Population affected by decrease in rainfall	30,400,000	3,600,000	100,000
Change in Aridity Index	−14.3%	+4.3%	+22.5%
Population affected by positive changes	200,000	26,900,000	30,500,000
Population affected by negative changes	30,400,000	3,600,000	100,000

upstream of dams in the MCMB. Runoff is calculated as the water balance accumulated downstream. As described in section 3.3 above, deforestation under our "Business as Usual" scenario occurs only where deforestation has been detected in the recent past, as analysed from the Terra-i data. The scenario assumed that no deforestation is allowed in the protected areas. As a result, the hydrological impact of the deforestation scenario was low in those dams whose catchments had been subject to little deforestation in the past, or that contain large protected areas. However, the Porce III dam catchment contains Medellin, Colombia's second city that has seen a population explosion and significant changes in land use around the city. Additionally, the area immediately upstream of the dam has high tree cover at present. Therefore the deforestation scenario used in this study highlights this catchment as a deforestation "hotspot" where further deforestation is more likely in the future than in other areas. Under this scenario, the change between the baseline run and the deforestation scenario shows an annual runoff decrease of 1.7%, so there is less water available for the dam's functions and for dilution of upstream pollution. Removal of the cloud forest in the Porce III catchment results in a decrease of 5.2% in fog deposition. Deforestation in cloud forest areas can therefore have a negative impact on the quantity and quality of water.

8 Conclusions

This study combined global and in situ hydrometeorological information with global, and regional hydrological models for the assessment of water resources indices in the Magdalena Cauca macrobasin (MCMB) in Colombia. This with the purpose of supporting policy formulation and water resources management in the watershed. The conclusions of the study are as follows:

i) The use of water resources reanalysis, together with rigorous hydrological mathematical modelling, has shown to be a good strategy for deriving water availability indices in the MCMB, that compare quite well with the values obtained only from in-situ data. In this regard, the methodology developed in this article can be useful to complement the indices estimations based only on observed information. Also, the methodology is suitable for assessing and comparing different datasets through simple indicators, such as the Aridity Index (AI) and the Water Regulation Index (WRI).

ii) These two indexes are part of the set of indicators calculated in the National Water Assessment Study, used to support water resources management in the basin. In this sense, the applicability of the methods and data implemented in this article highlights the importance of using earth observations and water resources reanalysis in the study of water availability even in a rich-information scenario, such as the MCMB.

iii) Regarding the AI estimates, although there are differences between the results obtained with the three precipitation products evaluated (WFDEI, MSWEP, and WorldClim), all of them seem to capture the regional trends. This is relevant to basins which lack information, and where water management and policies are more challenging. Use of global datasets at regional scale shows to be a promising strategy for assessing water resources in these basins.

iv) In comparison with the AI calculations, made using the in-situ interpolated precipitation, none of the datasets seem to capture the detailed spatial variability of the AI. The spatial resolution of the products used plays an important role in the estimation of the AI. Accordingly, downscaling procedures will contribute to improving the ability of the global datasets to identify local trends in the AI. As an example, the WorldClim dataset, with a 1 km resolution, is able to capture, through the AI, water pressure issues in the vicinities of the large cities within the basin.

v) Hydrological modelling at different spatial scales has been used to estimate the WRI for different sub-basins in the MCMB. Results from global models show that, even without calibration and with the significant uncertainties associated, some of the analyzed models can represent reasonably well the monthly discharges at certain streamflow gauges, although they have limitations at the daily timescale. Concerning the regional hydrological models, the parsimonious DWB model performs reasonably well in most of the streamflow gauge stations, with limitations in the lower Magdalena catchment, due to the lack of a routing component in the model and also because it is not able to represent the fluvial-wetland interactions correctly. The OpenStreams wflow-hbv model outperforms the VIC model, but only marginally. Both models have some limitations in high altitude areas, where forcing and in situ data are more uncertain, and also in the Mojana region (lower catchment), where the hydrological models implemented did not consider river-wetland interactions. At the daily scale, we obtained the best results with the OpenStreams wflow-hbv model.

vi) Calculations of the WRI, as a proxy for the interactions between basin conditions and discharge components, have been made using hydrological model results. WRI results obtained from the individual global models show an overall agreement with estimations made with in-situ data, with moderate regulation in the highlands and a high degree of regulation in the lowlands. The WRI results coming from the Tier I ensemble, show very good agreement with WRI results derived from observations, in the majority of the cases with values in the range $+-10\%$. In spite of the coarse resolution of this product, this reveals the ability and consistency of this dataset to represent the WRI index in the MCMB. WRI results from the regional models indicate that the best results were obtained with the OpenStreams wflow-hbv model due to its 1 km spatial resolution.

vii) WaterWorld can be used to improve estimates and map the indices required in the National Water Resource Evaluation (ENA) at 1 km resolution, and to map the impact of future scenarios of deforestation and climate change on these indices, and assess the impact of these scenarios on population. This can aid policymaking at the basin and sub-basin scale. We have shown that climate change produces uncertain results due to differences in GCM estimates in this area, but on average rainfall will increase and thus available water resources, but also a vulnerability to high rainfall events. Deforestation increases the water balance due to the lower evapotranspiration. In cloud forests, reducing the interception of fog in deforested areas means that the water balance may in fact decrease with impacts on the quantity and quality of water available for use.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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