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Projections of hydrology in the Tocantins-Araguaia Basin, Brazil: uncertainty assessment using the CMIP5 ensemble

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Abstract A semi-distributed hydrological model is developed, calibrated and validated against unregulated river discharge from the Tocantins-Araguaia River Basin, northern Brazil. Climate change impacts are simulated using projections from the 41 Coupled Model Intercomparison Project Phase 5 climate models for the period 2071–2100 under the RCP4.5 scenario. Scenario results are compared to a 1971–2000 baseline. Most climate models suggest declines in mean annual discharge although some predict increases. A large proportion suggest that the dry season experiences large declines in discharge, especially during the transition to the rising water period. Most models (>75%) suggest declines in annual minimum flows. This may have major implications for both current and planned hydropower schemes. There is greater uncertainty in projected changes in wet season and annual maximum discharges. Two techniques are investigated to reduce uncertainty in projections, but neither are able to provide more confidence in the simulated changes in discharge.

Key words Tocantins-Araguaia Basin; climate change; uncertainty; hydrological modelling; CMIP5

INTRODUCTION

Many recent studies have assessed the impacts of climate change on the water resources of different river basins around the world using a range of hydrological models (see for example Gosling *et al.* 2011). In many cases considerable uncertainty in the sign and magnitude of change in mean annual flow and the seasonal distribution of river discharge has been identified (e.g. Arnell, 2011, Hughes *et al.* 2011, Kingston *et al.* 2011, Xu *et al.* 2010). Several sources of uncertainty exist (Döll *et al.* 2015), the largest of which, in many cases, has been attributed to the different projections of future climate provided by different global climate models (e.g. Graham *et al.* 2007, Prudhomme and Davies, 2009). Nonetheless, other factors including those related to hydrological model structure may not be negligible (Haddeland *et al.* 2011, Thompson *et al.* 2013a). Most of the existing studies are driven by projections created by the previous generations of climate models, rather than those of the Coupled Model Intercomparison Project Phase 5 (CMIP5). We adopt the convention of referring to these models as GCMs (an abbreviation of General Circulation Model; despite the fact that some CMIP5 contributors can include interactive carbon cycles and so could be called Earth System Models) to prevent confusion with the hydrological model developed herein. The CMIP5 ensemble has only recently been available and is significantly larger than those of previous generations of GCMs (Knutti and Sedlacek 2013). This study hence employs the CMIP5 ensemble to investigate GCM-related uncertainty upon future water resources of the Tocantins-Araguaia River Basin, northern Brazil. To date, the impacts of climate change upon this basin have not been systematically investigated despite its importance to both human society, including major investments in hydropower generation, and biodiversity (Soito and Freitas 2011, Valente *et al.* 2013).

The CMIP5 GCMs forced under the Representative Concentration Pathway (RCP) 4.5 scenario (radiative forcing is stabilised at 4.5 W m^{-2} in the year 2100 without ever exceeding this value – Thomson *et al.* 2011) all project an increase in temperatures over the northern region of South America for the period 2081–2100 (Collins *et al.* 2013). Nonetheless, there is a range in the projected increases amongst the models with the 25th percentile showing an increase of between 1.0°C and 3.0°C and the 75th percentile showing an increase of between 2°C and 4°C (van Oldenborgh *et al.* 2013). Likewise there is large inter-GCM variation in the projections of precipitation change over the region for the same period. However, unlike the temperature projections, the GCMs do not show a consensus on even the sign of change in precipitation. The 25th percentile of models project a decline in precipitation of between 0 and 30%, while the 75th percentile show an increase of up to 10% over most of the region (van Oldenborgh *et al.* 2013). The underlying causes of the spread of projected precipitation change among the GCMs are still not well understood (Collins *et al.* 2013).

The aim of this study is to assess the hydrological impacts of projected climate change on the Tocantins-Araguaia River Basin by running RCP 4.5 scenario outputs from the CMIP5 GCMs for the period 2071–2100 through a conceptual, semi-distributed hydrological model calibrated and validated for a 1971–2000 baseline period. Simulated, unregulated discharge at a number of gauging stations for the 2071–2100 time slice is compared with baseline results to assess the impacts of climate change on river flows. The use of two alternative approaches to constrain uncertainty is investigated (ensemble weighting and identification of an emergent, observational constraint). The broader implications of future climate change on both the aquatic ecosystems of the river basin and hydropower are discussed.

METHODS

Tocantins-Araguaia River Basin

The Tocantins-Araguaia River Basin is located in the northern region of Brazil (Fig. 1). It has a total drainage area of 767 000 km^2, which makes up approximately 7.5% of Brazil's landmass (Barrow 1987). The Tocantins River originates from the Planalto Central do Goiás at an altitude of 1070 m above sea level and runs northwards, largely parallel to the Araguaia River, before their confluence some 2500 km downstream at Marabá. The Araguaia River is of great ecological significance as it contains the Bananal Islands along the middle of its course, which sustain the largest wetlands of the Cerrado biome (Valente *et al.* 2013). The average flow at Marabá, located toward the downstream end of the basin is around 11 000 m^3 s^{-1} and the river eventually flows into the Amazon River near Belém.

Mean annual rainfall over the river basin is 1752 mm and contrasts with mean annual potential evapotranspiration of 1768 mm (both based on CRU TS 3.10.01 data discussed below). The river basin has an extremely well defined hydrological regime, which is a consequence of the strongly seasonal rainfall (Ribeiro *et al.* 1995). The rainy season occurs from December to March, while the dry season extends from June to August. There is a lag time between precipitation and discharge due to the size of the catchment (Costa *et al.* 2003). The low gradients and inundation of the Bananal floodplains further contribute to this lag. As a result, the high flow season is between January and April, whilst low flows occur between August and October.

The landscape of the basin is dominated by a Cerrado savannah ecosystem, which is composed mainly of grassland, trees and shrubs (Valente *et al.* 2013). Approximately 44% of the plant species are endemic to the region, making it one of the world's top biodiversity hotspots (Myers *et al.* 2000). Riparian areas are estimated to be the habitat of 117 species of mammals, 120 species of reptiles and amphibians and 294 species of birds (La Rovere and Mendes, 2000). The rivers contain about 300 species of fish, most of which are migratory, including long-whiskered catfish (*Hypophthalmus marginatus*) and flannel mouth characiforms (*Prochilodus nigricans*) (Ribeiro *et al.* 1995). Freshwater dolphins, including the recently discovered *Inia araguaiaensis*, are also known to reside in the river (Hrbek *et al.* 2014).

Water management within the river basin is strongly focussed on harnessing its hydropower potential (Freitas and Soito 2009). Currently, there are seven hydroelectric dams in operation (Fig. 1), with three more planned for construction in the near future (Ministério de Minas e Energia 2013). These dams have been constructed solely for the generation of hydropower, with no use for flood regulation and irrigation (La Rovere and Mendes 2000). Most of the hydropower produced is used in electro-intensive export industries, especially aluminium production (Fearnside 2009).

Data

We choose to use only quality-assured data that has passed through external quality control procedures and plausibility checks. As such, monthly discharge data from 13 gauging stations located within the Tocantins-Araguaia River Basin were acquired from the Global Runoff Data Centre (Table 1, GRDC 2014). Although the baseline model period (discussed below) was 1971–2000, records for some stations did not cover this full period with a number beginning in 1974 and a few slightly later. The record for one, Tocantinopolis, ends in 1989 whilst others have periods of missing data (see Fig. 2).

A Digital Elevation Model (DEM) of the region was extracted from the United States Geological Survey (USGS) GTOPO30 dataset, which has a spatial resolution of approximately 1 km × 1 km (USGS-EROS Data Centre 1993). The 'Watershed Delineation' function of the ArcSWAT (Version 2012.10.1.9) extension for ArcGIS 10.1 (Winchell *et al.* 2013) and the DEM were used to define the stream network and the spatial extent of the river basin and each sub-catchment above the 13 gauging stations (Fig. 1).

Historical monthly mean temperature, diurnal temperature range and precipitation data for the period 1971–2000 were extracted from the CRU TS 3.10.01 dataset (Harris *et al.* 2014), which is available from the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer database (Trouet and Van Oldenborgh 2013). The gridded dataset has a resolution of 0.5° × 0.5° and the river basin lies within 297 grid cells. The mean temperature, diurnal temperature range and precipitation of each of the cells lying in the 13 sub-basins were averaged to give sub-basin values.

Potential evapotranspiration (PET) was calculated using the Hargreaves equation (Hargreaves and Samani 1985). Although the CRU TS 3.10.01 dataset provides a PET field computed using the Penman-Monteith approach (Harris *et al.* 2014), whilst other more complex estimates of PET could have been derived using CRU TS 3.10.01 data (e.g. Thompson *et al.* 2014a), not all of the required fields were at the time available from the CMIP5 archive for the computation of scenario Penman-Monteith PET. In addition, some meteorological data employed in approaches such as Penman-Monteith, such as humidity, wind speed and net radiation, tend to be less reliable in gridded datasets due to measurement difficulties and limited number of meteorological stations (New *et al.* 1999). The temperature-based Hargreaves approach, which is often used in situations where data are insufficient to calculate Penman-Monteith (e.g. Allen *et al.* 1998, Thompson 2012), was therefore used throughout for consistency and to avoid uncertainty associated with the application of different PET methods (e.g. Thompson *et al.* 2014a). PET sub-basin-averaged time series estimated from the CRU TS dataset using the Hargreaves approach show a similar seasonal response to those seen in the Penman-Monteith derived estimates of Harris *et al.* (2014).

Hydrological model

The hydrological model developed for the Tocantins-Araguaia River Basin was implemented in the STELLA systems modelling software (Version 7.0.3, High Performance Systems Inc, now isee systems). This high level visual-oriented software and simulation language has been employed in a number of hydrological modelling studies (e.g. Zhang and Mitsch 2005, Voinov *et al.* 2007, Thompson *et al.* 2013a). The model had a monthly time step with an initial baseline period of 1971–2000 being used to simulate river flows at the 13 gauging stations for which discharge records were acquired.

Each of the 13 sub-basins defined by the location of gauging stations was modelled within individual sub-models in STELLA, although the structure of each sub-model was identical except for the Conceição do Araguaia sub-basin which had an additional component to simulate the month-long delay in flow caused by the Bananal floodplains. This lag was based on a comparison of upstream and downstream discharge records and is assumed to be constant throughout the simulation period as well as for subsequent climate change scenarios. Sub-models were linked with discharge simulated by an upstream sub-model providing inflow to the sub-model of the next sub-basin downstream. A series of stores (surface water storage, soil moisture storage, groundwater storage and river channel storage) were defined within each sub-model and were linked via flows (overland flow, infiltration, throughflow, percolation and baseflow). Precipitation and evapotranspiration (defined as the product of monthly totals and sub-basin area) were specified as the meteorological inputs to each sub-model and were added to or removed from surface and soil moisture storage. Subsequent flows were defined based on a simple conceptual model of runoff processes. Overland flow, which contributed to river channel storage, was assumed when surface and soil stores exceeded specified maxima that were defined through calibration. Infiltration depleted surface storage and supplemented soil storage and was evaluated using an infiltration rate also defined through calibration. Throughflow, percolation and baseflow were simulated as the product of soil storage (throughflow and percolation) or groundwater storage (baseflow) and reservoir constants (possible values between 0 and 1) subject to threshold volumes of storage being exceeded. These thresholds and the reservoir constants were modified during calibration. Throughflow and baseflow contributed to river channel storage, which also received simulated discharge from upstream sub-models, whilst percolation entered groundwater storage. Finally discharge from the downstream end of the sub-catchment was simulated using the reservoir constant approach with the value of this term being established through calibration. Simulated monthly discharge volumes were distributed evenly through the month for comparison with observed discharge.

The Klemeš (1986) split-sample approach was adopted for calibration and validation. Calibration was undertaken by manually adjusting model parameters in an iterative manner whilst comparing model results with observed discharge records (Refsgaard and Storm 1996). This was undertaken in a downstream sequence beginning at the upper sub-catchments. For each sub-basin, the available discharge data for the period 1971–1985 were used for calibration, while the period 1986–2000 was used for validation. The Tucuruí and Serra da Mesa dams (Fig. 1) were closed in September 1984 and October 1996, respectively. In the absence of details of their design and operation these schemes were not included in the model. Formal calibration and validation of the downstream sub-basins affected by flow regulation by these dams was therefore limited to the period prior to dam construction.

Model performance was first determined through a visual comparison of simulated and observed discharges (Krause *et al.* 2005). This was followed by the calculation of statistical measures of model performance: Pearson's correlation coefficient (r), Nash-Sutcliffe coefficient (NSE) and percentage deviation of simulated mean flow from observed mean flow (Dv). The Pearson's correlation coefficient determines the degree of linear relationship between the simulated and observed discharge (Moriasi *et al.* 2007). The Nash-Sutcliffe coefficient determines how well the model is able to simulate the variation in discharge by comparing the magnitude of the residual variance with the measured data variance (Nash and Sutcliffe 1970). Dv serves as a measure of the ability of the model to simulate the average runoff at each gauging station. Model performance were judged according to performance ratings based on Henriksen *et al.* (2003) and Henriksen *et al.* (2008). An individual sub-model was deemed appropriate for use only when performance for the validation period was similar to that of the calibration period (Klemeš 1986).

Climate change scenarios

Projected temperature and precipitation for the 2071–2100 time slice and the RCP4.5 scenario were derived from simulation outputs of 41 GCMs that participated in the CMIP5 (Table 2). The delta factor approach was used to downscale GCM results to create scenarios of a higher spatial resolution suitable for application to the hydrological model (Wilby and Wigley 1997). Mean monthly maximum, mean and minimum temperatures as well as precipitation were derived for both the 1971–2000 baseline and 2071–2100 future time slice for all 41 GCMs. From these, monthly delta factors (expressed in °C for temperature and % for precipitation) were derived and used to perturb the original CRU data. Hargreaves PET was then re-evaluated using the new temperature time series. The advantage of this approach is that the new time series retains climate variability, but are unaffected by biases in the GCMs' simulation of it (Anandhi *et al.* 2011, Willems *et al.* 2012). It does have the disadvantage of being unable to incorporate projected changes in either interannual variability or extremes (Diaz-Nieto and Wilby 2005). Area-averaged delta factors were applied across the entire basin to avoid incorporating GCM grid-scale noise. Such noise contains little realism and hence valuable information. Moreover, the IPCC AR5 projections show that climate change across the study area is consistent under RCP 4.5 scenario for a given GCM (van Oldenborgh *et al.* 2013).

The idea behind the use of a model ensemble is that errors tend to cancel with the assumption that those errors are independent, whether they arise from internal conditions or model uncertainty. The use of a multi-model approach, such as that adopted in this study, has been increasingly popular. This is because, unlike a perturbed physics ensemble created with a single GCM, it incorporates the structural uncertainty that is inherent in the use of a range of GCMs with varying fundamental designs (Tebaldi and Knutti 2007). As such, as the number of models used increases, the level of uncertainty should decrease (Knutti *et al.* 2009). Some studies have provided empirical evidence to show that the multi-model ensemble mean tends to have a better agreement with observed data compared to any single model on its own (Lambert and Boer 2001, Gillett *et al.* 2002, Palmer *et al.* 2005). Hence, according to this argument, the CMIP5 ensemble mean should serve as a better indicator of the hydrological impacts of climate change than the results of a single GCM. Therefore an additional case was developed which established mean temperature and precipitation time series for the baseline and 2071–2100 time slice from the 41 GCMs prior to computation of the delta factors and perturbed meteorological inputs.

RESULTS

Hydrological model calibration and validation

Figure 2 shows observed and simulated discharge at the 13 gauging stations for the baseline simulation period of 1971–2000. The calibration and validation periods are indicated with data availability being responsible for some inter-gauging station differences in the length of these periods. In addition, and as discussed above, the model excludes the two existing hydropower dams (Tucuruí and Serra da Mesa) that regulate downstream river flow. For the Tucuruí Dam (closed September 1984), only one gauging station (of the same name) is impacted but its closure in 1984 does mean that flows are affected throughout the validation period. The Serra da Mesa Dam on the upper Tocantins River impacts discharge at the five gauging stations on this river as well as at Tucuruí. Its influence is, however, limited to the last four years of the validation period following dam closure in October 1996.

Figure 2 demonstrates good model performance at most gauging stations throughout the river basin for both the calibration and validation period for those gauging stations unaffected by upstream dams and for the period prior to dam construction at those stations downstream of the dams. The impact of the Serra da Mesa dam are clearly evident in the loss of the generally good agreement between observed and simulated discharge at the end of the validation period (Fig. 2A-D). These impacts are, unsurprisingly, most evident at the São Salvador gauging station. During the filling of the Serra da Mesa reservoir between 1996 and 1998 observed discharge is much lower than the naturalised flow simulated by the model. For example, the observed seasonal peak in March 1997 is 72% lower than that simulated by the model (Fig. 2A). Once the Serra da Mesa Dam filled, the observed flow in the last two years of the simulation period is characterised by higher flows during the dry season and lower flows during the wet season. The impacts of the Serra da Mesa Dam are also visible at gauging stations further downstream on the Tocantins River (Peixe, Miracema do Tocantins and Carolina, whilst data for Tocantinopolis are not available and are limited for Marabá). However, the differences between observed and simulated discharges become smaller with movement downstream due to the progressively larger contributions from runoff in lower sub-basins. Nonetheless reductions in seasonal peak discharges and higher baseflow are evident at all of these gauging stations. These changes are also apparent further downstream at Tucuruí although discharges are also influenced by the Tucuruí Dam. Closure of this dam in 1984 and the subsequent filling of its reservoir does appear to have had some influence on discharge although subsequently impacts are small due to the large volume of discharge in comparison to the reservoir volume (Fig. 2M).

Table 3, which provides values of the three performance statistics for both the calibration and validation periods of each gauging station, confirms the generally good performance of the model. For the calibration period five of the 13 gauging stations have NSE values in the 'excellent' category of the Henriksen *et al.* (2008) classification scheme, while the remaining eight are in the 'very good' category. This scheme was initially designed for comparing observed and simulated discharges at daily time steps. Higher NSE values are expected when comparing monthly observed and simulated discharges (Thompson *et al.* 2014a). Nonetheless, even if the lower boundary of the 'very good' class is raised from 0.65 to 0.75, 11 out of 13 gauging stations will still be in this category or higher. Gauging stations that have high NSE values tend to also have r and Dv values in the top two bands. Likewise for the validation period, good model performance is achieved for most gauging stations. Values of the performance indicators are in general close, although in most cases lower than, those for the calibration period. Even at Tucuruí, which is subject to the impacts of the Tucuruí Dam throughout the validation period (and the Serra da Mesa Dam for the last four years) the model performance statistics are classed as very good to excellent demonstrating the relatively small impact of this particular dam.

An obvious exception to the good performance of the model is the Fazenda Alegria gauging station on the Itacaiúnas River. NSE values are either classified as very good or good. However values of r are generally lower than at other gauging stations whilst the values of Dv demonstrate that the model overestimates river discharge by over 20% during the calibration period (although there are many gaps in the observed data), but underestimates discharge by a comparable magnitude during the validation period (Fig. 2L). A major shift in model performance occurs from 1987 onwards. The Itacaiúnas River drains a humid tropical upland where there were considerable mining developments and expansion of human settlements over the 1970s and 1980s (Barrow 1987). It is possible that these land use changes have impacted runoff characteristics that cannot be represented within the model. Whilst it was possible to reduce the overestimation of discharge during the calibration period, this only increased underestimation in the validation period. The results of this gauging station represent a compromise between these two extremes.

The problems with Fazenda Alegria may have implications for the Tucuruí gauging station, the only station below Fazenda Alegria and at the downstream end of the Tocantins-Araguaia River Basin. Discharge at Fazenda Alegria, however, only contributes approximately 4% of the total outflow from the basin. Although, as discussed above, the model performs well at Tucuruí despite the influence of upstream dams, it is not possible to undertake a formal validation at this gauging station. This, combined with problems with Fazenda Alegria, mean that the lowest gauging station that is used in subsequent analyses is Marabá (Fig. 2K) where the Tocantins and Araguaia rivers converge (Fig. 1). This station accounts for 91% of the total river discharge of the basin so that it is still considered appropriate for assessing the integrated impacts of climate change on the river basin.

Projected precipitation and PET

Figure 3 shows projected mean monthly precipitation and PET averaged across the Tocantins-Araguaia River Basin for each of the 41 CMIP5 GCMs as well as for the ensemble mean. It is clear that the 41 GCMs give rise to a range of projections for both precipitation and PET. However, there is greater uncertainty associated with precipitation rather than PET. Projected changes in mean annual precipitation vary between a decline of 440.3 mm (-25.1%) to an increase of 381.5 mm (21.8%). In contrast, mean annual PET increases for all the GCMs with the magnitude of these increases varying between 34.0 mm (1.92%) and 245.6 mm (13.9%). On a monthly basis the average difference between the maximum and minimum projected precipitation is 92.2 mm compared to only 22.5 mm for PET.

The CMIP5 ensemble mean projects a decline in precipitation from the baseline in most months, except during the wet period (December–February). At this time increases are, however, small and average only 4.0 mm or 1.4%. The average monthly precipitation decline for the remaining months is 12.9% with the greatest reduction occurring in October (-30.2 mm / -20.4%). Overall mean annual precipitation for the ensemble mean declines by 71.3 mm (-4.1%). The CMIP5 ensemble mean projects a consistent increase in PET from the baseline across the year. On average monthly PET increases by 9.7 mm (6.5%) contributing to an annual total increase of 116.5 mm (6.6%) The largest monthly increase of 14.4 mm (8.8%) occurs in October.

Projected river discharge

Figure 4 shows for each of the 41 GCMs and the ensemble mean the projected percentage changes from the baseline in mean annual discharge for six gauging stations. These stations are representative of results for the upper, middle and lower courses of the Tocantins and Araguaia rivers. As discussed above, calibration problems, potentially associated with land cover change, for the Fazenda Alegria sub-basin and knock-on downstream impacts, combined with limitations in observed discharge records for the Tucuruí gauging station, means that Marabá is the lowest station used in this analysis. The large range in projections by the 41 GCMs for each sub-basin clearly demonstrates very large uncertainties in projected unregulated river discharge. It further justifies the use of a multi-model ensemble in order to capture the envelope range of uncertainty (Tebaldi and Knutti 2007, Knutti *et al.* 2009). There is limited variability in the climate change signal amongst the gauging stations since the same change factors were applied to all sub-basins, an approach justified given the relatively homogeneous response to climate change across the catchment suggested by a review of results for the different GCMs in the IPCC AR5. Therefore the following analysis will focus predominantly on simulated discharge at Marabá, the lowest gauging station which provides an indication of the integrated impacts of climate change within the Tocantins-Araguaia River Basin.

Out of the 41 GCMs, 30 simulate a decline in mean annual discharge at Marabá, the remaining 11 projecting increases (Fig. 4F). The CMIP5 ensemble mean projects a 10.4% decline from the baseline 11 142 $m^3 s^{-1}$. This is a marginally larger decline than the average of the annual discharge changes from the 41 GCMs (9.2%). However, the inter-GCM range of projections is extremely large ranging from -53.8% (for the CanESM2 GCM) to +47.6% (IPSL-CM5A-MR GCM). Of the 30 models that project a decrease in mean annual discharge, 20 suggest that discharge will decrease by more than 10%. In contrast, more than half (six out of ten) of the GCMs associated with an increase in mean annual discharge project gains of less than 10%.

Although mean annual discharge is a convenient indicator to assess the overall impacts of climate change on the river basin, it is insufficient and often over simplistic when used in isolation (Gosling *et al.* 2011). Changes in other aspects of simulated discharge, including the annual maximum and minimum flows, should also be assessed not only because they are of great ecological significance (Poff *et al.* 1997). High flows are important for evaluating changes to flood risks, while low flows are critical in assessing impacts on reservoir yields and the potential for low head hydropower schemes (Shaw *et al.* 2011).

Figure 5 shows the projected flow regimes at the same six selected gauging stations for the baseline period and, for each of the 41 GCMs and the ensemble mean, the RCP4.5 scenario. At all six gauging stations, the flow regimes for the CMIP5 ensemble mean show that mean monthly discharges throughout the whole year are lower than those of the baseline. At the Marabá gauging station (Fig. 6), for example, the mean monthly discharge of the CMIP5 ensemble mean is on average 14.4% lower than that of the baseline. Across the basin the reduction in discharges are more obvious during the low water season compared to the high water season. This is apparent at Marabá (Fig. 6) where the CMIP5 ensemble mean suggests a decline in mean monthly discharge during the high water season (January–April) of 10.1% compared to 20.5% for the low water season (August–November). Moreover, while only 66.5% of GCMs project a decline in mean monthly discharges during the high water period, 87.0% of GCMs project declines during the low water period.

The largest decline in mean monthly discharge for the CMIP5 ensemble mean at all of the gauging stations occurs in November, the end of the dry season (Fig. 5). For Marabá this decline is 35.6% (Fig. 6). Declines in November discharges at gauging station on the upper courses of the Tocantins and Araguaia rivers – São Salvador (Fig. 5A), Miracema do Tocantins (Fig. 5B) and Trecho Medo (Fig. 5D) – appear to cause more pronounced delays in the start of the annual rise in discharge, compared to those stations on lower sections of the two rivers.

Assessment of uncertainty

Both the hydrological and climate models used in this study are subject to error introduced by different sources of uncertainty. With regards to the hydrological model, a source of data input uncertainty is the use of the CRU TS dataset, which is created based on the interpolation of data from weather stations in the region. Therefore the climate data inputs are only approximates (Harris *et al.* 2014) due to the absence of measured weather data in the river basin itself and the spatial distribution of weather stations providing data for CRU. Our use of the Hargreaves PET method instead of more sophisticated approaches (see methods) leads to some additional uncertainty (Thompson *et al.* 2014a). Furthermore, the observed discharge data, which were used for comparison against the simulated discharge, may be subjected to human or instrumental error in the observations of river stage and/or inaccuracies in the rating curves which are all developed for natural river sections subject to erosion and deposition (Shaw *et al.* 2011).

Parameter uncertainties arise when some of the physical processes of the hydrological or climate system cannot be explicitly resolved. Instead, they have to be incorporated through parameterisations, which contain some uncertain constants (Tebaldi and Knutti 2007). Structural uncertainties are associated with the inherent model design and so are impractical to investigate in isolation (Tebaldi and Knutti 2007). A multi-model ensemble, such as the CMIP5 used here, samples both structural and parameter uncertainty associated with the climate models. However, as it is an ensemble of opportunity rather than a specifically designed experiment, the sampling is neither optimal nor random, making probabilistic assessment of its outcome misleading. Parameter uncertainty, on the other hand, can be sampled systematically through the creation of perturbed physics ensembles (Collins *et al*. 2007).

It was not possible to assess the structural uncertainty associated with the STELLA model since it is the only hydrological model employed in this study. However, prior studies have shown that often, the structural uncertainties associated with a hydrological model are far less significant than GCM-related uncertainty (Kay *et al.* 2009, Blöschl and Montanari 2010, Kingston and Taylor 2010, Gosling *et al.* 2011, Thompson *et al.* 2013b).

Likewise, it is also evident from the results of this study that the combined parameter and structural uncertainties associated with the GCMs lead to a wide range of projections for discharge in the Tocantins-Araguaia River Basin under climate change. This range encompasses zero and the sign of any changes is not certain. Given that this range of flow projections was achieved despite the use of a calibrated and validated hydrological model, it would be expected that the spread of results would increase even more with the sampling of further uncertainty associated with the hydrological model. Therefore, we have not performed a systematic quantification of the uncertainties associated with the hydrological model as it would not help to reduce uncertainty and give a more confident message.

On the other hand, the CMIP5 ensemble, as discussed above, has been used to investigate the uncertainties associated with the GCMs. Moreover, the logic behind including the CMIP5 ensemble mean as an additional scenario to those of the individual GCMs is that by averaging over the full range of climate models, it is possible to eliminate parameter and structural uncertainties associated with the climate models. This has been shown to be effective for seasonal climate forecasting (Lambert and Boer 2001, Gillett *et al.* 2002, Palmer *et al.* 2005). However, this argument is only valid if the models under consideration are independent of each other (Pirtle *et al.* 2010). In recent years, the value of this assumption has been questioned, since institutions responsible for the different GCMs share literature, parameter values and even sections of their model codes with each other (Abramowitz 2010). Moreover, some institutions have submitted more than one GCM or GCM version to CMIP5. The extreme case is the Goddard Institute for Space Studies (GISS) who provided eight different GCMs. In such cases, these models are clearly not independent of each other and their biases from reality would similarly not be random (Tebaldi and Knutti 2007). Therefore, if these models were treated with equal weighting, those institutions responsible for a number of GCMs or multiple versions of one GCM or who have shared model codes with other institutions would likely have greater influence over the ensemble mean (Knutti *et al.* 2013). For example, the GISS models comprise four of the eight GCMs with the largest projected reductions in annual mean discharge at the Marabá gauging station (Fig. 4).

The correct treatment of the CMIP5 ensemble of opportunity is an active topic of statistical research (e.g. Chandler 2013). We adopt a pragmatic approach inspired by the concept of 'model genealogy' suggested by Masson and Knutti (2011) and Knutti *et al.* (2013) and with knowledge of the different GCMs heritage. Through this approach, we identified 12 groups to which we assigned each of the 41 GCMs. Five groups consist of only a single model, while the remaining seven groups contain between three and eight GCMs (Table 4). We treated each group as independent, but the GCMs within them as different realisations of the same overarching GCM. In each group, the GCM outputs were considered equally valid and averaged. A "weighted" CMIP5 ensemble mean was then calculated from the average of the climate variables of the 12 groups (as opposed to the 41 GCMs directly). The projected mean climate values of the 12 groups and this weighted CMIP5 ensemble mean were used to derive the delta factors for the meteorological inputs to the hydrological model. Results of this analysis were then re-analysed for the Marabá gauging station. We see this approach as providing the other extreme from the conventional assumption of GCM independence and anticipate that the 'true mean' of the ensemble lies between these two approaches.

The percentage change in mean annual discharge of the Marabá gauging station projected using this weighted approach is presented in Fig. 7. There is little difference between the weighted and unweighted CMIP5 ensemble means, indicating that independence of the GCMs is not a poor assumption in this situation. There is still uncertainty in the sign of projected changes of river discharge under climate change among the different GCM groups. This method of weighting has however reduced the range of the projections. The largest positive projected percentage change in mean annual discharge in the weighted analysis is 23.3% (IPSL Group), compared to 47.6% (IPSL-CM5A-MR) in the unweighted analysis. Nonetheless, the largest negative projected percentage change in mean annual discharge remains the same in both analyses as the GCM responsible, CanESM2, remains ungrouped. It is unclear whether the reduction in spread of projected changes occurs solely as a result of the smaller effective ensemble size. Meanwhile, the weighted analysis gives a greater percentage decline in discharge during the dry season at Marabá compared to the unweighted ensemble mean (Fig. 8). During the dry season (August–November), the average decline in mean monthly discharge as projected by the weighted CMIP5 ensemble mean is 22.1% compared to 20.5% for the unweighted CMIP5 ensemble mean (Fig. 8). Nonetheless, the general conclusions from this re-analysis do not differ much from those based on the unweighted analysis.

A recent development used to reduce uncertainty in climate projections is the identification of emergent constraints (e.g. Boé *et al.* 2009, Cox *et al.* 2013). These are quantities that have skill as good predictors of future response, yet can be estimated from observations. This can be thought of as a form of Bayesian GCM weighting, where the conventional ensemble distribution (a uniform prior) is updated in response to the additional relevant information provided by the observations to create a posterior distribution. With the availability of large GCM ensembles, it becomes easier to assess the impact of weak observational constraints.

We suspect that the projected changes in precipitation appear to dominate the uncertain discharge response (Fig. 3). One could hypothesize that erroneous future rainfall patterns (and hence discharge) would be related to model biases seen in the present simulated climate over the basin. We therefore investigate several physically plausible relationships (Table 5) to see if a correlation emerges across the CMIP5 ensemble. For example, one may expect projected changes in minimum discharge to be related to how well the GCM simulates dry season precipitation. Unfortunately, we are unable to find any obvious emergent relationships that could provide an observational constraint (the correlation coefficient between the aforementioned properties is, for example, only -0.15). Searching beyond obvious physical connections was not undertaken to avoid falsely detecting a chance relationship (Caldwell *et al.* 2014).

DISCUSSION

The STELLA hydrological model developed in this study has been able to simulate unregulated river flow in the Tocantins-Araguaia River Basin for the baseline period of 1971–2000 to a reasonable degree of accuracy based on the Henriksen *et al.* (2008) classification scheme (Table 3). However, there are several issues that have impacted the simulations. These include the presence of operational dams in the basin combined with a lack of knowledge of their operating regime. This limited the model's ability to simulated regulated river flow after the closures of the Serra da Mesa dam and Tucuruí dams. Therefore, the decision was made to exclude these from the hydrological model and to therefore simulate unregulated river flows.

We were able to simulate unregulated discharges at gauging stations affected by the Serra da Mesa dam as dam closure in late 1996 was towards the end of the simulation period therefore permitting model validation. Comparisons of post-1996 simulated unregulated discharge and observed regulated river flows reveal the impacts of the dam during the reservoir filling and dam operation periods. These impacts decline in magnitude downstream due to runoff contributions from lower sub-basins, such that while the impacts of the dam are apparent at São Salvador, its impacts are negligible at Marabá. Hence, it appears appropriate to employ the use of the hydrological model to investigate the integrated impacts of climate change at Marabá, even without simulating the operation of the Serra da Mesa dam.

However, simulation of unregulated discharges at the Tucuruí gauging station was not possible since the Tucuruí dam was closed in 1984, before the end of the calibration period. This prevented robust validation of the model at this station. Moreover, possible land-use changes in the Fazenda Alegria sub-basin, which lies directly upstream of Tucuruí, may have limited model performance at the Fazenda Alegria gauging station. For these two reasons, the Fazenda Alegria and Tucuruí gauging stations were excluded from the analyses of climate change impacts on river flows. The lowest point on the river system for which these analyses were undertaken, the Marabá gauging station, nonetheless still accounts for 91% of the total basin discharge.

Of the projected hydrological impacts of climate change, there are two particularly worrying trends that could potentially be detrimental to the river basin's aquatic ecosystems; (i) the projected reduction in the magnitude of low flows and (ii) the delay in the rise of the annual flood. A decrease in low flow could lead to increases in the incidence of periods of extreme low river flow and drying out of floodplains (Poff *et al.* 1997). Even if it is only for a relatively short period of time, such atmospheric exposures can lead to high mortality rates among benthic organisms and result in massive decreases in primary productivity (Weisberg *et al.* 1990). Reductions in the magnitudes of low flows could further restrict the geographic range of some aquatic organisms, limit dry season refugia (Ross *et al.* 1985, Schlosser 1991, Thompson *et al.* 2014b) and promote invasions by exotic species (Poff and Ward 1990, Bunn and Arthington 2002). Changes in floodplain flows, including those associated with flow-related modifications to vegetation, represent an additional source of uncertainty that could, for example, impact the hydrological processes represented within the model such as the floodplain storage and its impact on the downstream propagation of the annual flood.

Similarly, alterations in the timing of flow events could have ecological impacts since the life cycles of many aquatic and riparian species are synchronised to flows of different magnitudes (Welcomme and FAO 1985). The natural timing of high or low discharge provides life cycle signals for many aquatic species such as migration, spawning and egg hatching (Poff *et al.* 1997). The projected potential delay in the rise of the annual floods within the Tocantins-Araguaia River Basin is caused by large declines in November discharges (Fig. 6), a period which usually signals the start of the two to three month-long upstream summer fish migration (Ribeiro *et al.* 1995). A delay in the start of the rising water period could therefore affect the subsequent timings of spawning and egg hatching and possibly overall reproduction rates.

Furthermore, although the design lifespan of electro-mechanical equipment (e.g. turbines and generators) and hydro-mechanical steel structures (e.g. pipes and gates) are relatively short (20–50 years), the main structural components of hydropower plants (e.g. reservoir and dams) have lifespans of around 100 years (IEA, 2000 Ribeiro and da Silva 2010, Wieland 2010). The hydrological impacts of climate change on the Tocantins-Araguaia River Basin for the period 2071–2100 are therefore relevant to the existing dams within the river basin, with the earliest (Tucuruí) being constructed in 1984.

Hydroelectric generation capacity is determined by river discharge so that alterations in runoff would directly result in changes in the hydropower potential (Harrison and Whittington 2002). The CMIP5 ensemble mean suggests a reduction in mean annual flow towards the downstream end of the Tocantins-Araguaia River Basin of 10.4% although the maximum projected decline reaches 53.8% (Fig. 4F). Such declines would be unfavourable for the operation of the Tucuruí plant downstream of Marabá. Even with the large storage capacity of the Tucuruí reservoir, which confers it with some buffering capacity and allows for greater flexibility in plant operation (Hamududu and Killingtveit 2012, Aronica and Bonaccorso 2013), reductions in mean annual flow reaching a magnitude of over 50% would likely impact generating capacity. Moreover, the storage capacities of reservoirs tend to reduce over time due to sediment deposition, further reducing the resilience of these structures to climate change (Iimi 2007).

The CMIP5 ensemble mean also suggests a consistent decline in mean annual flow for all the sub-basins above Marabá (Fig. 4). There are currently six operational plants upstream of Marabá that, with the exception of Serra da Mesa dam, became operational after the simulation period employed in the current study. These dams have smaller storage capacities and hence are likely to be more vulnerable to decreases in river discharge and alterations in flow regime. It is possible that these hydropower plants may need to alter their operation rules in order to compensate for the reduced flows while electricity generation may need to be augmented by other power plants especially during the low flow season (de Lucena *et al.* 2009).

Given that there is less certainty over the impacts of climate change on high flows (Fig. 5), water resource managers need to be prepared for the potential of both increases and decreases in discharges during the annual flood period. Increases in high flows are of particular concern since higher peak discharges may necessitate changes in specifications of dam spillways in order to avoid the catastrophic consequences of dam failure. Ultimately, the proposals for new hydropower plants as well as the operation of existing plants within the Tocantins-Araguaia River Basin will need to take account of the hydrological impacts of projected climate change. Not only do such schemes need to be economically cost-effective but they must also ensure that the flows required to sustain the proper ecological functions of the river basin are not compromised, especially during the low flow season when results from this study suggest the largest changes are to be expected (Lehner *et al.* 2005).

CONCLUSION

A semi-distributed hydrological model is capable of reproducing observed river discharges in the Tocantins-Araguaia River Basin. The model is used to project the unregulated river discharge in the river basin using climate outputs from 41 GCMs run under the RCP4.5 scenario for the 2071–2100 time slice. The projected changes in unregulated river discharge encompass a wide range dominated by the large uncertainty in projected precipitation from the different GCMs (Gosling *et al.* 2011). Although there is a lack of definite consensus on the sign of projected changes in discharge, a larger proportion of GCMs suggest a decline in mean annual discharge. The least uncertainty (a consensus amongst over 80% of the GCMs) is associated with changes in the dry season for which declines in discharge are projected, especially during the transition to the rise of the annual flood. Although the CMIP5 ensemble mean still suggests declines in flow magnitude during the wet season, there is a less consensus among the GCMs, thereby reducing the confidence in projected changes. Re-analyses were carried out after re-grouping and weighting the GCMs based on their genealogy, but similar conclusions were obtained.

Both the declines in flow magnitude and alterations in flow regime under climate change may impact the ecological integrity of the Tocantins-Araguaia River Basin as both flora and fauna are highly sensitive to flow modifications (Poff *et al.* 1997). Moreover, the reductions in mean annual discharge combined with possible changes in the distribution of flow frequencies would decrease the hydropower potential of the river basin (Harrison and Whittington 2002). This suggests that the sustainability and resilience of existing and proposed hydropower schemes within the Tocantins-Araguaia River Basin needs to be assessed.

This analysis highlights the large role of uncertainty associated with climate models, especially with regards to precipitation. This is in line with the conclusions drawn from previous studies (Gosling *et al.* 2011, Hughes *et al.* 2011, Kingston *et al.* 2011, Nóbrega *et al.* 2011, Thompson *et al.* 2013b). There is an urgent need for improvements to be made with regards to our understanding of the climate system in order to either directly improve model performance or identify relevant observations that can act as effective constraints on future projections. Only then can there be a more robust assessment of the impacts of future climate change on freshwater resources within the Tocantins-Araguaia River Basin and elsewhere.

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References

Abramowitz, G., 2010. Model independence in multi-model ensemble prediction. *Australian Meteorological and Oceanographic Journal,* 59, 3–6.

Allen, R.G., Pereira, L.S., Raes, D. and Smith, M., 1998. *Crop evapotranspiration - guidelines for computing crop water requirements.* Rome: Food and Agriculture Organisation.

Anandhi, A., Frei, A., Pierson, D.C., Schneiderman, E.M., Zion, M.S., Lounsbury, D. and Matonse, A.H., 2011. Examination of change factor methodologies for climate change impact assessment. *Water Resources Research,* 47, W03501. doi:10.1029/2010WR009104.

Arnell, N., 2011. Uncertainty in the relationship between climate forcingand hydrological response in UK catchments. *Hydrology and Earth System Sciences,* 15, 897–912. doi:10.5194/hess-15-897-2011.

Aronica, G.T. and Bonaccorso, B., 2013. Climate Change Effects on Hydropower Potential in the Alcantara River Basin in Sicily (Italy). *Earth Interactions,* 17, 1–22. doi:10.1175/2012EI000508.1.

Barrow, C.J., 1987. The environmental impacts of the Tucuruí dam on the middle and lower Tocantins river basin, Brazil. *Regulated Rivers: Research & Management,* 1, 49–60. doi: 10.1002/rrr.3450010106.

Blöschl, G. and Montanari, A., 2010. Climate change impacts—throwing the dice? *Hydrological Processes*, 24, 374–381. doi: 10.1002/hyp.7574.

Boé, J., Hall, A. and Qu, X., 2009. Deep ocean heat uptake as a major source of spread in transient climate change simulations. *Geophysical Research Letters*, 36, L22701. doi: 10.1029/2009GL040845.

Bunn, S.E. and Arthington, A.H., 2002. Basic Principles and Ecological Consequences of Altered Flow Regimes for Aquatic Biodiversity. *Environmental Management,* 30, 492–507. doi: 10.1007/s00267-002-2737-0.

Caldwell, P.M., Bretherton, C.S., Zelinka, M.D., Klein, S.A., Santer, B.D. and Sanderson, B.M., 2014. Statistical significance of climate sensitivity predictors obtained by data mining. *Geophysical Research Letters,* 41, 1803–1808. doi: 10.1002/2014GL059205.

Chandler, R.E., 2013. Exploiting strength, discounting weakness: combining information from multiple climate simulators. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* 371, 1471–2962. doi: 10.1098/rsta.2012.0388.

Collins, M., Brierley, C.M., MacVean, M., Booth, B.B.B. and Harris, G.R., 2007. The sensitivity of the rate of transient climate change to ocean physics perturbations. *Journal of Climate*, 20, 2315–2320. doi:10.1175/JCLI4116.1.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W.J., Johns, T., Krinner, G., Shongwe, M., Tebaldi, C., Weaver, A.J. and Wehner, M., 2013. Long-term climate change: projections, commitments and irreversibility. *In:* T.F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley, eds. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge and New York: Cambridge University Press. doi:10.1017/CBO9781107415324.024.

Costa, M.H., Botta, A. and Cardille, J.A., 2003. Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia. *Journal of Hydrology,* 283, 206–217. doi:10.1016/S0022-1694(03)00267-1.

Cox, P.M., Pearson, D., Booth, B.B., Friedlingstein, P., Huntingford, C., Jones, C.D. and Luke, C. M., 2013. Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability. *Nature,* 494, 341–344. doi:10.1038/nature11882.

De Lucena, A.F.P., Szklo, A.S., Schaeffer, R., De Souza, R.R., Borba, B.S.M.C., Da Costa, I.V.L., Júnior, A.O.P. and Da Cunha, S.H.F., 2009. The vulnerability of renewable energy to climate change in Brazil. *Energy Policy,* 37, 879–889. doi:10.1016/j.enpol.2008.10.029.

Diaz-Nieto, J. and Wilby, R., 2005. A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. *Climatic Change,* 69, 245–268. doi:10.1007/s10584-005-1157-6.

Döll, P., Jiménez-Cisneros, B., Oki, T., Arnell, N.W., Benito, G., Cogley, J.G., Jiang, T., Kundzewicz, Z.W., Mwakalila, S., and Nishijima, A., 2015. Integrating risks of climate change into water management, *Hydrological Sciences Journal*, 60, 4–13. doi: 10.1080/02626667.2014.967250.

Fearnside, P., 2009. Brazil's environmental policies for the Amazon: lessons from the last 20 years. Conference on *Environmental Policy, Social Movements, and Science for the Brazilian Amazon* Chicago: University of Chicago.

Freitas, M. and Soito, J., 2009. Vulnerability to climate change and water management: hydropower generation in Brazil. *WIT Transactions on Ecology and the Environment,* 124, 217–228. doi: 10.2495/RM090201.

Gillett, N.P., Zwiers, F.W., Weaver, A.J., Hegerl, G.C., Allen, M.R. and Stott, P.A., 2002. Detecting anthropogenic influence with a multi-model ensemble. *Geophysical Research Letters,* 29, 1970. doi:10.1029/2002GL015836.

GRDC, 2014. The Global Runoff Data Centre, 56068 Koblenz, Germany.

Gosling, S.N., Taylor, R.G., Arnell, N.W. and Todd, M.C., 2011. A comparative analysis of projected impacts of climate change on river runoff from global and catchment-scale hydrological models. *Hydrology and Earth System Sciences,* 15, 279–294. doi:10.5194/hess-15-279-2011.

Graham, L.P., Andréasson, J. and Carlsson, B., 2007. Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods – a case study on the Lule River basin. *Climatic Change,* 81, 293–307. doi:10.1007/s10584-006-9215-2.

Haddeland, I., Clark, D.B., Franssen, W., Ludwig, F., Vos, F., Arnell, N.W., Bertrand, N., Best, M., Folwell, S., Gerten, D., Gomes, S., Gosling, S.N., Hagemann, S., Hanasaki, N., Harding, R., Heinke, J., Kabat, P., Koirala, S., Oki, T., Polcher, J., Stacke, T., Viterbo, P., Weedon, G. P. and Yeh, P., 2011. Multimodel estimate of the global terrestrial water balance: setup and first results. *Journal of Hydrometeorology,* 12, 869–884. doi:10.1175/2011JHM1324.1.

Hamududu, B. and Killingtveit, A., 2012. Assessing climate change impacts on global hydropower. *Energies,* 5, 305–322. doi:10.3390/en5020305.

Hargreaves, G. H. & Samani, Z. A. 1985. Reference crop evapotranspiration from temperature. *Applied Engineering in Agriculture,* 1, 96–99. doi: 10.13031/2013.26773.

Harris, I., Jones, P.D., Osborn, T. J. and Lister, D.H. 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology,* 34, 623–642. doi:10.1002/joc.3711.

Harrison, G.P. and Whittington, H.W., 2002. Vulnerability of hydropower projects to climate change. *Generation, Transmission and Distribution, IEE Proceedings,* 149, 249–255. doi: 10.1049/ip-gtd:2002017.

Henriksen, H.J., Troldborg, L., Højberg, A.L. and Refsgaard, J.C., 2008. Assessment of exploitable groundwater resources of Denmark by use of ensemble resource indicators and a numerical groundwater–surface water model. *Journal of Hydrology,* 348, 224–240. doi:10.1016/j.jhydrol.2007.09.056.

Henriksen, H.J., Troldborg, L., Nyegaard, P., Sonnenborg, T.O., Refsgaard, J.C. and Madsen, B., 2003. Methodology for construction, calibration and validation of a national hydrological model for Denmark. *Journal of Hydrology,* 280, 52–71. doi:10.1016/S0022-1694(03)00186-0.

Hrbek, T., Da Silva, V.M.F., Dutra, N., Gravena, W., Martin, A.R. and Farias, I.P. 2014. A New species of river dolphin from Brazil or: how little do we know our biodiversity. *PLoS ONE,* 9, e83623. doi: 10.1371/journal.pone.0083623.

Hughes, D.A., Kingston, D.G. and Todd, M.C., 2011. Uncertainty in water resources availability in the Okavango River basin as a result of climate change. *Hydrology and Earth System Sciences,* 15, 931–941. doi:10.5194/hess-15-931-2011.

IEA, 2000. Hydropower and the Environment: Present Context and Guidelines for Future Action. *Implementing Agreement for Hydropower Technologies and Programmes.* Paris: International Energy Agency.

Iimi, A., 2007. Estimating global climate change impacts on hydropower projects: applications in India, Sri Lanka and Vietnam. *World Bank Policy Research Working Paper*. doi:10.1596/1813-9450-4344.

Kay, A.L., Davies, H.N., Bell, V. A. and Jones, R.G., 2009. Comparison of uncertainty sources for climate change impacts: flood frequency in England. *Climatic Change,* 92, 41–63. doi: 10.1007/s10584-008-9471-4.

Kingston, D.G. and Taylor, R.G., 2010. Sources of uncertainty in climate change impacts on river discharge and groundwater in a headwater catchment of the Upper Nile Basin, Uganda. *Hydrology and Earth System Sciences,* 14, 1297–1308. doi:10.5194/hess-14-1297-2010.

Kingston, D.G., Thompson, J.R. and Kite, G., 2011. Uncertainty in climate change projections of discharge for the Mekong River Basin. *Hydrology and Earth System Sciences,* 15, 1459–1471. doi:10.5194/hess-15-1459-2011.

Klemeš, V., 1986. Operational testing of hydrological simulation models. *Hydrological Sciences Journal,* 31, 13–24. doi:10.1080/02626668609491024.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J. and Meehl, G.A., 2009. Challenges in Combining Projections from Multiple Climate Models. *Journal of Climate,* 23, 2739–2758. doi: 10.1175/2009JCLI3361.1.

Knutti, R., Masson, D. and Gettelman, A., 2013. Climate model genealogy: Generation CMIP5 and how we got there. *Geophysical Research Letters,* 40, 1194–1199. doi:10.1002/grl.50256.

Knutti, R. and Sedlacek, J., 2013. Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Clim. Change,* 3, 369–373. doi:10.1038/nclimate1716.

Krause, P., Boyle, D. P. & Bäse, F. 2005. Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences,* 5, 89–97. doi:10.5194/adgeo-5-89-2005.

La Rovere, E. and Mendes, F., 2000. *Tucuruí Hydropower Complex, Brazil. A WCD Case Study prepared as an Input to the World Commission on Dams*. Cape Town: World Commission on Dams Secretariat.

Lambert, S. J. and Boer, G.J., 2001. CMIP1 evaluation and intercomparison of coupled climate models. *Climate Dynamics,* 17, 83–106. doi: 10.1007/PL00013736.

Lehner, B., Czisch, G. and Vassolo, S., 2005. The impact of global change on the hydropower potential of Europe: a model-based analysis. *Energy Policy,* 33, 839–855. doi:10.1016/j.enpol.2003.10.018.

Masson, D. and Knutti, R., 2011. Climate model genealogy. *Geophysical Research Letters,* 38, L08703. doi:10.1029/2011GL046864.

Mastrandrea, M.D., Field, C.B., Stocker, T.F., Edenhofer, O., Ebi, K.L., Frame, D.J., Held, H., Kriegler, E., Mach, K.J., Matschoss, P.R., Plattner, G.-K., Yohe, G. W. and Zwiers, F.W. 2010. *Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties.* IPCC Cross-Working Group Meeting on Consistent Treatment of Uncertainties, 6-7 July 2010 Jasper Ridge, CA, USA.

MinistéRio De Minas E Energia 2013. *Plano Decenal de Expansão de Energia 2022*. Brasilia: MinistéRio De Minas E Energia.

Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R. and Veith, T., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE,* 50, 885–900. doi: 10.13031/2013.23153.

Myers, N., Mittermeier, R.A., Mittermeier, C.G., Da Fonseca, G.A.B. and Kent, J. 2000. Biodiversity hotspots for conservation priorities. *Nature,* 403, 853–858. doi:10.1038/35002501.

Nash, J.E. and Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology,* 10, 282–290. doi:10.1016/0022-1694(70)90255-6.

New, M., Hulme, M., and Jones, P.D., 1999. Representing twentieth century space-time climate variability, Part I: Development of a 1961–1990 mean monthly terrestrial climatology. *Journal of Climate* 12, 829–856. doi:10.1175/1520-0442(1999)012<0829:RTCSTC>2.0.CO;2.

Nóbrega, M.T., Collischonn, W., Tucci, C.E.M. and Paz, A.R., 2011. Uncertainty in climate change impacts on water resources in the Rio Grande Basin, Brazil. *Hydrology and Earth System Sciences,* 15, 585–595. doi:10.5194/hess-15-585-2011.

Palmer, T., Doblas-Reyes, F., Hagedorn, R. and Weisheimer, A., 2005. Probabilistic prediction of climate using multi-model ensembles: from basics to applications. *Philosophical Transactions of the Royal Society B: Biological Sciences,* 360, 1991–1998. doi:10.1098/rstb.2005.1750.

Pirtle, Z., Meyer, R. and Hamilton, A., 2010. What does it mean when climate models agree? A case for assessing independence among general circulation models. *Environmental Science & Policy,* 13, 351–361. doi:10.1016/j.envsci.2010.04.004.

Poff, N. L., Allan, J. D., Bain, M.B., Karr, J. R., Prestegaard, K. L., Richter, B. D., Sparks, R. E. and Stromberg, J. C., 1997. The natural flow regime. *BioScience,* 47, 769–784. doi: 10.2307/1313099.

Poff, N.L. and Ward, J.V. 1990. Physical habitat template of lotic systems: Recovery in the context of historical pattern of spatiotemporal heterogeneity. *Environmental Management,* 14, 629–645. doi:10.1007/BF02394714.

Prudhomme, C. and Davies, H., 2009. Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 1: baseline climate. *Climatic Change,* 93, 177–195. doi: 10.1007/s10584-008-9461-6.

Refsgaard, J. C. and Storm, B., 1996. Construction, calibration and validation of hydrological models. *In:* M. Abbott and J. Refsgaard, eds. *Distributed Hydrological Modelling.* Dordrecht: Kluwer, 41–54. doi:10.1007/978-94-009-0257-2_3.

Ribeiro, F.D.M. and Da Silva, G.A., 2010. Life-cycle inventory for hydroelectric generation: a Brazilian case study. *Journal of Cleaner Production,* 18, 44–54. doi: doi:10.1016/j.jclepro.2009.09.006.

Ribeiro, M.C.L.D.B., Petrere, M. and Juras, A.A., 1995. Ecological integrity and fisheries ecology of the Araguaia—Tocantins River Basin, Brazil. *Regulated Rivers: Research & Management,* 11, 325–350. doi:10.1002/rrr.3450110308.

Ross, S.T., Matthews, W.J. and Echelle, A.A., 1985. Persistence of stream fish assemblages: effects of environmental change. *American Naturalist*, 126, 24–40.

Schlosser, I.J., 1991. Stream fish ecology: a landscape perspective. *Bioscience,* 41, 704–712.

Shaw, E. M., Beven, K.J., Chappell, N.A. and Lamb, R., 2011. *Hydrology in practice,* London and New York: Spon Press.

Soito, J.L.D.S. and Freitas, M.A.V., 2011. Amazon and the expansion of hydropower in Brazil: Vulnerability, impacts and possibilities for adaptation to global climate change. *Renewable and Sustainable Energy Reviews,* 15, 3165–3177. doi:10.1016/j.rser.2011.04.006.

Tebaldi, C. and Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* 365, 2053–2075. doi: 10.1098/rsta.2007.2076.

Thompson, J. R., 2012. Modelling the impacts of climate change on upland catchments in southwest Scotland using MIKE SHE and the UKCP09 probabilistic projections. *Hydrological Research,* 43, 507–530. doi:10.1098/rsta.2007.2076.

Thompson, J.R**.**, Crawley, A. and Kingston, D.G., 2013b. Climate change and the Inner Niger Delta – An assessment of GCM-related uncertainty. *In:* M. Borin, M. Malagoli, M. Salvato and B, Tanis, eds. *Proceedings of Wetland Systems: Ecology, Functioning and Management,* Padova, Italy, 1–4 September 2013, 69-70.

Thompson, J.R., Green, A.J. and Kingston, D.G., 2014a. Potential evapotranspiration-related uncertainty in climate change impacts on river flow: An assessment for the Mekong River basin. *Journal of Hydrology,* 510, 259–279. doi:10.1016/j.jhydrol.2013.12.010.

Thompson, J.R., Green, A.J., Kingston, D.G. and Gosling, S.N., 2013a. Assessment of uncertainty in river flow projections for the Mekong River using multiple GCMs and hydrological models. *Journal of Hydrology,* 486, 1–30. doi:10.1016/j.jhydrol.2013.01.029.

Thompson, J.R., Laizé, C.L.R., Green, A.J., Acreman, M.C. and Kingston, D.G., 2014b. Climate change uncertainty in environmental flows for the Mekong River. *Hydrological Sciences Journal,* 59, 259–279. doi:10.1080/02626667.2013.842074.

Thomson, A.M., Calvin, K.V., Smith, S.J., Kyle, G.P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M.A., Clarke, L.E. and Edmonds J.A., 2011. RCP4.5: a pathway for stabilization of radiative forcing by 2100. *Climatic Change*, 109, 77–94. doi: 10.1007/s10584-011-0151-4.

Trouet, V. and Van Oldenborgh, G. J., 2013. KNMI Climate Explorer: A Web-Based Research Tool for High-Resolution Paleoclimatology. *Tree-Ring Research,* 69, 3–13. doi:10.3959/1536-1098-69.1.3.

USGS-EROS Data Centre, 1993. GTOPO30 documentation (README file). Siox Falls, South Dakota: United States Geological Survey EROS Data Centre.

Valente, C.R., Latrubesse, E.M. and Ferreira, L.G., 2013. Relationships among vegetation, geomorphology and hydrology in the Bananal Island tropical wetlands, Araguaia River basin, Central Brazil. *Journal of South American Earth Sciences,* 46, 150–160. doi: doi:10.1016/j.jsames.2012.12.003.

Van Oldenborgh, G.J.,M., Collins, J., Arblaster, J.H., Christensen, J., Marotzke, S.B., Power, M., Rummukainen, M. and Zhou, T. 2013. Annex I: atlas of global and regional climate projections. *In:* T.F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley, eds. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge and New York: Cambridge University Press. doi:10.1017/CBO9781107415324.029.

Voinov, A., Costanza, R., Fitz, C. and Maxwell, T., 2007. Patuxent landscape model: 1. Hydrological model development. *Water Resources,* 34, 163–170. doi: 10.1134/S0097807807020066.

Weisberg, S.B., Janicki, A.J., Gerritsen, J. and Wilson, H.T., 1990. Enhancement of benthic macroinvertebrates by minimum flow from a hydroelectric dam. *Regulated Rivers: Research & Management,* 5, 265–277. doi:10.1002/rrr.3450050307.

Welcomme, R.L. and FAO, 1985. *River Fisheries*. Rome: United Nations Food and Agriculture Organization.

Wieland, M., 2010. Life span of storage dams. *International Water Power and Dam Construction,* 62, 32–35.

Wilby, R.L. and Wigley, T.M.L., 1997. Downscaling general circulation model output: a review of methods and limitations. *Progress in Physical Geography,* 21, 530–548. doi: 10.1177/030913339702100403.

Willems, P., Olsson, J., Arnbjerg-Nielsen, K., Beecham, S., Pathirana, A., Bülow Gregerson, I., Madsen, H. and Nguyen, V.T.V., 2012. *Impacts of climate change on rainfall extremes and urban drainage systems,* London: IWA Publishing.

Xu, H., Taylor, R.G. and Xu, Y., 2010. Quantifying uncertainty in the impacts of climate change on river discharge in sub-catchments of the River Yangtze and Yellow Basins, China. *Hydrology and Earth System Sciences,* 7, 6823–6850. doi:10.5194/hess-15-333-2011.

Tables

Table 1. Gauging stations within the Tocantins-Araguaia River Basin.

River	Gauging station	Latitude (°)	Longitude (°)
Araguaia	Trecho Medo	-14.0867	-51.6964
	Aruanã	-14.9019	-51.0819
	São Felix do Araguaia	-11.6181	-50.6625
	Conceição do Araguaia	-8.2694	-49.2594
	Araguatins	-5.6344	-48.1297
Itacaiúnas	Fazenda Alegria	-5.4867	-49.2214
Tocantins	São Salvador	-12.7425	-48.2367
	Peixe	-12.0231	-48.5328
	Miracema do Tocantins	-9.5675	-48.3786
	Carolina	-7.3375	-47.4731
	Tocantinopolis	-6.2886	-47.3919
	Marabá	-5.3386	-49.1244
	Tucuruí	-3.7578	-49.6533

Table 2. CMIP5 GCMs used in this study.

	Model	Institution
1	ACCESS1.0	Commonwealth Scientific and Industrial Research Organisation (CSIRO)
2	ACCESS1.3	and Bureau of Meteorology (BOM), Australia
3	BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration
4	BCC-CSM1.1(m)	
5	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University
6	CanESM2	Canadian Centre for Climate Modelling and Analysis
7	CCSM4	National Center for Atmospheric Research
8	CESM1(BGC)	Community Earth System Model Contributors
9	CESM1(CAM5)	
10	CMCC-CM	Centro Euro-Mediterraneo per I Cambiamenti Climatici
11	CMCC-CMS	
12	CNRM-CM5	Centre National de Recherches Météorologiques/ Centre Européen de Recherche et Formation Avancée en Calcul Scientifique
13	CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organisation in collaboration with Queensland Climate Change Centre of Excellence
14	EC-EARTH	EC-Earth consortium
15	FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences
16	FIO-ESM	The First Institute of Oceanography, SOA, China
17	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory
18	GFDL-ESM2G	
19	GFDL-ESM2M	
20	GISS-E2-H p1	NASA Goddard Institute for Space Studies
21	GISS-E2-H p2	
22	GISS-E2-H p3	
23	GISS-E2-H-CC	
24	GISS-E2-R p1	
25	GISS-E2-R p2	
26	GISS-E2-R p3	
27	GISS-E2-R-CC	
28	HadGEM2-AO	Met Office Hadley Centre (additional HadGEM2-ES realizations
29	HadGEM2-CC	contributed by Instituto Nacional de Pesquisas Espaciais)
30	Had-GEM2-ES	
31	INM-CM4	Institute for Numerical Mathematics
32	IPSL-CM5A-LR	Institut Pierre-Simon Laplace
33	IPSL-CM5A-MR	
34	IPSL-CM5B-LR	
35	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
36	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and
37	MIROC-ESM-CHEM	Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
38	MPI-ESM-MR	Max-Planck-Institut für Meteorologie (Max Planck Institute for
39	MPI-ESM-MR	Meteorology)
40	MRI-CGCM3	Meteorological Research Institute
41	NorESM1-M	Norwegian Climate Centre

Table 3. Model performance statistics for 13 gauging stations within the Tocantins-Araguaia River Basin for the calibration (1971–1985+) and validation (1986–2000+) periods.

	Calibration+			Validation+		
Gauging Station	r	NSE	Dv	r	NSE	Dv
São Salvador	0.88 ✓✓✓	0.77 ✓✓✓✓	-0.68 ✓✓✓✓✓	0.91 ✓✓✓✓	0.74 ✓✓✓✓	-15.09 ✓✓
Peixe	0.92 ✓✓✓✓	0.85 ✓✓✓✓✓	-2.46 ✓✓✓✓✓	0.93 ✓✓✓✓	0.82 ✓✓✓✓	0.68 ✓✓✓✓✓
Miracema do Tocantins	0.91 ✓✓✓✓	0.82 ✓✓✓✓	-4.62 ✓✓✓✓✓	0.90 ✓✓✓✓	0.81 ✓✓✓✓	-7.09 ✓✓✓✓
Carolina	0.92 ✓✓✓✓	0.83 ✓✓✓✓	0.32 ✓✓✓✓✓	0.92 ✓✓✓✓	0.81 ✓✓✓✓	-2.03 ✓✓✓✓✓
Tocantinopolis	0.91 ✓✓✓✓	0.81 ✓✓✓✓	-0.15 ✓✓✓✓✓	0.95 ✓✓✓✓	0.85 ✓✓✓✓	-6.29 ✓✓✓✓
Trecho Medo	0.84 ✓✓	0.66 ✓✓✓✓	-2.89 ✓✓✓✓✓	0.88 ✓✓✓	0.75 ✓✓✓✓	6.72 ✓✓✓✓
Aruanã	0.90 ✓✓✓✓	0.81 ✓✓✓✓	2.17 ✓✓✓✓✓	0.89 ✓✓✓	0.79 ✓✓✓✓	-3.43 ✓✓✓✓✓
São Felix do Araguaia	0.89 ✓✓✓	0.78 ✓✓✓✓	0.58 ✓✓✓✓✓	0.92 ✓✓✓✓	0.83 ✓✓✓✓	-7.13 ✓✓✓✓
Conceição do Araguaia	0.93 ✓✓✓✓	0.86 ✓✓✓✓✓	-4.06 ✓✓✓✓✓	0.93 ✓✓✓✓	0.82 ✓✓✓✓	-13.15 ✓✓✓
Araguatins	0.94 ✓✓✓✓	0.89 ✓✓✓✓✓	-2.42 ✓✓✓✓✓	0.93 ✓✓✓✓	0.87 ✓✓✓✓✓	-3.76 ✓✓✓✓✓
Marabá	0.96 ✓✓✓✓✓	0.92 ✓✓✓✓✓	-3.24 ✓✓✓✓✓	0.96 ✓✓✓✓✓	0.91 ✓✓✓✓✓	-5.93 ✓✓✓✓
Fazenda Alegria	0.87 ✓✓✓	0.68 ✓✓✓✓	-21.17 ✓	0.82 ✓✓	0.61 ✓✓✓	25.75 ✓
Tucuruí†	0.96 ✓✓✓✓✓	0.91 ✓✓✓✓✓	-6.98 ✓✓✓✓	0.93 ✓✓✓✓	0.85 ✓✓✓✓✓	-8.31 ✓✓✓✓

Performance indicator [a]	Excellent	Very Good	Good	Poor	Very Poor
	✓✓✓✓✓	✓✓✓✓	✓✓✓	✓✓	✓
r [b]	≥ 0.95	0.90 – 0.94	0.85 – 0.89	0.80 – 0.84	< 0.80
NSE [c]	≥ 0.85	0.65 – 0.84	0.50 – 0.64	0.20 – 0.49	< 0.20
Dv [d]	< 5	5 - 9	10 – 14	15 – 19	≥ 20

+ Calibration and validation periods for individual gauging stations vary according to the availability of observed data (Fig. 2) whilst the validation period for stations on the Tocantins River ends in October 1996 with the closure of the Serra da Mesa Dam, † The Tucuruí Dam (completed 1984) impacts discharge at Tucuruí throughout the simulation period so that whilst performance indicators are provided, robust validation at this gauging station is not possible, a. Performance ratings adapted from Henriksen *et al.* (2003) and Henriksen *et al.* (2008), b. Pearson correlation coefficient, c. Nash-Sutcliffe coefficient, d. Percentage deviation in simulated mean flow from observed mean flow.

Table 4. GCM groups based on model genealogy.

Group Name	Number of GCMs	GCMs
CanESM2	1	CanESM2
CSIRO-Mk3.6.0	1	CSIRO-Mk3.6.0
FGOALS-g2	1	FGOALS-g2
INM-CM4	1	INM-CM4
MRI-CGCM3	1	MRI-CGCM3
GFDL	3	GFDL-CM3
		GFDL-ESM2G
		GFDL-ESM2M
GISS	8	GISS-E2-H p1
		GISS-E2-H p2
		GISS-E2-H p3
		GISS-E2-H-CC
		GISS-E2-R p1
		GISS-E2-R p2
		GISS-E2-R p3
		GISS-E2-R-CC
IPSL	3	IPSL-CM5A-LR
		IPSL-CM5A-MR
		IPSL-CM5B-LR
MIROC	3	MIROC5
		MIROC-ESM
		MIROC-ESM-CHEM
UKMO	5	ACCESS1.0
		ACCESS1.3
		HadGEM2-AO
		HadGEM2-CC
		Had-GEM2-ES
European	6	CMCC-CM
		CMCC-CMS
		CNRM-CM5
		EC-EARTH
		MPI-ESM-MR
		MPI-ESM-MR
NCAR	8	BCC-CSM1.1
		BCC-CSM1.1(m)
		BNU-ESM
		CCSM4
		CESM1(BGC)
		CESM1(CAM5)
		FIO-ESM
		NorESM1-M

Table 5. Correlations between various properties simulated by the 41 GCMs that can be compared to observations precipitation (columns) and properties of the hydrological projections. None of the correlations are statistically significant.

Projected change in discharge at Marabá	Basin-averaged climatological precipitation simulated over 1971-2010 Annual Mean	Summer (DJF)	Winter (JJA)	Range
Annual Mean	-0.05	-0.02	-0.11	0.14
Maximum Monthly	-0.11	-0.08	-0.13	0.08
Minimum Monthly	0.02	0.00	-0.04	0.13
Annual Range	-0.13	-0.09	-0.14	0.06

Figure captions

Figure 1. The Tocantins-Araguaia River Basin including the sub-catchments and their downstream gauging stations for which separate sub-models were developed.

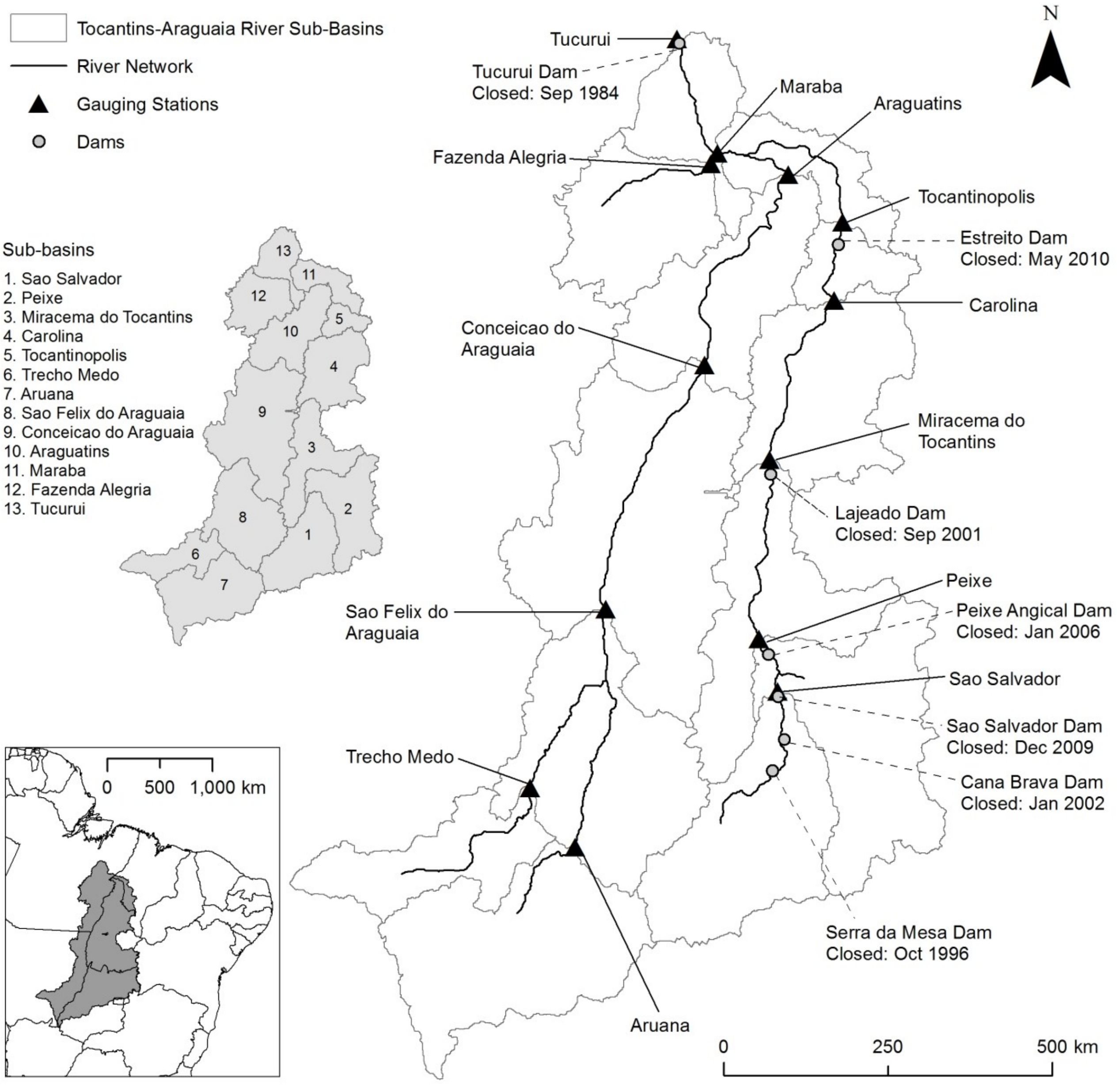


Figure 2. Monthly mean observed and simulated discharges for 13 gauging stations within the Tocantins-Araguaia River Basin for the period 1971–2000. The calibration (1971–1985) and validation (1986–2000) periods are indicated. Shaded sections indicate periods when the discharge is regulated by upstream dams.

Fig2a

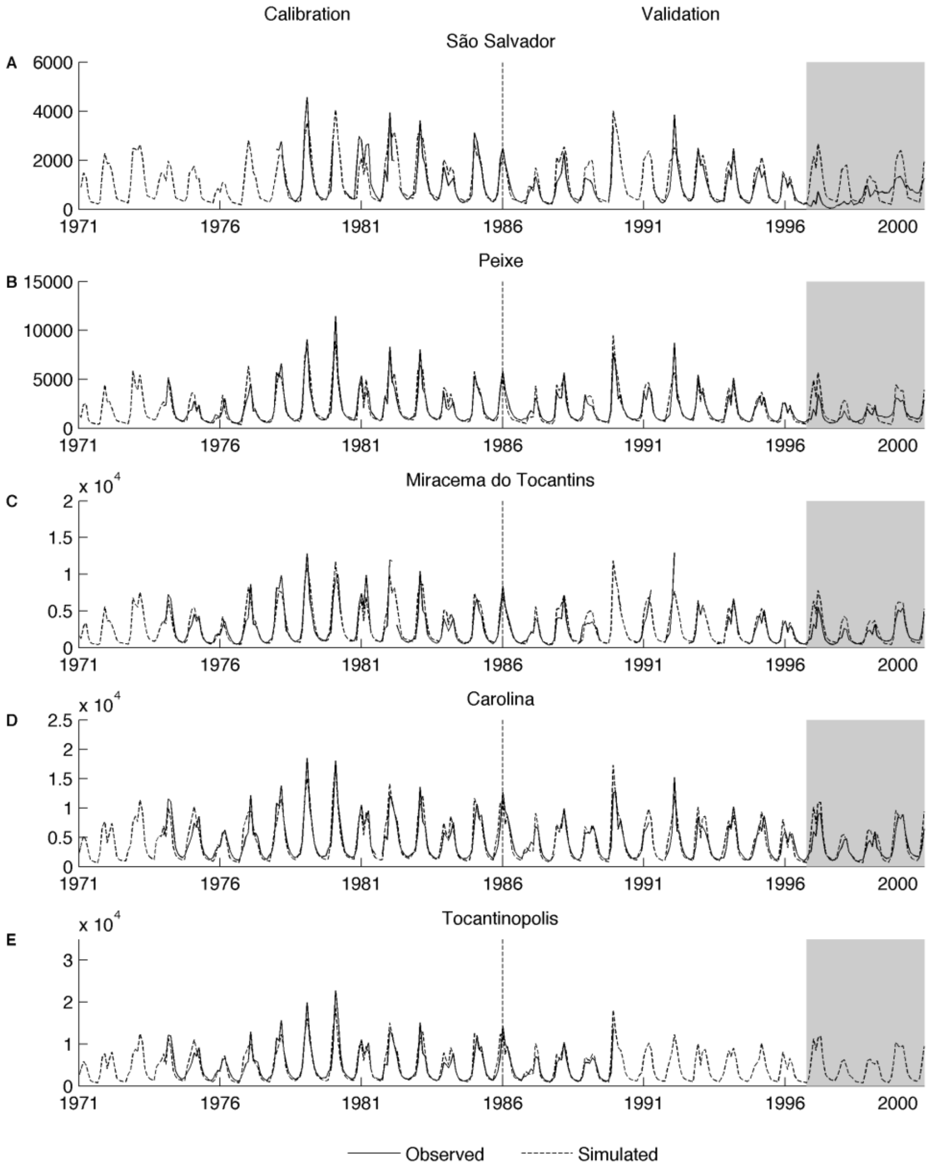
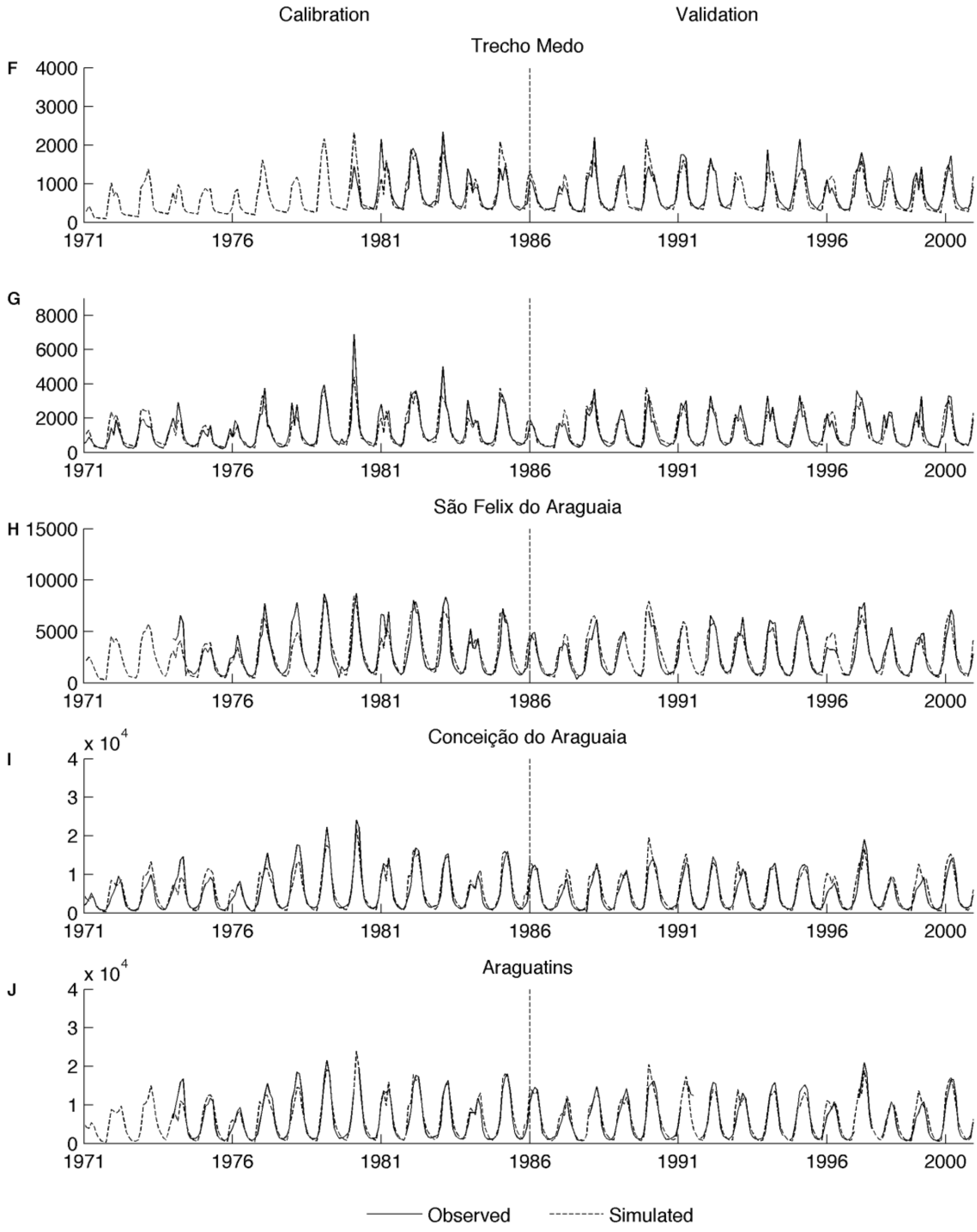
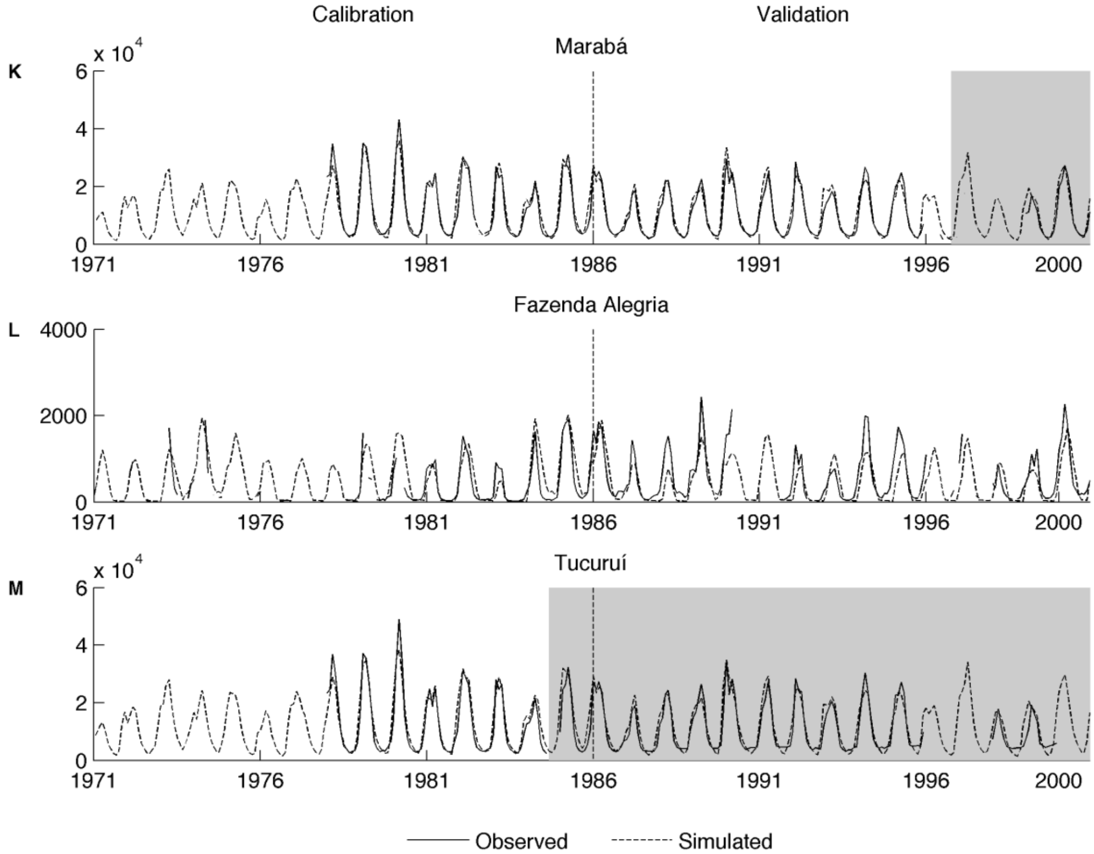


Fig2b



Calibration
Validation
Trecho Medo
F
G
São Felix do Araguaia
H
Conceição do Araguaia
I
Araguatins
J
x 10^4
1971
1976
1981
1986
1991
1996
2000
Observed
Simulated

Fig2c



Calibration
Validation
Marabá
K
x 10^4
6
4
2
0
1971
1976
1981
1986
1991
1996
2000
Fazenda Alegria
L
4000
2000
0
Tucuruí
M
x 10^4
Observed
Simulated

Figure 3. (A) Mean monthly precipitation and (B) PET over the Tocantins-Araguaia River Basin for the baseline, each GCM and the ensemble mean. Note different y-axis scales.

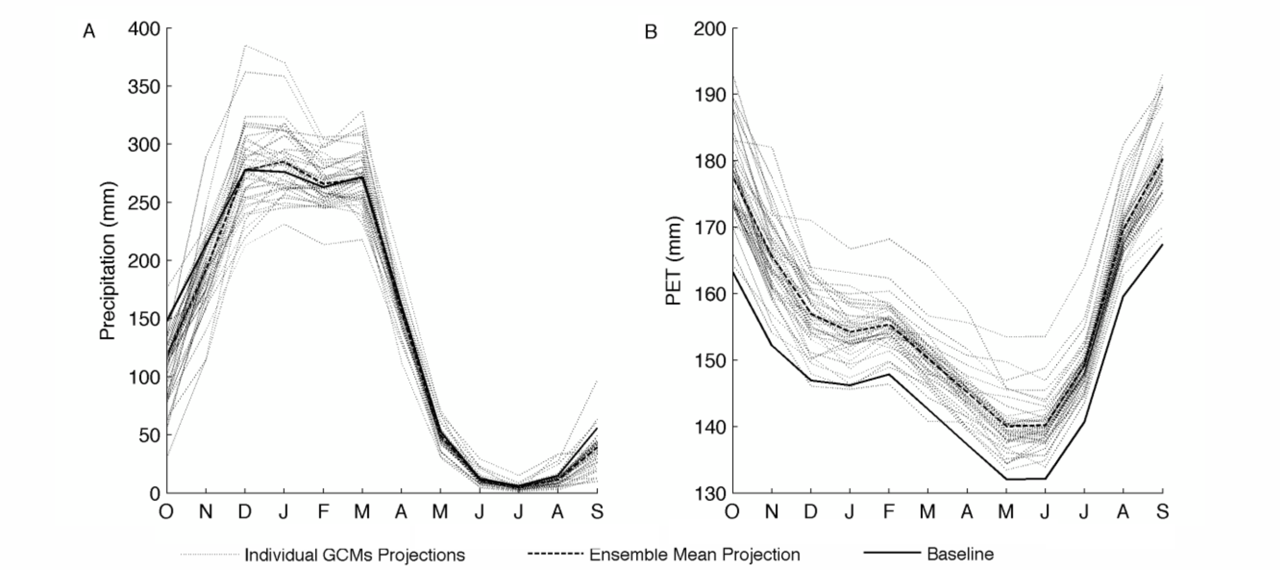


Figure 4. Percentage changes from the baseline in mean annual discharge at six gauging stations within the Tocantins-Araguaia River Basin for each GCM and the ensemble mean (highlighted). GCMs are ordered according to Table 2.

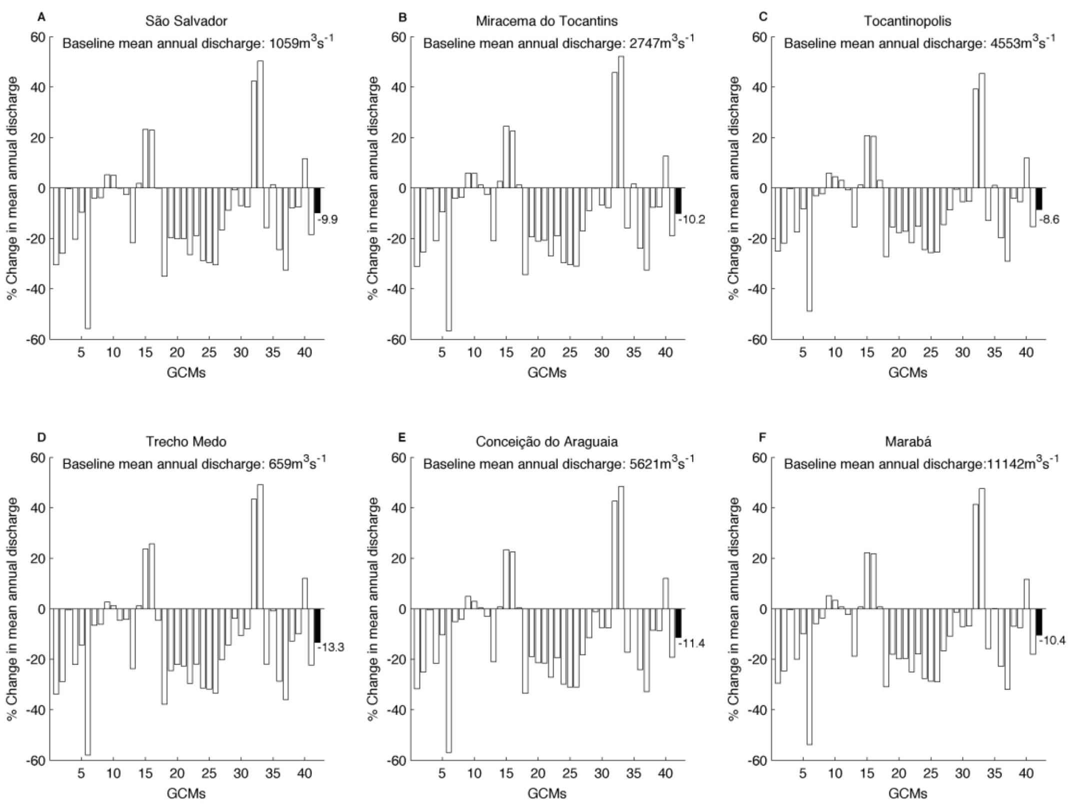


Figure 5. River regimes for the baseline, each GCM and the ensemble mean for six gauging stations within the Tocantins-Araguaia River Basin. Shaded bands represent percentile ranges of the distribution of the CMIP5 ensemble.

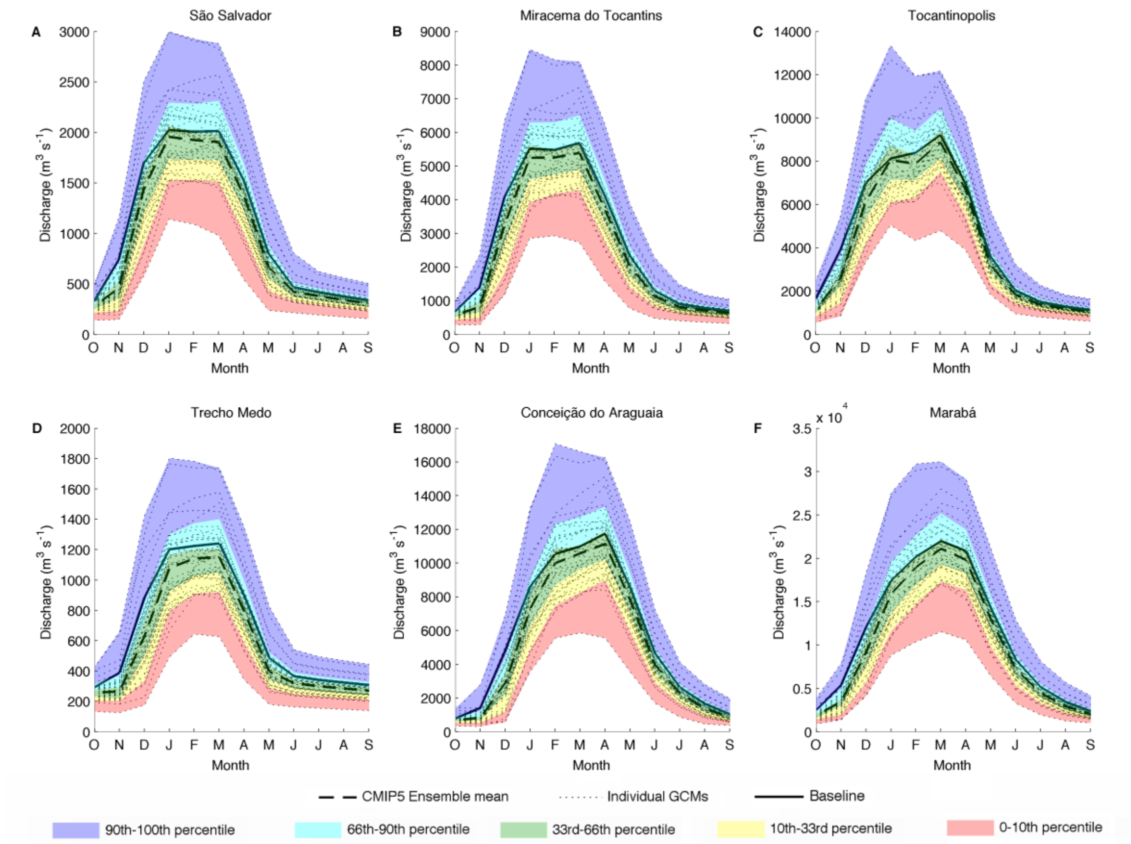


Figure 6. Percentage changes from the baseline in the mean monthly discharges at Marabá for each GCM and the ensemble mean. Shaded bands represent percentile ranges of the distribution of the CMIP5 ensemble.

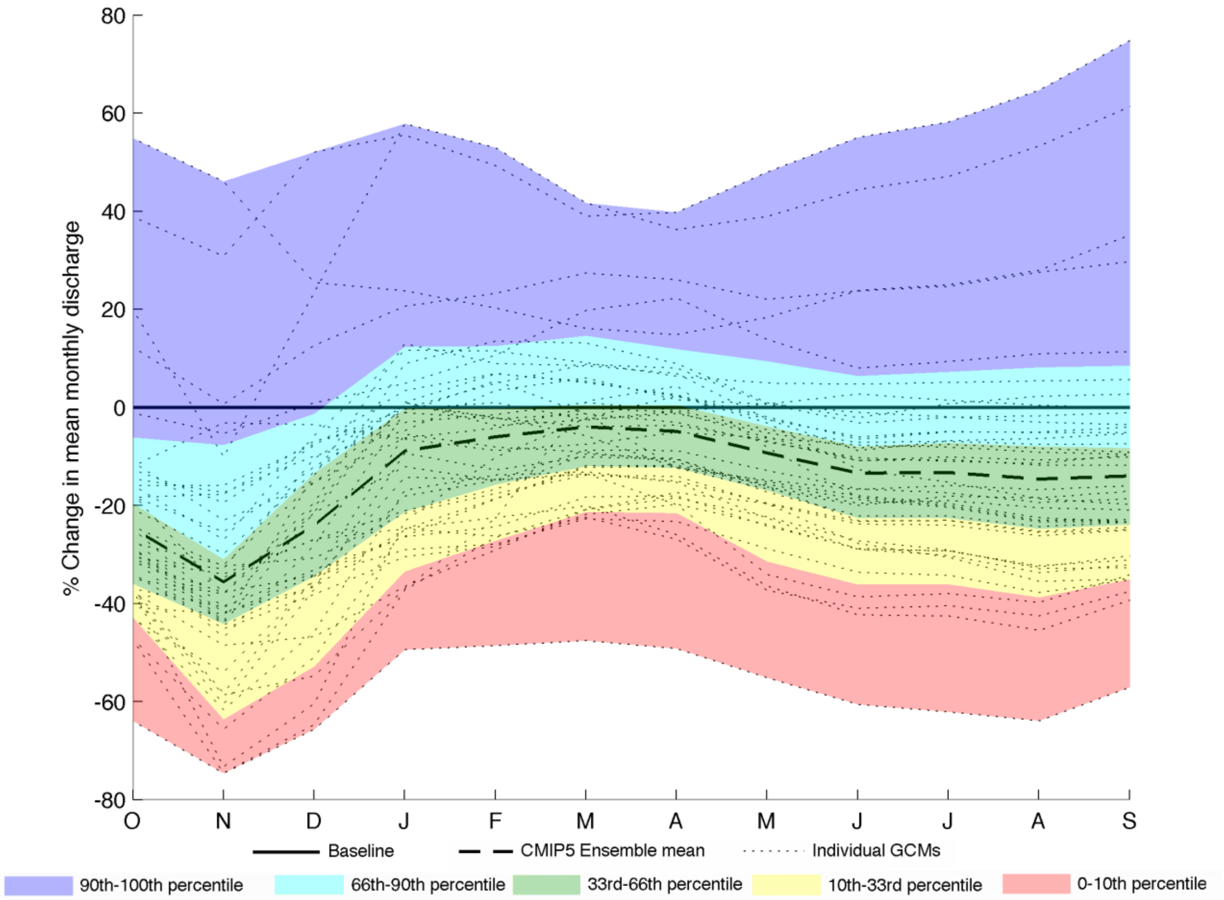


Figure 7. Percentage changes from the baseline in mean annual discharge at Marabá for each group of GCMs and the weighted (black) and unweighted (grey) ensemble means.

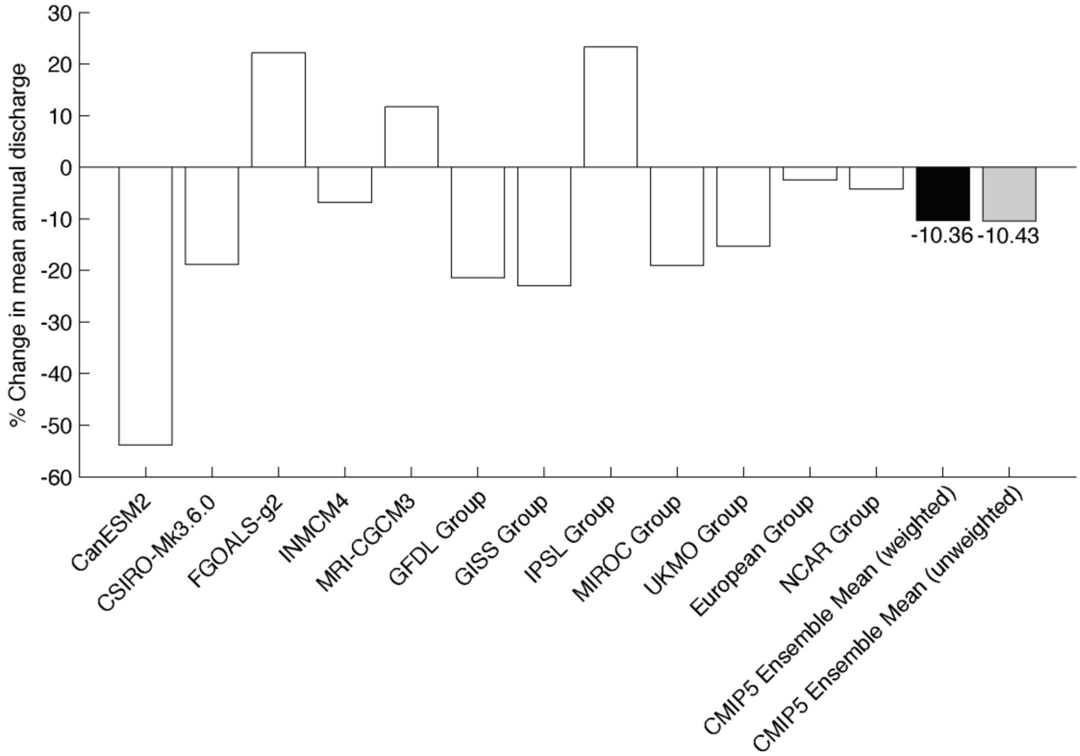


Figure 8. (A) River regimes for the baseline, each group of GCMs and the weighted and unweighted ensemble means; (B) percentage differences in mean monthly discharge for each group of GCMs and the weighted and unweighted ensemble means.