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On the sources of hydrological prediction uncertainty in the Amazon

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Abstract

Recent extreme events in the Amazon River basin and the vulnerability of local population motivate the development of hydrological forecast systems (HFSs) using process based models for this region. In this direction, the knowledge of the source of errors in HFSs may guide the choice on improving model structure, model forcings or developing data assimilation (DA) systems for estimation of initial model states. We evaluate the relative importance of hydrologic initial conditions (ICs) and model meteorological forcings (MFs) errors (precisely precipitation) as sources of stream flow forecast uncertainty in the Amazon River basin. We used a hindcast approach developed by Wood and Lettenmaier (2008) that contrasts Ensemble Streamflow Prediction (ESP) and a reverse Ensemble Streamflow Prediction (reverse-ESP). Simulations were performed using the physically-based and distributed hydrological model MGB-IPH, comprising surface energy and water balance, soil water, river and floodplain hydrodynamics processes. Model was forced using TRMM 3B42 precipitation estimates. Results show that uncertainty on initial conditions play an important role for discharge predictability even for large lead times (∼ 1 to 3 months) on main Amazonian Rivers. ICs of surface waters state variables are the major source of hydrological forecast uncertainty, mainly in rivers with low slope and large floodplains. ICs of groundwater state variables are important mostly during low flow period and southeast part of the Amazon, where lithology and the strong rainfall seasonality with a marked dry season may be the explaining factors. Analyses indicate that hydrological forecasts based on a hydrological model forced with historical meteorological data and optimal initial conditions, may be feasible. Also, development of DA methods is encouraged for this region.

1 Introduction

Recent extreme hydrological events have occurred in the past years in the Amazon River basin, such as the 2009 flood (Chen et al., 2010) and the 1996 (Tomasella et al., 2010), 2005 (Marengo et al., 2008; Zeng et al., 2008; Chen et al., 2009) and 2010 (Espinoza et al., 2011; Marengo et al., 2011) droughts. These extreme events caused several impacts on local population, since most settlements lie along Amazon Rivers where susceptibility to floods is large. Also, local population strongly depends on Amazon Rivers for transportation of people and goods, agriculture, generation of hydroelectricity, etc. The vulnerability to hydrological extremes could be reduced with information provided by Hydrological Forecast Systems (HFSs).

In this direction, the attempts for developing hydrological forecasts in the Amazon are all based in statistical methods. Uvo and Grahan (1998) and Uvo et al. (2000) developed seasonal discharge forecasts (March–May period) for 6 river stream gauges in the Amazon based on rain gauge data, streamflow data and Pacific and Atlantic Ocean sea surface temperatures (SSTs) using a canonical correlation analysis in the first and an artificial neural network approach in the latter. The authors conclude that, in the Amazon, it is possible to forecast seasonal runoff one season in advance with a certain degree of accuracy using empirical models and SST data. Schongart and Junk (2007) presented retrospective forecasts of the maximum water level in Central Amazonia using El Niño – Southern Oscillation (ENSO) indices. Cappalaere et al. (1995) developed flood forecasts methods for Central Amazonia (Manaus) for lead times ranging from 10 to 60 days, using statistical-type modelling of the stage time series recorded at the main river gauges in the Brazilian Amazon basin.

However, hydrological forecast systems (HFS) based on physically based hydrological models such as Wood et al. (2002), Collischonn et al. (2005) or Thielen et al. (2009) were not evaluated in the region, although hydrological modelling of the Amazon is being continually developed (e.g., Beighley et al., 2009; Decharme et al., 2008; Coe et al., 2007; Getirana et al., 2010; Paiva et al., 2011a,b, 2012; Trigg et al., 2009; Yamazaki et al., 2011).

Prediction errors of the HFSs arise from uncertainty on: (i) model structure and parameters, (ii) atmospheric forcing such as precipitation and (iii) initial states (e.g., preceding soil moisture or volume of water stored in rivers and floodplains). The type of model forcings can range from simple climatology to an ensemble of historical meteorology (Day, 1985) or to more complex weather forecasts obtained from General or Regional Circulation Models (e.g., Collischonn et al., 2005; Wood et al., 2002). In contrast, several data assimilation methods (Reichle, 2008; Liu and Gupta, 2007) could be employed to improve initial states estimates. Numerous hydrologic remote sensing products that could be assimilated are been developed in current years, such as: river water levels from nadir altimeters (Alsdorf et al., 2007; Santos da Silva et al., 2010), Terrestrial Water Storage from GRACE mission (Tapley et al., 2004a,b; Chen et al., 2009), soil moisture estimates from SMOS mission (Kerr et al., 2001), flooded inundation extent (Hess et al., 2003; Papa et al., 2010), energy fluxes and evapotranspiration (e.g., Vinukollu et al., 2010) and in future flooded extent with water level from the SWOT mission (Durand et al., 2010). Therefore, the knowledge of the relative importance of each source of errors plays an important role on the hydrological predictability and also supports the choice of technique to be first developed: improving model structure, improving or looking for better model forcings or developing data assimilation systems for better initial conditions estimates. In the latter case, it is also important to evaluate what are the key state variables and what data to assimilate.

In this direction, Wood and Lettenmaier (2008) developed an approach to evaluate the relative importance of errors in hydrologic initial conditions – ICs and model meteorological forcings – MFs as sources of hydrologic uncertainty. Latter, Shukla and Lettenmaier (2011) and Shukla et al. (2011) applied this approach to evaluate seasonal forecasts of cumulative runoff and soil moisture in the United States and globally, respectively. We use a similar approach to evaluate the relative importance of hydrologic initial conditions and model meteorological forcings errors (precisely precipitation) as sources of stream flow forecast uncertainty in the Amazon River basin. We access (i) when each of these features are more important, i.e. at each lead time uncertainty arising from MFs errors becomes larger than from ICs errors and in which season (ii) where, i.e. in which rivers; (iii) what are the key state variables contributing for uncertainty; and (iv) how it relates to Amazon River basin characteristics.

2 Methods

2.1 ESP versus rev-ESP approach

We used a hindcast approach developed by Wood and Lettenmaier (2008) that contrasts Ensemble Streamflow Prediction (ESP) and a reverse Ensemble Streamflow Prediction (reverse-ESP) (see Fig. 1). This approach uses ensemble model runs from a large scale distributed and process based hydrological model to evaluate the relative importance of errors in hydrologic initial conditions – ICs (e.g., soil moisture, groundwater storage, river discharge, floodplain storage, etc.) and model meteorological forcings – MFs (e.g., precipitation, surface air temperature, incoming solar radiation, etc.) as sources of stream flow forecast uncertainty.

In the ESP (Day, 1985), the model uses "perfect" initial conditions and runs forced by an ensemble of observed meteorological data from past years. An estimate of "perfect" initial conditions is computed using a hydrological model driven by observed meteorological forcings up to the time of forecast (e.g., forecast starts with model states from 15 June 2000). Then, an ensemble forecast is obtained using observed meteorological data resampled from past years (e.g., meteorological data from 15 June to 25 September of years 1998, 1999, ..., 2009). As a result, ESP shows a proxy of stream flow forecast uncertainty due to meteorological forcing errors (Wood and Schaake, 2008). In contrast, in reverse-ESP the model runs from an ensemble of simulated initial conditions (ICs) from past years forced by a perfect forecast. The ICs ensemble is obtained using the hydrological model forced by observed meteorological data resampled from past years during the spinup period (up to the date of forecast) (e.g., model initial states from 15 June of years 1998, 1999, ..., 2009). Observed meteorological data from current year is used as perfect meteorological forecast (e.g., meteorological data from 15 June to 25 September. 2000). Consequently, the reverse-ESP produces a proxy of stream flow forecast uncertainty due to model initial conditions errors. Model climatology, where either ICs and MFs are unknown, is used as a reference for comparing ESP and reverse-ESP model runs.

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We use the ensemble spread (either for ESP, reverse-ESP and model climatology) as a measure of uncertainty in stream flow forecasts. For a given forecast j starting at the time interval t_0 and at τ lead time, the ensemble spread S is computed as the mean square deviation using simulated discharge Q_{sim} as a reference:

$$S(\tau, j) = \frac{1}{N}\sum_{i=1}^{N}(Q_{\text{ens}_i} - Q_{\text{sim}})^2 \tag{1}$$

where N is the ensemble size, Q_{ens_i} is stream flow from ensemble member i. The indexes t and τ were omitted for simplicity. S is computed for the ESP (S_{ESP}), reverse-ESP ($S_{\text{rev-ESP}}$) and model climatology (S_{CLIM}) ensembles. For a proper evaluation of stream flow uncertainty in different time periods, the model climatology is used as a reference and relative spreads are computed as $S^*_{\text{ESP}} = S_{\text{ESP}}/S_{\text{CLIM}}$ and $S^*_{\text{rev-ESP}} = S_{\text{rev-ESP}}/S_{\text{CLIM}}$. Finally, results are averaged from all forecasts:

$$S^*(\tau) = \frac{1}{M}\sum_{j=1}^{M} S^*(\tau, j) \tag{2}$$

where M is the total number of forecasts performed in the test period and $S^*(\tau)$ is the relative ensemble spread as function of the lead time τ.

The comparison of the spread of both sets of ensembles allows the evaluation of the relative importance of the ICs and MFs on model predictability as functions of lead time. Moreover, a proxy of the river "memory" T can be obtained by verifying in which lead time τ the spread of ESP ensemble becomes larger than the reverse-ESP:

$$T = \min(\tau) | S^*_{\text{rev-ESP}}(\tau) < S^*_{\text{ESP}}(\tau) \tag{3}$$

2.2 Hydrological model

We used the MGB-IPH model (Collischonn et al., 2007; Paiva et al., 2011a), which is a large scale, distributed and process based hydrological model with a hydrodynamic module described in (Paiva et al., 2011a). It simulates surface energy and water balance and also discharge, water level and flood inundation on a complex river network. We used results from a model application in the Amazon River basin (Fig. 2a) presented in Paiva et al. (2012). The model was forced using TRMM 3B42 precipitation estimates (Huffman et al., 2007), with spatial resolution of 0.25° × 0.25° and daily time step for a period spanning 12 yr (1998–2009) and meteorological data obtained from the CRU CL 2.0 dataset (New et al., 2002). The model parameters related to soil water budget were calibrated using discharge data from stream gauges. Then, the model was validated against discharge and water level data from stream gauge stations, water levels derived from ENVISAT satellite altimetry data (Santos da Silva et al., 2010), Terrestrial Water Storage from GRACE mission (Tapley et al., 2004a,b) and flood inundations extent from Papa et al. (2010).

2.3 Model runs

We performed 6 different model runs: (i) a retrospective simulation from which ensemble of model climatology is derived and used as initial conditions for rev-ESP runs; (ii) a ESP run; (iii) a reverse-ESP run and three restricted reverse-ESP runs, where in the first only (iv) surface waters state variables (river discharge and water level, floodplain storage and surface runoff) are considered, in the second only (v) soil moisture state variable is considered and in the latter only (vi) groundwater state variables are considered. In all model runs, simulations used the 1998 to 2009 time period and ensembles have 12 members. ESP and reverse-ESP model runs generated 4 forecasts per year with up to 100 days lead time starting at 15 March, 15 June, 15 September and 15 December. Notice that since we are using meteorological data obtained from the CRU CL 2.0 dataset (New et al., 2002), which provides only climatological values, uncertainty of meteorological variables different from precipitation is not accounted. We choose this simplification because MGB-IPH model using CRU CL 2.0 showed a feasible performance when results were compared with observations (Paiva et al., 2012) and most of Amazon discharge variability is due to precipitation variability.

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3 Results

3.1 Forecast uncertainty in main rivers

We first explore forecast uncertainty results in 6 sites located in the main tributaries of Amazon River basin using the 2003/2004 hydrological year as an example (Fig. 3). Results show to be different for each site, although some characteristics are found in all of them.

In upper Solimões River, discharge starts to rise in September, and the spread of the ESP run rapidly surpasses the spread of the reverse-ESP run, showing that the importance of uncertainties in MFs is larger than from ICs. This situation changes in the other forecasts (at high water period in forecasts starting in 15 December and 15 March and in flow recession starting in 15 June) when the uncertainty in ICs appears to be more important than MFs. On average, the spread of the ESP ensemble S^*_{ESP} takes 35 days to surpass the spread of the reverse-ESP ensemble ($T \sim 35$ days).

At the Negro River site, discharges rise at the MAM period, and differently from upper Solimões River, the forecast uncertainty due to ICs shows to be comparable with uncertainty due to MFs even for large lead times. This characteristic is also present at high water (JJA) and flow recession periods (SON and DJF), and as a consequence only after ~ 55 days uncertainty in MFs becomes more important that in ICs.

At the rivers draining the southeast part of the Amazon, namely Madeira, Purus and Tapajós Rivers, some common features are found. In DJF period, when discharge slowly starts to rise, and in MAM period, when it increases rapidly almost to flood peak, ICs uncertainties are important at the beginning of forecasts but the weight of MFs uncertainty becomes larger for smaller lead times. In contrast, at high water periods (JJA), flow recession and low water period (SON), the spread of reverse-ESP ensemble greatly surpasses the spread of the ESP ensemble, showing that ICs errors may have a large influence in flow forecasts uncertainty. T values of Purus, Tapajós and Madeira Rivers showed to be different and approximately 30, 40 and 50 days, respectively.

In the Amazon main steam analyses shows that the spread of reverse-ESP ensemble greatly surpass the spread of ESP ensemble in all periods of the year, including high water (MAM), low water (SON), rising (DJF) and falling (JJA) periods. Uncertainty in MFs becomes more important than in ICs only after ~ 70 days.

MFs seem to play an important role in forecast uncertainty at the rising water period, but this is not valid or not so strong in some of the largest rivers, such as Solimões, Negro and Amazon. Perhaps this is due to the flood travel times in these rivers. In all rivers, the influence of ICs greatly surpasses MF's in high water period and mostly in flow recession and low water period. This characteristic in flow recession and low water period is very strong in rivers draining southeast part of the Amazon, where rainfall seasonality is stronger and there is a very marked dry season (Nobre et al., 2009). In all Amazon large rivers, T values can be considered very large, ranging from ~ 30 days at Purus Rivers to ~ 70 days in the Amazon River, showing that uncertainty on ICs may play an important role for hydrological predictability even for large lead times (~ 2 or 3 months).

3.2 Spatial analysis

We investigate the spatial distribution of T values, indicating at which lead time uncertainty in MFs becomes more important that ICs for hydrological predictability and serving as a proxy of river "memory". According to Fig. 4a, large T values are found at almost all Amazonian Rivers. T values smaller than 10 days are found mostly in headwater and in the Andean region at west part of the Amazon, where high river slopes are present (see also Fig. 2a). In most of Amazon main tributaries, including Solimões, Juruá, Purus, Madeira, Tapajós, Xingu and Negro River, it is larger than 30 days and in Amazon main steam it is between 2 and 3 months. Results show that ICs may be the main source of discharge forecast uncertainty even for large lead times (~ 1 to 3 months) in most Amazonian Rivers.

Results from restricted reverse-ESP runs (Fig. 4b–d) show larger T values in analyzes considering only surface waters state variables (Fig. 4b). This suggests that ICs of surface waters state variables, which include river discharge and water levels, surface runoff and floodplain storage, are the major source of hydrological forecast uncertainty. This characteristic is present mostly in Solimões, Negro, Purus, Japurá, Madeira and Amazon Rivers that are located in low slope regions (Fig. 2a) with large seasonally inundated floodplains (see Fig. 2b). T values in analyses using soil moisture restricted reverse-ESP run (Fig. 4c) are always less than 10 days, showing that ICs of soil moisture are not as important as ICs of other state variables. Finally, groundwater state variables showed to be important mostly in Tapajós and Xingu River basins located at southeast part of the Amazon. This can be related to the strong rainfall seasonality of this region where the dry season is very marked. Also, lithology may be an explaining factor, since this region is located mostly over the Brazilian Shield (Fig. 2a,c).

The relatively importance of MFs and ICs as sources of hydrological prediction uncertainty is variable according to the period of the year, as shown by seasonal analyses of T values (Fig. 5). At rivers draining extensive floodplains, such as Solimões, Negro, Juruá, Madeira and Purus, T values are always large, especially in high water and falling period (MAM and JJA, see also Fig. 3). In these time periods, T values larger than 90 days are found in the Amazon main steam.

The southeast part of the basin, including Xingu, Tapajos and Brazilian Madeira River basins, presents the most expressive seasonal variation of T values. At high water periods (DJF and MAM, see also Fig. 3), T values range from 10 to 30 days. But it increases a lot in low water period (JJA, SON) reaching values larger than 90 days. It shows that in this region, ICs are more important for hydrological prediction during low flows.

Results show that in rivers with extensive floodplains, ICs of surface waters state variables are the major source of prediction uncertainty and its importance increases during high water and falling period. This characteristic is present in Solimões, Juruá, Purus, Negro, Madeira, Amazon Rivers, all with extensive floodplains (Fig. 2a,b). This behavior may be related to the large flood wave travel times of these rivers, where these flood waves are delayed because floodplains store large volumes of water and release it slowly.

On the other hand, at southeast part of the basin, mainly at Tapajós and Xingu Rivers, ICs play an important role for prediction of low flows and groundwater state variables showed to be important. This region is the one that presents the strongest rainfall seasonality with a marked dry season. It is also located mostly in the Brazilian Shield, where lithological characteristics differ from the rest of the basin (Fig. 2a,c). So, a possible explanation for this behavior is that during low flows period, river discharge may be dominated by base flow, which is directly related to groundwater storage.

Finally, in a first comparison, our results disagree with Shukla et al. (2011), who applied the same methodology in a global analysis and found that MFs uncertainty dominate the hydrological prediction uncertainty in the Amazon, even for shorter lead times. However, the authors studied the cumulative runoff, which do not take into account flow routing throughout river, floodplain and groundwater reservoirs and probably that is the reason for the disagreement between results.

4 Conclusions

We investigate the importance of model initial conditions ICs and meteorological forcings MFs as sources of hydrological predictions uncertainty in the Amazon River basin. Our investigations show that in the Amazon River basin:

1. Uncertainty on initial conditions may play an important role for discharge forecasts even for large lead times (∼ 1 to 3 months) on main Amazonian Rivers. This suggests that an Ensemble Streamflow Prediction approach (ESP), based on a hydrological model forced with historical meteorological data and using optimal initial conditions, may be feasible for hydrological forecasting even for large lead times (∼ 1 to 3 months). Also, development of data assimilation methods is encouraged for reducing model initial conditions uncertainty.

2. ICs of surface waters state variables are the major source of hydrological forecast uncertainty, mainly in rivers with low slope and large floodplains, such as Solimões, Juruá, Japurá, Madeira, Negro and Amazon Rivers. ICs of groundwater state variables are important mostly in southeast part of the Amazon, in Tapajós as Xingu Rivers. Soil moisture is not as important as other state variables as a source of hydrological prediction uncertainty.
3. The relatively importance of MFs and ICs as sources of hydrological prediction uncertainty is variable according to the period of the year.
4. At rivers draining extensive floodplains, ICs are more important in all time periods but especially in high water and falling period (MAM and JJA). We speculate that this may be related to the large flood wave travel times of these rivers, where these flood waves are delayed because floodplains store large volumes of water and release it slowly.
5. MFs are more important in the beginning of rainy season when hydrographs are rising, especially at the rivers draining southeast.
6. At southeast part of the basin, mainly at Tapajós and Xingu Rivers, ICs play an important role for prediction of low flows (JJA, SON) and groundwater state variables showed to be important. We speculate that it is because this region is the one that presents the strongest rainfall seasonality with a marked dry season. Lithology may be an explaining factor, since this region is located mostly over the Brazilian Shield.

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References

Alsdorf, D. E., Rodrıguez E., and Lettenmaier D. P.: Measuring surface water from space, Rev. Geophys., 45, RG2002, doi:10.1029/2006RG000197, 2007.

Beighley, R. E., Eggert, K. G., Dunne, T., He, Y., Gummadi, V., Verdin, K. L.: Simulating hydrologic and hydraulic processes throughout the Amazon River Basin, Hydrol. Process., 23, 1221–1235, 2009.

Cappelaere, B., Lubès-Niel, H., Berkhoff, C., Thépaut, H., Guyot, J. L., de Oliveira, E., and Rodrigues, M.: Prévisions des crues de l'Amazone, in: Hydrologie tropicale: géoscience et outil pour le développement, Actes de la conférence de Paris, Mai 1995, IAHS Publ. no. 238, 355–366, 1996.

Chen, J. L., Wilson, C. R., Tapley, B. D., Zang, Z. L., and Niu, G. Y.: The 2005 drought event in the Amazon River basin as measured by GRACE and estimated by climate models, J. Geophys. Res., 114, B05404, doi:10.1029/2008JB006056, 2009.

Chen, J. L., Wilson, C. R., and Tapley, B. D.: The 2009 exceptional Amazon flood and interannual terrestrial water storage change observed by GRACE, Water Resour. Res., 46, W12526, doi:10.1029/2010WR009383, 2010.

Coe, M. T., Costa, M. H., and Howard, E. A.: Simulating the surface waters of the Amazon River basin: Impacts of new river geomorphic and flow parameterizations, Hydrol. Process., 22, 2542–2553, 2007.

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Collischonn, W., Haas, R., Andreolli, I., and Tucci, C. E. M.: Forecasting river Uruguay flow using rainfall forecasts from a regional weather-prediction model, J. Hydrol., 305, 87–98, 2005.

Collischonn, W., Allasia, D. G., Silva, B. C., and Tucci, C. E. M.: The MGB-IPH model for large-scale rainfall-runoff modeling, Hydrol. Sci. J., 52, 878–895, 2007.

Day, G. N.: Extended streamflow forecasting using NWSRFS, J. Water Resour. Plann. Manage., 111, 157–170, 1985.

Decharme, B., Douville, H., Prigent, C., Papa, F., and Aires F.: A new river flooding scheme for global climate applications: off-line evaluation over South America, J. Geophys. Res., 113, D11110, doi:10.1029/2007JD009376, 2008.

Durand, M., Fu, L. L., Lettenmaier, D. P., Alsdorf, D. E., Rodríguez, E., and Fernandez, D. E.: The surface water and ocean topography mission: Observing terrestrial surface water and oceanic submesoscale eddies, Proc. IEEE, 98, 766–779, 2010.

Durr, H. H., Meybeck, M., and Durr, S. H.: Lithologic composition of the Earth's continental surfaces derived from a new digital map emphasizing riverine material transfer, Global Biogeochem. Cy., 19, GB4S10, doi:10.1029/2005GB002515, 2005.

Espinoza, J. C., Ronchail, J., Guyot, J. L., Junquas, C., Vauchel, P., Lavado, W., Drapeau, G., and Pombosa, R.: Climate variability and extreme drought in the upper Solimões River (Western Amazon Basin): Understanding the exceptional 2010 drought, Geophys. Res. Lett., 38, L13406, doi:10.1029/2011GL047862, 2011.

Farr, T. G., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M.,Rodriguez, E., Rosen, P., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J.,Werner, M., Burbank, D., Oskin, M., and Alsdorf, D.: The shuttle radartopography mission, Rev. Geophys., 45, RG2004, doi:10.1029/2005RG000183, 2007.

Getirana, A. C. V., Bonnet, M.-P., Rotunno Filho, O. C., Collischonn, W., Guyot, J.-L., Seyler, F., Mansur, W. J.: Hydrological modelling and water balance of the Negro River basin: evaluation based on in situ and spatial altimetry data, Hydrol. Process., 24, 3219–3236, 2010.

Hess, L. L., Melack, J. M., Novo, E. M. L. M., Barbosa, C. C. F., Gastil, M.: Dual-season mapping of wetland inundation and vegetation for the Central Amazon basin, Remote Sens. Environ., 87, 404–428, 2003.

Huffman, G., Adler, R., Bolvin, D., Gu, G., Nelkin, E., Bowman, K., Hong, Y., Stocker, E., Wolff, D.: The TRMM Multisatellite Precipitation Analysis (TCMA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales, J. Hydrometeorol., 8, 38–55, 2007.

Liu, Y. and Gupta, H. V.: Uncertainty in hydrologic modeling: toward an integrated data assimilation framework, Water Resour. Res., 43, W07401, doi:10.1029/2006WR005756, 2007.

Kerr, Y., Waldteufel, P., Wigneron, J.-P., Martinuzzi, J.-M., Font, J., and Berger, M.: Soil moisture retrieval from space: the soil moisture and ocean salinity (SMOS) mission, IEEE T. Geosci. Remote Sens., 39, 1729–1736, 2001.

Marengo, J., Nobre, C., Tomasella, J., Oyama, M., de Oliveira, G., de Oliveira, R., Camargo, H., and Alves, L.: The drought in Amazonia in 2005, J. Climate, 21, 495–516, 2008.

Marengo, J. A., Tomasella, J., Alves, L. M., Soares, W. R., and Rodriguez, D. A.: The drought of 2010 in the context of historical droughts in the Amazon region, Geophys. Res. Lett., 38, L12703, doi:10.1029/2011GL047436, 2011.

New, M., Lister, D., Hulme, M., and Makin, I.: A high-resolution data set of surface climate over global land areas, Clim. Res., 21, 1–25, 2002.

Nobre, C. A., Obregón, G. O., Marengo, J. A., Fu, R., and Poveda, G.: Characteristics of Amazonian climate: main features, in: Amazonia and Global Change, Geophys. Mono. Ser., 186, 149–162, doi:10.1029/2008GM000720, 2009.

Paiva, R. C. D., Collischonn, W., and Tucci, C. E. M.: Large scale hydrologic and hydrodynamic modeling using limited data and a GIS based approach, J. Hydrol., 406, 170–181, 2011a.

Paiva, R. C. D., Collischonn, W., and Buarque, D. C.: Validation of a full hydrodynamic model for large scale hydrologic modelling in the Amazon, Hydrol. Process., doi:10.1002/hyp.8425, accepted, 2011b.

Paiva, R. C. D., Collischonn, W., Bonnet, M. P., Buarque, D. C., Frappart, F., Calmant, S., and Mendes, C. B.: Large scale hydrologic and hydrodynamic modelling of the Amazon River basin, Water Resour. Res., in review, 2012.

Papa, F., Prigent, C., Aires, F., Jimenez, C., Rossow, W. B., and Matthews, E.: Interannual variability of surface water extent at global scale, J. Geophys. Res., 115, D12111, doi:10.1029/2009JD012674, 2010.

Reichle, R. H.: Data Assimilation methods in Earth sciences, Adv. Water Resour., 31, 1411–1418, 2008.

Santos da Silva, J., Calmant, S., Seyler, F., Rotunno Filho, O. C., Cochonneau, G., Mansur, W. J.: Water levels in the Amazon basin derived from the ERS 2 and ENVISAT radar altimetry missions, Remote Sens. Environ., 114, 2160–2181, 2010.

Schongart, J. and Junk, W. J.: Forecasting the flood-pulse in Central Amazonia by ENSO-indices, J. Hydrol., 335, 124–132, 2007.

Shukla, S. and Lettenmaier, D. P.: Seasonal hydrologic prediction in the United States: understanding the role of initial hydrologic conditions and seasonal climate forecast skill, Hydrol. Earth Syst. Sci., 15, 3529–3538, doi:10.5194/hess-15-3529-2011, 2011.

Shukla, S., Sheffield, J., Wood, E. F., Lettenmaier, D. P.: Relative contributions of initial hydrologic conditions and seasonal climate forecast skill to seasonal hydrologic prediction globally, Abstract H51N-05 presented at 2011 Fall Meeting, AGU, San Francisco, Calif., 5–9 December 2011, 2011.

Tapley, B. D., Bettadpur, S., Watkins, M., and Reigber, C.: The gravity recovery and climate experiment: mission overview and early results, Geophys. Res. Lett., 31, L09607, doi:10.1029/2004GL019920, 2004a.

Tapley, B. D., Bettadpur, S., Ries, J. C., Thompson, P. F., and Watkins, M.: GRACE measurements of mass variability in the Earth system, Science, 305, 503–505, 2004b.

Thielen, J., Bartholmes, J., Ramos, M.-H., and de Roo, A.: The European Flood Alert System – Part 1: Concept and development, Hydrol. Earth Syst. Sci., 13, 125–140, doi:10.5194/hess-13-125-2009, 2009.

Tomasella, J., Borma, L. S., Marengo, J. A., Rodriguez, D. A., Cuartas, L. A. Nobre, C. A., and Prado, M. C. R.: The droughts of 1996–1997 and 2004–2005 in Amazonia: hydrological response in the river main-stem, Hydrol. Process., 25, 1228–1242, doi:10.1002/hyp.7889, 2010.

Trigg, M. A., Wilson, M. D., Bates, P. D., Horritt, M. S., Alsdorf, D. E., Forsberg B. R., and Vega, M. C.: Amazon flood wave hydraulics, J. Hydrol., 374, 92–105, 2009.

Uvo, C. B. and Graham, N. E.: Seasonal runoff forecast for Northern South America: A statistical model, Water Resour. Res., 34, 3515–3524, doi:10.1029/98WR02854, 1998.

Uvo, C. B., Tölle, U., and Berndtsson, R.: Forecasting discharge in Amazonia using artificial neural networks, Int. J. Climatol., 20, 1495–1507, doi:10.1002/1097-0088(200010)20:12<1495::AID-JOC549>3.0.CO;2-F, 2000.

Vinukollu, R. K., Wood, E. F., Ferguson, C. R., and Fisher, J. B.: Global estimates of evapotranspiration for climate studies using multi-sensor remote sensing data: evaluation of three process-based approaches, Remote Sens. Environ., 115, 801–823, doi:10.1016/j.rse.2010.11.006, 2010.

Wood, A. W. and Lettenmaier, D. P.: An ensemble approach for attribution of hydrologic prediction uncertainty, Geophys. Res. Lett., 35, L14401, doi:10.1029/2008GL034648, 2008.

Wood, A. W. and Schaake J. C.: Correcting errors in streamflow forecast ensemble mean and spread, J. Hydrometeorol., 9, 132–148, 2008.

Wood, A. W., Maurer, E., Kumar, A., and Lettenmaier, D. P.: Long-range experimental hydrologic forecasting for the Eastern United States, J. Geophys. Res., 107, 4429, doi:10.1029/2001JD000659, 2002.

Yamazaki, D., Kanae, S., Kim, H., and Oki, T.: A physically based description of floodplain inundation dynamics in a global river routing model, Water Resour. Res., 47, W04501, doi:10.1029/2010WR009726, 2011.

Zeng, N., Yoon, J. H., Marengo, J. A., Subuamaniam, A., Nobre, C. A., Mariotti, A., and Neelin, J. D.: Causes and impact of the 2005 Amazon drought, Environ. Res. Lett., 3, 014002, doi:10.1088/1748-9326/3/1/014002, 2008.

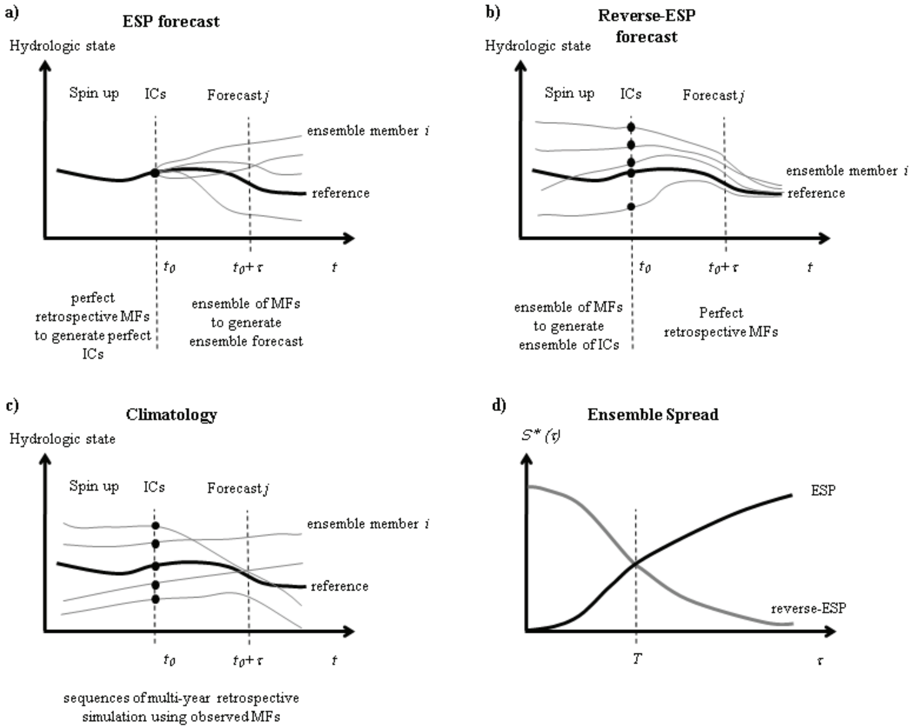

Fig. 1. Schematic representation of evolution of hydrologic states in spinup and forecast for **(a)** ESP approach, **(b)** reverse-ESP approach, **(c)** climatology and **(d)** relative ensemble spread S^* as function of lead time τ. Modified from Wood and Lettenmaier (2008).

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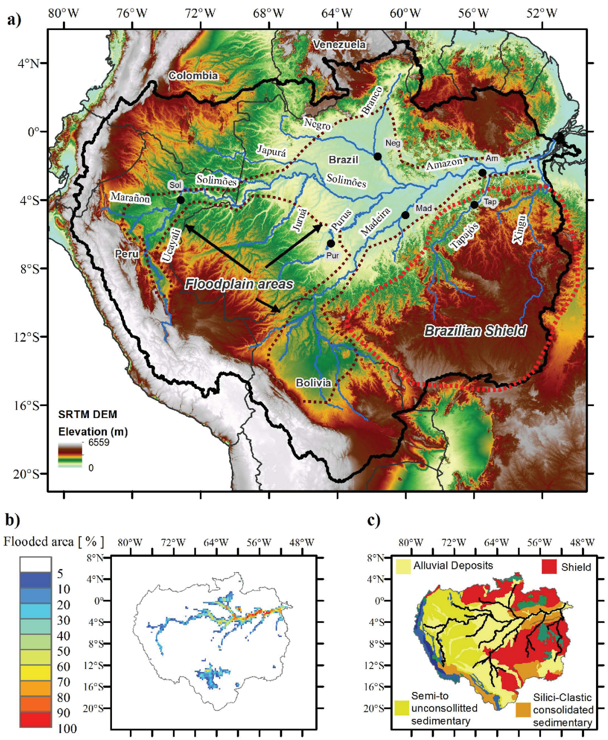

Fig. 2. **(a)** Amazon River basin with main tributaries, international limits, relief from SRTM DEM (Farr et al., 2007) and sites used in analyses (black circles), **(b)** Mean flooded area (%) derived from Papa et al. (2010) and **(c)** Lithological map derived from Durr et al. (2005).

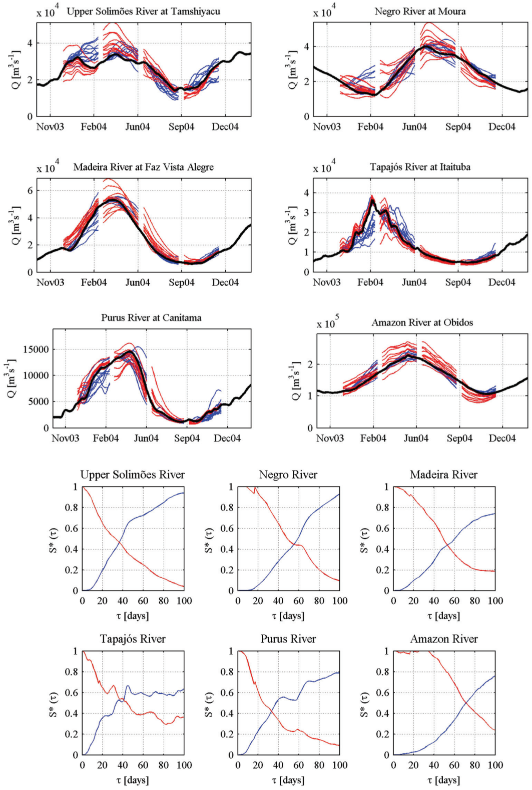

Fig. 3. Retrospective simulation (black), ESP (blue) and reverse-ESP (red) discharge results and relative ensemble spread $S^{*}(\tau)$ as function of the lead time τ. Results are presented at upper Solimões (Sol), Negro (Neg), Madeira (Mad), Tapajós (Tap), Purus (Pur) and Amazon (Am) Rivers at sites shown in Fig. 2a.

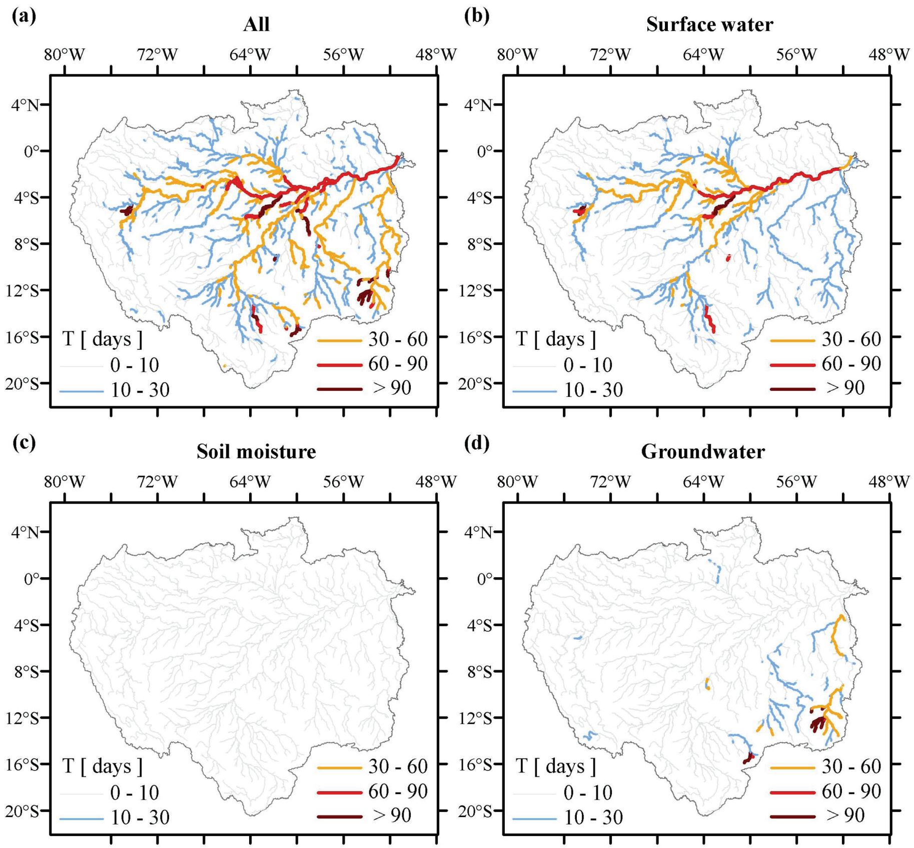

Fig. 4. Spatial distribution of T values considering **(a)** all, **(b)** surface water, **(c)** soil moisture and **(d)** groundwater model states variables. Results are shown only in rivers reaches with upstream drainage area larger than 3000 km^2.

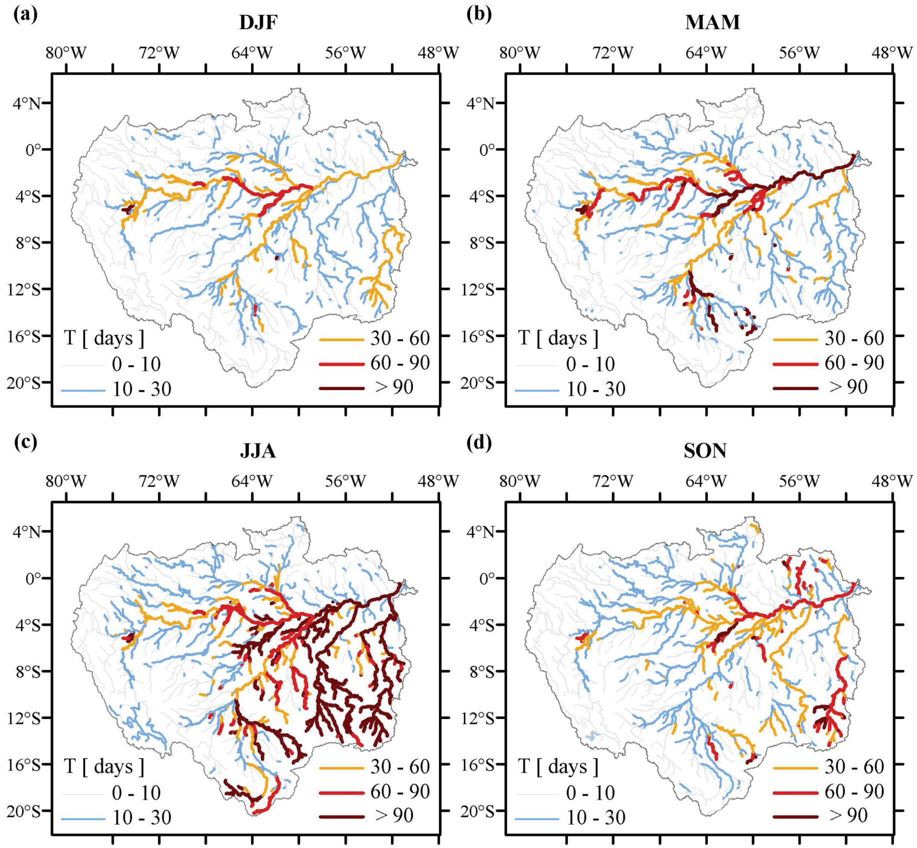

Fig. 5. Spatial distribution of *T* values considering **(a)** DJF, **(b)** MAM, **(c)** JJA and **(d)** SON time periods. Results are shown only in rivers reaches with upstream drainage area larger than 3000 km^2.

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