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Coupling numerical weather prediction and hydrological modelling for runoff forecast in southern Brazil

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ABSTRACT

Hydrological modelling is largely applied to forecast the effects of extreme rainfall on runoff dynamics. Little research has been done on coupling numerical weather prediction (NWP) and hydrological modelling to forecast runoff in southern Brazil given the limited hydrometeorological and NWP data available for the region. In this study, we evaluate a coupling method of NWP and a semi-distributed hydrological model to forecast runoff for a humid subtropical catchment (286 km²) in southern Brazil, state of Santa Catarina, municipality of Vidal Ramos. The HEC-HMS hydrological model was manually calibrated and validated using data of 2013. Four post-processing techniques of rainfall estimates were applied on rainfall products of two NWP models (BRAMS and GFS), providing rainfall input data for forecasting runoff. Then, a scenario of runoff forecast of an event in June 2014 was analyzed. We found the tested coupling method was able to forecast runoff with a lead time of 24 hours in which the best post-processing technique of rainfall is the “poor man ensemble” between the 90th quantile sampling of BRAMS and the mean of the GFS product. Hence, the validation of NWP products must be done carefully to avoid the propagation of uncertainties through a flood forecasting system.

Key-words: Hydrological Modelling, Numerical Weather Prediction, Runoff Forecast, NWP Post-Processing Techniques

Acoplamento de previsão numérica da atmosfera e modelagem hidrológica para a previsão do escoamento superficial no sul do Brasil

RESUMO

A modelagem hidrológica é amplamente aplicada para a previsão dos efeitos de chuvas extremas na dinâmica do escoamento superficial. Entretanto, pouca pesquisa tem sido feita no acoplamento da previsão numérica da atmosfera (NWP) e modelagem hidrológica no Sul do Brasil, dada a limitação imposta pela falta de dados hidrometeorológicos e oriundos de NWPs na região. Neste estudo, são avaliados métodos de acoplamento entre NWPs e modelagem hidrológica semi-distribuída para a previsão do escoamento superficial de uma bacia hidrográfica subtropical úmida (286 km²) no Sul do Brasil, estado de Santa Catarina, município de Vidal Ramos. O modelo hidrológico HEC-HMS foi calibrado e validado manualmente com dados do ano de 2013. Quatro técnicas de pós-processamento de estimativas de chuva foram aplicadas em dois produtos de modelos de NWPs (BRAMS e GFS), que foram utilizados como dados de entrada para a previsão do escoamento superficial. Por fim, um cenário de previsão do escoamento superficial foi analisado em Junho de 2014. O método de acoplamento utilizado neste estudo foi capaz de prever o escoamento superficial com antecedência de 24 horas, onde o melhor método de pós-processamento da chuva foi o “poor man ensemble” entre a amostragem do 90º quartil do produto BRAMS e a média do GFS. Dessa forma, é importante ressaltar que o procedimento de validação dos produtos de NWPs deve ser realizado cuidadosamente para evitar a propagação de incertezas em um sistema de previsão do escoamento superficial.

Palavras-chave: Modelagem Hidrológica, Previsão Numérica da Atmosfera, Previsão do Escoamento Superficial, Técnicas de Pós-Processamento de NWPs

Introduction

Hydrological modelling is largely applied to forecast the effects of extreme rainfall on runoff dynamics. However, little research has been done on coupling numerical weather prediction (NWP) and hydrological modelling to forecast runoff in southern Brazil, considering the limited hydrometeorological and NWP available data for the region. Development of reliable coupling methods to forecast runoff would help mitigation actions to become effective, providing basic information for emergency plans which enhance the preparedness of riparian communities.

Flood is defined as an event when water level from any water body rises above normal limits (ASCE, 1996). In Brazilian legislation, the normal limit is considered to be when water overflow the river banks and inundates the floodplain (Brazil, 2007). Rainfall is considered to be the main cause of river floods, however, watershed characteristics and Landuse/Landcover (LULC) also play a major role in the development of floods. Small headwater watersheds usually experienced floods caused by intense, local, and short-duration rainfall events typically generated by convective or orographic atmospheric systems (ASCE, 1996; Tucci, 2012).

A valuable application of hydrological models is the forecast of short-term flood risk. Once a hydrological model has been calibrated for the characteristics of a particular watershed it can be used to forecast floods (Beven, 2012). The ensemble of NWP and hydrological modelling is increasing fastly in operational hydrological forecast due to mainly its capacity of using available data and models in an objective approach. These methodologies also allow an enhance in accuracy and lead time of flood forecast (Seo et al., 2014; Yu et al., 2016). Even though uncertainties still remain and arises mainly from NWP rainfall estimates (Siddique et al., 2015), hydrometeorological data, and the hydrological models structure (Kauffeldt et al., 2016).

Flood forecast through hydrological modelling relates the optimal use of both weather forecast and scenarios of hydrological modelling and increase the likelihood of emergency plans to become effective (Jasper, Gurtz and Lang, 2002). Liguori et al. (2012) state that the use of NWP models associated with hydrological models could generate meaningful results with a lead time that allows the population to become prepared to

intense rainfall events and its associated consequences. In Brazil, mitigation actions are poorly applied despite the range of tools and data provided by agencies that monitor and share hydrometeorological information. Although the NWP model called Brazilian Regional Atmospheric Modelling System (BRAMS) is vastly used in other applications. The BRAMS model allows mesoscale rainfall forecast up to 96 hours, with a time step of 6 hours (Leivas et al., 2011).

Several successful attempts have been made to create optimal event forecast related to intense rainfall in the world. Studies have found flood forecast can be made with a lead time which ranges from 12 h (Liu et al., 2015) up to 5 days (Artinyan et al., 2016). Although, the uncertainties of flood forecast become greater after 48 h due to mainly uncertainties associated with NWP estimates (Yang et al., 2015; Liu et al., 2015). An enhance in spatiotemporal resolution of NWP is known to decrease the uncertainties in the estimation of peak runoff and peak timing (Shi et al., 2015; Tao and Barros, 2013). Uncertainties on rainfall forecast arisen from the NWP models must be addressed in the total uncertainty of flood forecast (Wu, Lu and Wu, 2014), and must be communicated to local decision makers (Shamir et al., 2013). Rainfall tends to be underestimated by the NWP models, which might contribute to enhancing the total uncertainty of flood forecast (Shamir et al., 2013; Yucel, 2015). Peak and timing of runoff appear to be well estimated by coupling methodologies of NWP and hydrological models. Though the uncertainties regard the hydrological modelling might be caused by routing methods for peak timing (Artinyan et al., 2016) and by the mechanisms of runoff generation (i.e., soil moisture and baseflow contribution) for peak runoff (Tao and Barros, 2013).

Among the consequences of floods to society, we could highlight the impacts in infrastructure, human health, and real state (Haddad and Teixeira, 2015). Global data from the International Disaster Database (EM-DAT) has shown that between 1976 and 2006 floods account for US\$ 337 billion of financial loss. In the state of Santa Catarina, where the study area is located, between 2000 and 2003 floods account for US\$ 137 million (Goerl, Kobiyama, and Pellerin, 2012), a proportionally high value considering the global financial loss. According to Plag et al. (2010), the increasing exposure to hazards due to urban expansion in developing

countries is the major factor that contributes to natural phenomena become natural hazards. Reducing the damages caused by natural hazards requires appropriate prevention and adaptation of society (Plag et al., 2010). The coupling of NWP and hydrological modelling can be highly effective for emergency plans, once local authorities will know in advance where and when floods might occur (Tucci, 2012).

In this study, we evaluated a coupling method of numerical weather prediction (NWP) and semi-distributed hydrological modelling to forecast runoff for a catchment in southern Brazil, considering four post-processing techniques of rainfall NWP estimates.

Material e methods

Study Area

The upper *Itajaí-Mirim* river catchment (286 km²) is defined by the downstream gauge station hosted by the National Water Agency of Brazil. The catchment covers almost the whole area of the municipality of Vidal Ramos (Fig. 1). The *Vidal Ramos* municipality has only 6,290 inhabitants which mainly depend on rural and mineral resources exploitation activities. However, this catchment is located in the headwater area of a much larger watershed (*Itajaí-Mirim* watershed of 15,134 km²) where major urban centers are located, such as *Brusque* (102,025 inh) and *Itajaí* (173,452 inh). Thus, forecasting runoff in this area would help other downstream communities to increase their preparedness. Moreover, the *Itajaí-Mirim* watershed holds the greatest number of years with flood records in the *Rio do Itajaí* watershed (Clarke, 1996).

Figure 1. Area of interest with the sub-catchments, southern Brazil, state of Santa Catarina, municipality of Vidal Ramos.

According to the Köppen classification system, the climate in the region is defined as a subtropical climate (Cfa). This type of climate dominates Southern Brazil and is characterized by a mean temperature of 18 °C in the winter and 22 °C in the summer. Rainfall is well distributed throughout the year, although tend to be slightly higher in spring and summer. Annual rainfall rate lies within 1,600 mm (Pandolfo et al., 2002).

Most of the intense rainfall occurs in spring and summer. In spring, precipitation is mainly driven by mesoscale convective complexes which bring humidity from Northern Argentina causing instability in southern Brazil. In summer, rainfall is produced by daylight heating which develops late afternoon storms through local convection. Intense and continuous rainfall could be produced in summer by the South Atlantic Convergence Zone carrying a large amount of moist air from the Amazon region to southern Brazil (Monteiro, 2001).

Bedrock under the area of interest is composed mainly of sedimentary rocks of the Parana Basin such as sandstones, siltstone, mudstone, shale, diamictites, varvites, conglomerates, and coal deposits. Some metamorphic rocks can also locally extrude over the catchment assigning resistance to differential erosion (Brazilian Geological Survey, 2014).

Two major geomorphologic groups are found within the catchment. One is characterized by the presence of pediments shaped by headwater river systems, alternating plateaus and high relief hills. The other is highly shaped by denudation of ancient bedrock formations resulting in fluvial valleys with flat bottoms varying from 212 and 288 m high. Both geomorphologic groups provide conditions to develop high energy hydrological systems (Santa Catarina, 1986). Some landmarks such as bank erosion, river margin creeping, and pebbles on the bed load indicate this high energy hydrological system.

Soil types found in the watershed, according to the US Soil Taxonomy Classification (1999), are the utisol, inceptisol, and entisol. Inceptisol and entisol are well drained with textures varying from silt and sand on its major components. On the other hand, the utisol can be poorly drained due to the content of clay texture

which might develop a quasi-impervious layer (Brazilian Agriculture Research Company, 2005).

Landuse/Landcover (LULC) is predominantly natural subtropical forest (38%) followed by natural grassland (28%). Agrarian environments then contribute by a large amount of area in the catchment with the following landuses: bare soil (23%), cropland (5%), pasture (4%) and tilled soil (1.8%). Impervious surfaces only cover 0.2% of the watershed. In summary, forests and rural LULC's dominate the watershed.

Geographic and Hydrometeorological Data

Three spatial data were used to estimate parameters as input data for the hydrological model. A Digital Elevation Model (DEM) with a spatial resolution of 1 m was used to delimitate watershed boundaries and the river system, as well as to extract geomorphic metrics. Satellite imagery from OLI/Landsat 8 was the baseline to classify landuse in the catchment. The OLI sensor is capable of generating images with spatial resolution of 15 m at the panchromatic band. Ultimately, soil classification maps from the Agriculture Research Company of Brazil with a scale of 1:250,000 were used to analyze soil properties.

Hydrometeorological data were downloaded from <http://www.hidroweb.ana.gov.br> hosted by the Water National Agency of Brazil (ANA). Rainfall and discharge data are available at a daily time step from 1988 to 2014, with some data gaps in the recent years. Besides rainfall and discharge data, water levels and topobathymetric profiles are routinely taken at this river section.

Modelling Framework

Hydrological modelling was performed using the Hydrologic Modelling System (HEC-HMS) software developed by the Hydrologic Engineering Center of United States. The Soil Conservation Service Curve Number (SCS-CN) was used to simulate runoff generation. Runoff routing in the sub-catchments was performed through the Clark Unit Hydrograph method. Baseflow volume was predicted by recession analysis. Rainfall input was considered to be equally distributed within the watershed (Fig. 2).

Figure 2. Flowchart of the modelling framework.

SCS Curve Number is a rainfall-runoff model that relies on one measurable parameter the CN number. The CN parameter is determined by a combination of three variables: soil types, soil condition and predominantly vegetation. Antecedent moisture can be accounted over newer

model version (Beven, 2012); however, an average value between dry and wet soils prior to the annual maximum flood was used. In this study, CN values were determined for each sub-catchment based on soil types, condition and LULC (Table 1).

Table 1. Area, curve number, storage coefficient and time of concentration for each catchment.

Sub-catchment	Area (km ²)	Curve Number	Storage Coefficient (h)	Time of Concentration (h)
Rio Itajaí-Mirim	96.89	97.6	2.027	9.36
Rio Garrafão	48.91	89.5	1.206	5.13
Rio do Macaco	19.46	97.3	0.400	1.82
Rio Santa Luiza	30.65	90.4	1.268	4.31
Rio do Veado	18.43	98.6	0.789	2.93
Rio das Pacas	9.11	98.6	0.821	2.42
Rio Antinha	33.90	97.8	0.448	1.96
Rio dos Bugres	10.49	93.5	0.379	1.71
Rio Itajaí-Mirim 2	19.00	82.0	5.455	4.31

The Clark Unit Hydrograph method is a two parameter routing model where the development of a hydrograph is driven by the amount of effective rainfall that will contribute to the catchment outlet at one given time step (Beven, 2012). The first parameter that must be determined is the storage coefficient and it

accounts for the timing of effective rainfall. Storage coefficient was calculated according to Dooge (1973). The second parameter is the time of concentration, which is determined by the time that effective rainfall will take to flow from the farthest point of a catchment to its outlet (United States Geological Survey, 2000). Time of

concentration was deduced in agreement with Kirpich (1940). Storage coefficient and time of concentration are given in Table 1.

Sub-superficial and subterranean flow (baseflow) were computed as the lowest discharge prior to the simulated storm. It was defined as 8.52 m³/s at the catchment outlet for the scenario simulation, and then it was converted by a function of area as 0.0298 m³/s/km². In this way, baseflow could be calculated for each sub-catchment. Baseflow was modelled in a way that once rainfall has started the baseflow decrease at a recession rate of 0.9. On the other hand, once runoff has reached its peak the baseflow increase at a rate of 0.4 to 0.5.

The Muskingum method was used to model channel routing. The Muskingum method works as a relationship between the continuity and storage equation in the river channel. It is determined by the following equation:

$$S = K[XI + (1 - X)O]$$

where: S is channel storage, I represents the input runoff in a channel and O is the output runoff in a channel. X and K are parameters. X represents the weight of discharge integration in space; while K , represents the average time, in hours, of peak discharge from the input to the output of the channel (Tucci, 2012). The values of X were considered to be constant (0.5) in the catchment. On the other hand, K values range from 0.374 to 3.708 hours after calibration.

Calibration was performed between January and June of 2013. Variables and parameters used in the calibration process were described in the aforementioned topics. Validation was performed in the period of July and December of 2013. Parameters were optimized during the calibration procedure using the peak discharge relative error (ε_p) objective function:

$$\varepsilon_p = \left[\left(\frac{Qp_{est}}{Qp_{obs}} - 1 \right) \times 100 \right]$$

where: Qp_{est} is the estimated peak discharge (m³/s) and Qp_{obs} is the observed peak discharge (m³/s). According to Ravazzani et al.

(2016), the ε_p objective function is indicated for hydrological modelling where the aim is to simulate flood inducing peak discharges. Values of ε_p around $\pm 25\%$ are acceptable as they might be induced by discharge measurements uncertainties (Di Baldassarre and Montanari, 2009).

NWP Data Processing

Data from numerical weather prediction for rainfall were obtained from the Brazilian Regional Atmospheric Modelling System – BRAMS provided by the National Institute for Space Research (INPE). The BRAMS model generates products with a 12 hours time-step, with a horizon forecast time of 96 hours and spatial resolution of 5 kilometers (Leivas et al., 2011). We chose to work with a 24 hours lead time. In order to best represent the spatiotemporal distribution of rainfall, three methods of spatial sampling (mean, median, and the 90th quantile) were applied to average rainfall as a spatially uniform value.

The 90th quantile BRAMS product was blended to the Global Forecast System (GFS) NWP to improve rainfall forecasts. The averaging of multiple ensembles has been proven to increase the accuracy of rainfall forecasts, known as the “poor man ensemble”. This method is defined by the arithmetic mean of multiple NWP models for each timestep (Cane et al., 2013). In total, four scenarios of rainfall and runoff forecast were made considering different post-processing techniques of rainfall estimated by NWP models: mean (P mean), median (P median), 90th quantile (P 90 quant), and the 90th quantile/GFS blend (P 90q_GFS).

Runoff Forecast Scenario

A scenario of 7 days was simulated with rainfall input data derived from BRAMS/GFS products, between June 4 and 10 of 2014. The period presented a rainfall intensity peak of 72.3 mm and a total amount of 168.5 mm (Fig. 3). As calibration and validation were performed with a 24 hours time step, the scenario was simulated using the same time step. Simulations from BRAMS/GFS model for rainfall were also validated through statistical analysis.

Figure 3. 90th quantile BRAMS product for the runoff forecast scenario. Only days with considerable rainfall are shown.

Models Efficiency Analysis

Nash-Sutcliffe Coefficient (NSE) was used to assess the reliability of runoff simulations. The coefficient varies from 1 to $-\infty$, where values near 1 represent perfect fit results while near 0 poor results (Nash and Sutcliffe, 1970). The formula is presented below:

$$NSE = 1 - \left[\frac{\sum_{t=1}^T (Q_o^t - Q_s^t)^2}{\sum_{t=1}^T (Q_o^t - Q_m)^2} \right]$$

where: Q_o = observed discharge (m^3/s), Q_s = simulated discharge (m^3/s), and Q_m = mean observed discharge (m^3/s)

In order to assess rainfall reliability, a bias statistical analysis was performed. The bias analysis presents the mean deviation (or tendency) of a model compared with observed rainfall. When bias is positive that indicates an overestimation of the model and the backwards is also true for negative values (Ferreira, Varone and Alves, 2012). The formula is given below:

$$Bias = \frac{1}{n} \sum (E - M)$$

where: E = estimated rainfall (mm), M = measured rainfall (mm), and n = number of observations.

The Root Mean Square Error (RMSE) was also used to back-up the aforementioned statistical analysis. This analysis represents the precision of the model; and the closer the values are from zero more precise is the model (Ferreira, Varone and Alves, 2012). The formula is given below:

$$RMSE = \sqrt{\frac{\sum (E - M)^2}{n}}$$

where: E = estimated rainfall (mm), M = measured rainfall (mm), and n = number of observations.

Results

Hydrological Model Calibration and Validation

Calibration presented a NSE of 0.72 with a peak discharge occurring on March 05. In the peak discharge the difference between observed and simulated discharge was of 45.8 m³/s, wherein observed discharge was 191.1 m³/s and simulated discharge was 145.3 m³/s. The calibration presented good results and was able to portrait the behaviour of peak discharges in this period. The

mean ϵ_p was -14.2%, meaning that the model underestimates discharge peaks by 14.2% (Fig. 4).

Validation presented similar results with a NSE of 0.79, while peak discharge occurred on September 21. The peak discharge presented a better fit compared to calibration diverging only 21.8 m³/s, where the observed discharge was 288.0 m³/s and simulated 309.8 m³/s. The mean ϵ_p for the validation period was -11.7% (Fig. 4).

Figure 4. Calibration event with NSE of 0.72 (left) and validation with NSE of 0.79 (right).

Weather Prediction

The event predicted by the NWP models is characterized by a stationary cold front; such events are common in southern Brazilian winter. The cold front reached the state of Santa Catarina on June 06 and continued to move northeastward. The highest accumulated rainfall was seen on June 09 (86.7 mm) and the atmospheric system is depleted on June 10 (Fig. 3).

Daily forecasts from the NWP models for the four post-processing techniques are summarized in Figure 5. The Taylor diagram summarizes information regarding $RMSE$, standard deviation, and correlation coefficient (Taylor, 2001). Validation of the NWP models has shown that different post-processing techniques have significantly enhanced the forecasts of rainfall. Correlation coefficient increased from 0.74 (P mean) to 0.95 for the blended product (P 90q_GFS). Similarly, $RMSE$ decreases from 23.79 mm (P mean) to 10.32 mm (P 90q_GFS). Pennelly, Reuter and Flesh (2014) also found similar $RMSE$ results between 3 and 10 mm analysing the US regional model WRF in the South Saskatchewan River watershed, in Canada. The smallest bias was also found in the P 90q_GFS forecast with -1.49 mm, in other words,

the models underestimate the rainfall values by 1.49 mm. Ferreira, Varone and Alves (2012) found results of underestimation with a bias value of -0.42 mm for the BRAMS model in Brazil.

Figure 5. Taylor diagram of rainfall forecasts validation for each post-processing technique. Points near the centered $RMSE$ at the bottom of the diagram represent the best rainfall forecasts.

Coupling NWP and Hydrological Modelling

Runoff was simulated from rainfall data predicted by the BRAMS/GFS model. Two peak discharges were observed on June 06 and June 09. The first peak discharge has been underestimated by the hydrological model, presenting a $\mathcal{E}_p$ of -20.71%. The second peak discharge had almost a perfect fit with a $\mathcal{E}_p$ of -0.98%. These results were found for the Q 90q_GFS simulation. All hydrological simulations tend to be slightly smaller than the observed runoff, mostly on the first four days of simulation (Fig. 6). Peak discharges were found highly related with the area of sub-catchments (Fig. 7).

Figure 6. Runoff forecast scenario simulation in June 2014.

Figure 7. Spatial distribution of peak discharges for the forecasted event.

Table 2. Efficiency metrics for rainfall and runoff forecasts

Simulation	P <i>RMSE</i> (mm)	P <i>Bias</i> (mm)	P <i>CC</i>	Q <i>NSE</i>	Q $\mathcal{E}_p$ (%)
Q mean	23.79	7.63	0.74	0.24	-10.08
Q median	22.56	-7.63	0.76	0.27	-11.52
Q 90 quant	20.65	-2.97	0.81	0.43	3.27
Q 90q_GFS	10.32	-1.49	0.95	0.71	-0.98

The best *NSE* was obtained for the Q 90q_GFS simulation, with 0.71, very close to the calibration and validation processes. *NSE* values for Q mean, Q median, and Q 90 quant were 0.24, 0.27, and 0.43, respectively (Table 02). This has shown a large enhance in simulation fit regarding different rainfall post-processing techniques as an input of the hydrological model.

Discussion

Results have shown runoff forecasting is mainly affected by uncertainty regarding the forecasts of rainfall. As we increase the performance of rainfall estimates by the NWP models, forecasts of runoff enhance almost exponentially (Table 02). Kobold and Suselj (2005) have previously found uncertainties in rainfall estimates lead to an increase in peak discharge error of 1.6 times. We could see that runoff forecasts have already enhanced greatly in the Q 90 quant simulation. An enhance in efficiency by the Q 90 quant is related to the smoothing effect on rainfall variability that the mean or median spatial sampling methods imply, this may hide the most intense storm cells. Cane et al. (2013) have also found the 90th quantile rainfall spatial sampling as the best estimate concerning runoff forecasting. However, we see the best post-processing technique of rainfall estimation (*CC* of 0.95) when using a blended product of the 90th quantile of a regional NWP (BRAMS) and a global NWP (GFS), the so-called “poor man ensemble”.

As rainfall is the most relevant variable in the generation of runoff (ASCE, 1996), it is expected that hydrological models are profoundly affected by its uncertainties. This holds true not only for a precise quantitative forecast of rainfall but mainly by uncertainties in the spatiotemporal structure of storms. Uncertainties in rainfall might be exacerbated by forecasting runoff at a daily timestep in small watersheds, as decreasing (finer) spatiotemporal resolutions of NWPs contributes to enhancing runoff forecasting accuracy (Tao and Barros, 2013; Shi et al., 2015). Even though

storms resulting from cold fronts in southern Brazil tend to be well time-space distributed. Beven (2012) also states runoff forecasting may be complex in small headwater watersheds due to a smaller lead time, thus, runoff forecast depends most on rainfall forecast.

Poor estimation of small peaks, less than 50 m³/s, could be a side effect of calibrating a model for flood forecasting. This model behaviour is seen in the calibration and validation procedures (Fig. 4). As we are interested in estimating peak discharges, parameters related to runoff generation are set high in order to preserve the simulation of flood-inducing discharges. Calibrating a model using this approach may represent a problem in water balance studies. However, in the forecast of floods, these uncertainties are overcome by the need to predict higher peak discharges (Montesarchio, Lombardo and Napolitano, 2009).

In the forecasted event (June 2014) the first peak discharge is underestimated by a $\mathcal{E}_p$ of -20.71%, due to an underestimation of rainfall by the NWP models (Fig. 6). Neither BRAMS or GFS models could capture the observed rainfall of 72.31 mm for June 06. Even though, the P 90q_GFS simulation has forecasted a volume of 49.42 mm, the highest among all the rainfall post-processing techniques. Underestimation of rainfall has been previously observed by Shamir et al. (2013) and Yucel (2015), where they stated that NWP models usually underestimate the forecasts of rainfall, contributing to enhance flood forecast uncertainties.

The efficiency of flood forecasting systems may not be assessed only by metrics such as the *NSE* and *RMSE*, as they are built mainly to evaluate hydrograph shape rather than peak discharges. Although it is well known peak discharges have a great influence on *NSE* due to the magnitude of error these events induce on the coefficient (Di Baldassarre and Montanari, 2009; Ravazzani et al., 2016). *NSE* efficiency metric must always be associated with other metrics specially built to assess peak discharge such as the $\mathcal{E}_p$ (Cane et al., 2013) and contingency tables

based on threshold peak discharges (Montesarchio, Lombardo and Napolitano, 2009).

Conclusions

This study evaluated the coupling method of numerical weather prediction – NWP and semi-distributed hydrological modelling to forecast runoff for a catchment (286 km²) in southern Brazil, considering different post-processing technique of rainfall. We have found coupling method was able to forecast runoff with a lead time of 24 hours in which the best post-processing technique of rainfall is the “poor man ensemble” between the 90th quantile sampling of BRAMS and the GFS product. Still, we acknowledge the major uncertainties in forecasting runoff arise from NWP rainfall estimates. Thus, the validation of NWP products must be done carefully to avoid the propagation of uncertainties through a flood forecasting system. Additionally, we advise a multi-criteria efficiency analysis to assess flood forecast reliability.

Further recommendations include: assess the impacts of post-processing techniques of rainfall predicted by NWP models in flood forecasting systems; increase the number of analyzed events comprising different water regime periods; perform flood forecasting with smaller lead times and spatiotemporal resolutions in order to identify small scale hydrological processes; and as much of the work done in hydrological modelling the need to measure more hydrological variables and parameters, in a larger coverage, should be addressed in future studies.

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