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Precipitation forecasts for rainfall runoff predictions. A case study in poorly gauged Ribb and Gumara catchments, upper Blue Nile, Ethiopia

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ABSTRACT

Flow forecasting in poorly gauged, flood-prone Ribb and Gumara sub-catchments of the Blue Nile was studied with the aim of testing the performance of Quantitative Precipitation Forecasts (QPFs). Four types of QPFs namely MM5 forecasts with a spatial resolution of 2 km; the Maximum, Mean and Minimum members (MaxEPS, MeanEPS and MinEPS where EPS stands for Ensemble Prediction System) of the fixed, low resolution (2.5 by 2.5 degrees) National Oceanic and Atmospheric Administration Global Forecast System (NOAA GFS) ensemble forecasts were used. Both the MM5 and the EPS were not calibrated (bias correction, downscaling (for EPS), etc.). In addition, zero forecasts assuming no rainfall in the coming days, and monthly average forecasts assuming average monthly rainfall in the coming days, were used. These rainfall forecasts were then used to drive the Hydrologic Engineering Center's–Hydrologic Modeling System, HEC–HMS, hydrologic model for flow predictions. The results show that flow predictions using MaxEPS and MM5 precipitation forecasts over-predicted the peak flow for most of the seven events analyzed, whereas under-predicted peak flow was found using zero- and monthly average rainfall. The comparison of observed and predicted flow hydrographs shows that MM5, MaxEPS and MeanEPS precipitation forecasts were able to capture the rainfall signal that caused peak flows. Flow predictions based on MaxEPS and MeanEPS gave results that were quantitatively close to the observed flow for most events, whereas flow predictions based on MM5 resulted in large overestimations for some events. In follow-up research for this particular case study, calibration of the MM5 model will be performed. The overall analysis shows that freely available atmospheric forecasting products can provide additional information on upcoming rainfall and peak flow events in areas where only base-line forecasts such as no-rainfall or climatology are available.

1. Introduction

Flow forecasting involves the process of using observed and, if required, forecasted rainfall over a catchment as input to a hydrologic model to determine the outflow at a given location. The quality of flow forecasts or flood forecasts depends to a high degree on the quality of the rainfall input (Hapuarachi et al., 2011). This can be achieved from continuous rainfall measurements on sub-daily or hourly basis, from sufficient number of rainfall gauging stations over the area of application. Unfortunately, this is not always the case in many developing countries including Ethiopia, where such an observation network is yet to be developed. For example, the catchments discussed in this study are poorly gauged and in some cases the daily time series data from the gauging stations may even exhibit significant gaps. According to some Global Climate Models (GCMs) there will be an increase in June-July–August (JJA) precipitation in east Africa (IPCC AR4 report, 2007). Therefore, with the possible increase in risk of flooding in the Nile basin that comes with the increase in precipitation, additional information sources have to be found to support flow forecasting further to serve local public with proper early warning systems.

Flow forecasts for 2 or 3 days are referred to as medium (or short) term forecasts in flood early warning systems (Cloke and Pappenberger, 2009). These forecasts can be obtained either by channel routing or by simulating processes that transform rainfall into runoff; the former being simpler than the later (Collischonn et al., 2004). Nevertheless, forecasting based on rainfall runoff transformation is essential whenever the required lead time is significantly longer than the time taken to route flow along the river channel (Lettenmaier and Wood, 1993).

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Estimate of future rainfall is always required in flow forecasting when the forecast lead time is greater than the sum of the time of concentration and time of flood propagation in a catchment (Collischonn et al., 2004). The estimate of future precipitation during this lead-time can be obtained by different techniques, for example, by using Quantitative Precipitation Forecasts (QPFs) from Numerical Weather Prediction (NWP) models. If no other information is available, assuming no further precipitation over the area (Zero forecasts) or monthly average rainfall for the coming days can be used.

NWP is based on computer models that simulate processes affecting the weather in atmosphere, land surfaces and oceans (Kimura, 2002). The forecasts from global NWP models can be further downscaled to the local condition by feeding them as a boundary condition to Limited Area Models (LAMs). These models are able to account for local topography of the area and to produce more accurate rainfall forecasts especially when local precipitation is dependent on topographic features or orographic effects (Brown et al., 2008).

The use of QPFs from NWPs to extend the lead time of flow forecasts has been applied in many studies (Collischonn et al., 2004, 2007; Rabuffetti et al., 2009). Using QPF rainfall forecasts in flow prediction brings the uncertainities from NWP models into view. One such source of uncertainity from NWP in predicting atmospheric circulation is the high sensitivity to the initial conditions, because of the non-linear characteristics of the governing equations (Kimura, 2002). In addition, for flow forecasting in poorly gauged catchments, like those in this study, the availability of well calibrated and validated hydrologic models will be limited, adding further to the uncertainty of the results.

This study evaluates the performance of QPFs in the context of flow forecasting of two poorly gauged catchments in Ethiopia where the flow forecasting is ultimately intended to be used in flood early warning. The performance of QPFs was analyzed indirectly by comparison between observed and predicted flow hydrographs. This is done for several observed peak flow events in the study area.

1.1. Study area and data

The study area comprises the Ribb and Gumara catchments located to the east of Lake Tana, upper Blue Nile, Ethiopia. The eastern part of Ribb and Gumara catchments is bordered by Farta plateau that ranges from 2400 m to 4000 m as shown in Fig. 1. The Ribb and Gumara rivers originate from these mountainous areas and finally attain a gentle slope in the Fogera flood plains near Lake Tana. The flood carrying capacity of the river reaches being very small, results in the inundation of the Fogera flood plain by Ribb and Gumara rivers during heavy rainfall.

The total catchment area of Ribb and Gumara Rivers is respectively 1790 km^2 and 1500 km^2. The total length of Ribb river is 105 km and that of Gumara is 96 km. Gumara River has a higher discharge with the average and maximum being 35 m^3/s and 297 m^3/s, respectively. The average and maximum flow in Ribb River are 14 m^3/s and 102 m^3/s, respectively.

Daily rainfall and flow data of 2000–2006 was obtained from gauging stations in and around the catchments. The data was limited to these years because in previous years, data series exhibits significant gaps that mainly occur during the rainy season. In addition at the time of this study recent data from 2007 to 2010 was not available from the Ethiopian Meteorological Agency. As indicated by Fig. 1, the Ribb and Gumara are poorly gauged catchments with very few rainfall and flow gauging stations. There are only two rainfall gauging stations located in the Ribb catchment. As to the Gumara catchment, it is literally ungauged with regards to rainfall measurement. It was therefore necessary to use other stations located near Ribb and Gumara catchments to estimate the areal rainfall.

Gaps due to missing data are also very common in the data collected from the gauging stations in this study. In practice closely located stations can be used to fill the missing data in neighboring stations. However, since in this study the missing data in most stations occur in overlapping periods, two different techniques were applied to fulfill this purpose. First the correlation between the rainfall gauging stations found inside and near the catchment was compared with two other gauging stations (Bahir Dar and Gonder) located further away from the catchments but with more complete data set. This resulted in daily correlations ranging from 0.13 to 0.38 between Bahir Dar and Gonder and the study area gauging stations. As a second alternative the correlation between these stations and Tropical Rainfall Measuring Mission (TRMM) datasets of 0.25 by 0.25 degree resolution from National Aeronautics and Space Administration (NASA) was also analyzed. This gave daily correlation values ranging from 0.36 to 0.41 between TRMM and the study area gauging stations. Therefore TRMM datasets were used to fill missing data. This was done by assigning values from TRMM datasets for the corresponding days where data is missing in the ground station rainfall time series.

1.2. Hydrologic model

The hydrologic model for the flow prediction was constructed using the Hydrologic Engineering Center's Hydrologic Modeling System (HEC–HMS) developed by the US Army Corps of Engineers (http://www.hec.usace.army.mil/software/hec-hms/). The model was then calibrated and validated separately for Ribb and Gumara catchments. Each of these two catchments was first divided into three sub-basins by using Arc-GIS and HEC-GeoHMS (Geospatial Hydrologic Modeling Extension). Both catchments were divided into three sub-basins following the confluence points of major river branches of the Ribb and Gumara catchments as shown in Fig. 1. Then initial estimates of hydrologic parameters were produced using HEC-GeoHMS. The Soil Moisture Accounting (SMA) method of HEC–HMS was used to describe the different processes that convert the precipitation falling on the catchment into runoff. The reason to choose SMA loss model is because it is suitable for simulation of the long term (wet and dry periods) relationship between rainfall and runoff (Feldman, 2000). Due to lack of cross-sectional and morphological data, the Clark unit hydrograph and the Muskingum channel routing methods were used to describe the runoff transformation and routing process. The linear reservoir model was used to describe the base-flow component of the runoff. This model has been suggested to be suitable to go together with SMA loss model (Feldman, 2000). The Thiessen polygon method was used to derive the gauge weights that convert the point rainfall from the gauging stations into areal rainfall.

The model was calibrated using data of 4 years from January 1, 2000 to December 31, 2003. The validation of the model made use of another 2 years data from January 1, 2004 to December 31, 2005. We were limited with these periods due to the observed data limitation we had. Although these periods are short we have encountered works done with short calibration and validation periods that gave acceptable results (Wallner et al., 2012). The calibration procedure followed automatic calibration proceeded by considerable manual calibration. For the automatic calibration the Peak Weighted Root Mean Squared Error (PWRMSE) and Volume Percent Error (VPE) objective functions from HEC optimization manager were used. To minimize these objective functions the Univariate Gradient (UG) search algorithm of HEC–HMS was used. In addition the Root Mean Squared Error (RMSE), Normalized RMSE (NRMSE), Nash–Sutcliffe Coefficient (NSC) and Coefficient of determination (R^2) were also used as external measures of performance.