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Revisiting Systems Type Black-Box Rainfall-Runoff Models for Flow Forecasting Application

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Abstract

Often we tend to spend huge amount of time and resources to setup and use complex hydrological models for simple goal of flow estimation. Running complex models becomes even more difficult when the amount of available data is scarce as we usually face in many parts of Africa. The aim of this study is to evaluate and revitalize the systems type black box model against complex hydrological models for easy flow estimation application. Six systems type black box models, the Simple Linear Model (SLM), Non-Parametric Simple Linear Model (NP-SLM), Linear Perturbation Model (LPM), Non-Parametric Linear Perturbation Model (NP-LPM) and Linearly Varying Gain Factor Model (LVGFM), a non-linear black box type artificial Neural Network model (ANN) are compared with three complex hydrological models of those under SMAR, HBV and SWAT. The models are compared based on daily rainfall and stream flow data (1980-2000) on Gilgel Abbay watershed. Event-based analysis was also conducted using 100 selected runoff events. In terms of the event rainfall-runoff relationship, it was indicated that the event runoff is largely a function of the amount of rainfall. The event rainfall-runoff relationships explained as much as 62% for the wet periods without the integration of the evaporating demands. Although rainfall intensity, duration and catchment characteristics play a role, in this watershed, rainfall amount affects substantial part of the runoff response consolidating that a simple rainfall-runoff relationship can describe the runoff in this watershed. Comparison of systems type black box and complex hydrological models in the study area indicates that the LPM and the ANN models perform better than the complex hydrological models such as SMARG, HBV and SWAT in terms of R^2 and Nash Sutcliffe Efficiency (NSE) criteria. This confirms that simpler models (that take only rainfall as input) can surpass their complex counterparts in performance for continuous simulation and reproducing the

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hydrographs or flow estimation. There is a strong justification, therefore, for the claim that increasing the model complexity, thereby increasing the number of parameters, does not necessarily enhance the model performance. It is suggested that, in practical hydrology, the simpler models, may still play a significant role as effective simulation tools, and countries with scarce hydrological data should revitalize application of such systems type black box modelling schemes that depend only on rainfall and runoff data sets which could be easily available.

Keywords

Black Box Models, Distributed Models, Rainfall-Runoff Relationships, Event

1. Introduction

Rainfall-runoff relationships are complicated processes which may be highly non-linear and exhibit both temporal and spatial variations. Understanding their relationship is essential for practical basin management practices. Several hydrological models have been developed to simulate rainfall-runoff relationships across the world [1]. These can be classified as empirical black box models, conceptual and physically based distributed models [1]. Black box models are empirical, involving mathematical equations that have been assessed, not from the physical processes in the catchment, but from analysis of concurrent input and output time series. Conceptual (lumped) models treat the catchment as a single unit, with state variables that represent average values over the catchment area, such as storage in the saturated zone. Another approach to hydrological processes modeling is the attempt to construct models based on the governing equations describing all the surface and subsurface flow processes in the catchment called physically distributed models. Each of these types of models has their own advantages and limitations [1]. For instance, in areas where getting sufficient hydro-meteorological data are problematic or the purpose of hydrological modeling is limited to flow estimation, applications of linear systems theoretic models (black box models) are inevitably important for water related development. However, to choose between the various available hydrological models to suit a practical demand and find the most appropriate model for the specified basin is a big challenge. Many models are in practice simple linear system theoretic models (black box models) [1] which do often not represent the non-linear dynamics, which are inherent in the process of rainfall-runoff transformation.

[2] and [3] observed that the rainfall information alone is not sufficient to calculate the runoff from a catchment as the initial state (such as amount of soil moisture and orographic features) of the catchment plays an important role in determining the runoff rate behavior. The rainfall-runoff relationship in mountainous regions is influenced by the steep gradient profiles (*i.e.* inter flow and sheet flow) and less influenced by soil composition [4]. Nevertheless, soil composition in less steep environment plays a major role in runoff generation due to the presence of very to moderately drained soils [4]-[7]. Therefore, higher streamflows and runoff coefficients (R/P, where R is runoff and P precipitation) are usually associated with mountainous area [8], while smaller R/P ratios are expected for low-topographic gradient watersheds [8]-[10] argue that runoff in lower land plain watersheds have a much larger variability than upland watersheds because of a wider range of variable source areas, including ephemeral water storage in depressions in a low gradient terrain.

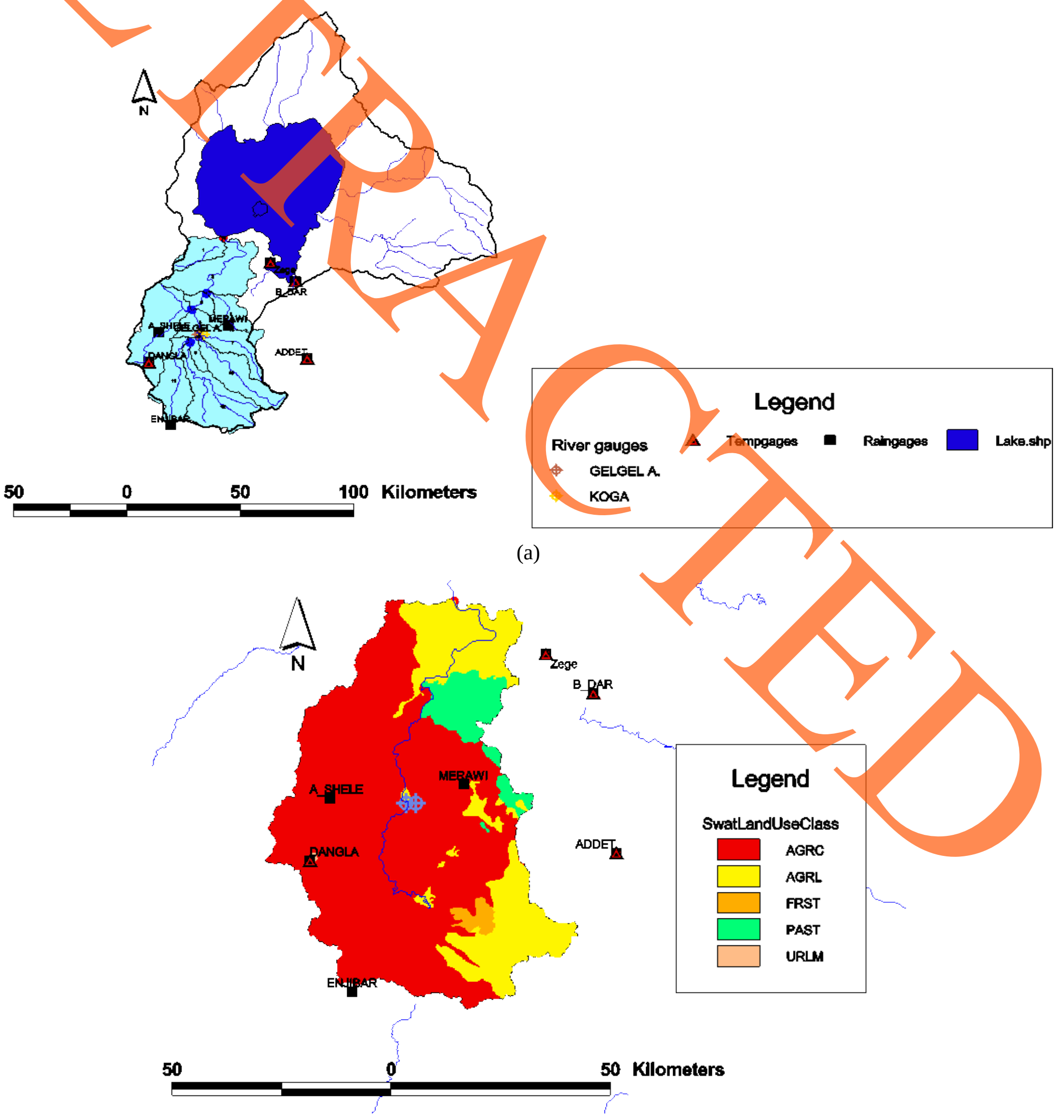
Evapotranspiration is another factor that affects the hydrological processes of the watershed in shallow water tables [11]. It is mainly influenced by humidity gradients, solar energy, wind speed, soil properties and vegetation type [12] [13]. Other studies have found that depending on the soil moisture status, lowland watersheds were highly responsive to rainfall by producing more frequent and greater amounts of runoff, with peak flow rates also depending on the surface depressional storage [8]. Furthermore, some rainfall-runoff simulation models have demonstrated that the degree of water saturation in the soil prior to a precipitation event (the antecedent soil moisture condition, AMSC) correlates with the portioning of the event rainfall into infiltration and stream flow [14]-[16].

Seasonal climate variability affects both the soil moisture and the characteristics of the storm events that in turn affect the runoff generation pattern [11]. Some of these characteristics are rainfall intensity, frequency, duration, and direction [17]. Although the antecedence soil moisture condition of the watershed influences water available for runoff, evapotranspiration and infiltration via soil water storage, it is highly variable and difficult to measure [18].

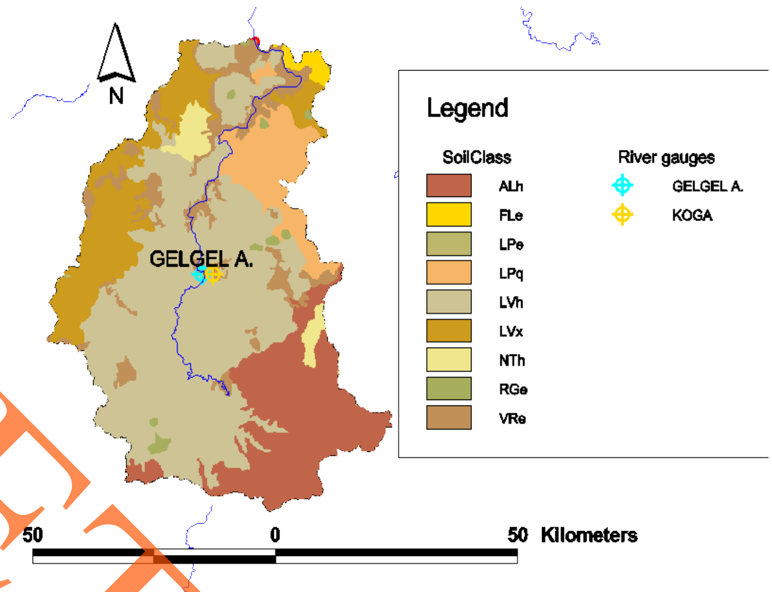
The main objective of this study is to evaluate the performance of nine rainfall-runoff models (from simple to complex) whether model complexity is important for flow estimation in the context of data scarce areas in Africa. There is a tendency to use complex models such as SWAT for simple purpose of flow estimation in many African watersheds. The amount of spatial and temporal data sets required to calibrate complex models such as SWAT doesn't warranty the purpose if the purpose of the modeling is simply to estimate flow for water resources development application. Therefore, this study attempts to revitalize application of simple rainfall-runoff hydrological models for use in water resources application. The study is conducted on Gilgel Abbay catchment of Blue Nile basin (Ethiopia) using 21 years (1980-2000) historical data of daily rainfall, temperature and stream flow. Finally we compare the results from the individual rainfall-runoff models with several methods of combining the outputs to investigate if there is added value in making ensemble means.

2. The Study Area

The Gilgel Abbay catchment (4051 km^2) is one of the largest among the four main sub-catchments in Lake Tana sub basin of the upper Blue Nile basin, Ethiopia (**Figure 1**), providing about 60% of the lake inflow. It is located



(b)



(c)

Figure 1. (a) Distribution of meteorological stations and gauging station, (b) land use and (c) soil map in the Gilgel Abbay catchment.

at 10˚44'N latitude and 37˚23'E longitude. The catchment includes the two gauged sub-basins; Upper Gilgel Abbay (1664 km^2) and Koga (307 km^2), see **Figure 1**, with elevation ranging from 1787 m to 3518 m. The topography is rugged in the southern part of the catchment and the periphery to the west and southeast, while the remaining part is a typical plateau with gentle slopes. The soil is dominated by clays and clay loams (**Figure 1(c)**). The dominant land use units are agricultural (65%) and agro-pastoral land (33%) [19], among this rainfed agriculture is the predominant cover of the Upper Gilgel Abbay (74%) and Koga (64%) sub-catchments (**Figure 1(b)**).

Upper Gilgel Abbay has its main rainy season between June and September, receiving about 70% to 90% of the annual rainfall during this season [20]-[22]. Annual area average rainfall (1964-2005) ranged from 834 to 2106 mm, with July representing the wettest month (356 mm) and January representing the driest month (3 mm) on average. Rainfall observations indicate significant spatial variability in rainfall following the topography, with decreasing amounts from south to north. Long-term (1980-2000) minimum and maximum annual air temperature values recorded at Merawi (2020 m.as.l.) and Dangla (2180 m.as.l.) stations ranged from 11˚C to 37.7˚C, respectively with temporal temperature variations being small throughout the year [19].

3. Data Assessments and Method

3.1. Historical Data

We used daily rainfall and temperature data (1980-2000) from seven and four stations, respectively (**Figure 1(a)**). Daily Stream flow data for Gilgel Abbay is taken from the then Ministry of Water and Energy (now Ministry of Water, Irrigation and Electricity). The meteorological data of rainfall and temperature is obtained from National Meteorological Agency (NMA). Missing values in rainfall and temperature were treated using the SWAT built-in weather generator developed by [23]. The daily area representative precipitation was calculated using thiessen polygon method.

3.2. Event Selection

We selected storm events based on discharge rates greater than 1.84 m^3/s (minimum mean discharge separated from base flow per day),where the base flow is calculated by using variable storage method, total mean daily area averaged rainfall values greater than 2.3 mm; and a period of 48 hours or more in between rain events (**Table 1**). A rain event is defined as the rainfall amount which contributes runoff event in a period of 48 hours [11]. These criteria were selected to identify detectable single peak events and minimize influence of prior rainfall on

Table 1. Basic hydrological characteristics for analyzed runoff events (n = 100) and t-test results calculated for peak rate, runoff, rainfall, R/P, rain previous 5- and 30-days, SD = standard deviation.

Date	Begin flow (m^3/s)	Rain in mm	Runoff (mm)	R/P	Q peak	Rain 5-day	Rain 30-day
11-Feb-80	0.45	4.4	0.363	0.08	7.001	0.00	4.4
17-Apr-80	0.00	37.5	0.531	0.01	6.17	12.20	16.1
22-Jul-80	96.90	167.3	19.83	0.12	412.617	40.4	309
8-Aug-80	44.63	149.9	16.72	0.11	321.92	41.4	350.5
8-Oct-80	11.92	34	3.53	0.10	93.251	27.1	106.8
9-Jun-81	4.22	17	1.43	0.08	49.143	16	57.2
19-Aug-81	0.48	154.7	17.14	0.11	330.124	40.1	546.4
13-Sep-81	46.39	54.21	11.62	0.21	239.536	28.2	183.01
3-Oct-81	21.58	60.6	8.88	0.15	171.042	2.9	119.51
25-Nov-81	1.68	5.7	0.569	0.10	18.932	0.20	8
5-Jan-82	0.21	19.9	0.320	0.02	6.44	0.00	19.9
20-Aug-82	13.69	141.8	14.68	0.10	282.703	68.2	342.9
8-Sep-82	23.73	71.7	9.89	0.14	230.509	35.1	269.5
12-Oct-82	32.34	39	5.41	0.14	104.096	8.5	117.8
11-Mar-83	0.11	3.32	0.53	0.16	12.112	1.21	3.32
18-Jun-83	6.03	50.6	3.15	0.06	60.661	6.4	68.9
17-Jul-83	45.14	78.6	12.68	0.16	248.767	25.9	151.9
23-Aug-83	42.88	185.6	16.86	0.09	324.641	95.9	478.5
21-Mar-84	0.10	10	0.142	0.01	3.256	0.50	11.6
31-May-84	4.13	42.91	2.94	0.07	56.664	20.7	57.31
12-Jul-84	51.74	116	13.91	0.12	267.847	28.7	412.8
8-Aug-84	19.15	146.3	13.78	0.09	330.124	60.1	378.6
11-Sep-84	11.57	113.4	13.66	0.12	263	25.1	258.6
27-Mar-85	0.00	12.6	0.199	0.02	3.833	0.00	12.6
8-Sep-85	25.80	114.21	13.16	0.12	253.46	29.4	302.6
12-Nov-85	0.89	10.6	0.531	0.05	13.335	0.00	50.2
5-Apr-86	0.25	74.6	0.142	0.00	2.733	3.30	19.5
14-Jun-86	14.80	40.2	2.37	0.06	62.72	31.1	61.4
17-Jul-86	21.41	85.3	7.76	0.09	241.825	55.9	264.3
17-Aug-86	26.06	92	10.63	0.12	230.509	29.4	276.9
22-Oct-86	5.61	28.2	2.37	0.08	142.6	21.1	76.6
20-Nov-86	1.17	17.1	0.589	0.03	16.46	0.00	17.1
14-Jan-87	0.14	3.2	0.199	0.06	5.157	3.20	3.2
5-Mar-87	0.10	44.2	0.320	0.01	3.635	0.00	0
29-Apr-87	0.43	13.2	0.232	0.02	4.466	0.00	27.7
14-Jun-87	31.11	82.5	7.49	0.09	144.289	46.4	147.5
1-Jul-87	41.68	89.1	7.49	0.08	253.46	46.7	172.5
19-Aug-87	25.90	127.2	11.97	0.09	234.997	34.2	264.9
15-Sep-87	53.33	73.4	12.20	0.17	234.997	46.8	224.7
24-Feb-88	0.17	25.6	0.268	0.01	5.157	0.00	30.3
12-Apr-88	0.08	2.3	0.096	0.04	2.118	0.00	2.3
12-Aug-88	46.81	107.4	14.42	0.13	277.699	32.4	357.5

Continued

11-Sep-88	11.95	83.8	10.84	0.13	219.511	47.6	235.9
9-Oct-88	3.62	98.2	5.55	0.06	140.922	51	197.4
13-Mar-89	0.00	16.6	0.255	0.02	3.442	0.00	2.8
17-Jul-89	27.75	97.4	19.83	0.20	406.365	62.8	161.9
13-Aug-89	17.98	137.3	16.30	0.12	438.188	54.2	441.6
7-Sep-89	25.72	62.6	12.09	0.19	234.997	28.4	226.7
7-Nov-89	4.23	7.8	0.930	0.12	26.332	3.10	6.7
15-Mar-90	0.20	18.9	0.133	0.01	2.901	12.80	19.9
14-Jun-90	0.35	9.9	0.96	0.10	90.648	0.8	24.1
22-Jul-90	38.67	136.3	11.29	0.08	248.767	55.7	255.8
13-Sep-90	20.90	70.1	8.03	0.11	277.699	26.3	171
7-Oct-90	22.55	54.2	4.57	0.08	121.692	2.3	133.9
11-Aug-91	23.44	155.3	16.86	0.11	341.251	62.6	416
22-Sep-91	13.15	110.7	12.68	0.11	352.596	83	265.4
6-Oct-91	7.55	79.9	4.57	0.06	101.319	55.6	254.1
12-May-92	0.16	13.7	2.28	0.17	43.911	13.7	152.4
7-Jul-92	56.32	80	10.41	0.13	200.503	15.6	93.4
14-Oct-92	13.94	72.2	7.85	0.11	151.163	36.5	183.4
8-Nov-92	6.89	49.7	4.443	0.09	85.573	6.10	75.9
7-Dec-92	2.00	17.9	0.671	0.04	19.451	0.00	20.6
5-Sep-93	18.47	121.2	19.83	0.16	381.915	74.8	198.3
9-Oct-93	49.80	73.9	10.41	0.14	200.503	23.2	136.3
7-Nov-93	8.98	75.3	1.867	0.02	40.613	0.00	38.7
27-Feb-94	0.21	20.4	0.210	0.01	4.038	20.40	20.4
11-Aug-94	32.74	72.5	16.02	0.22	308.515	17.5	333.7
5-Oct-94	9.75	17.3	1.83	0.11	44.759	4.2	85.2
10-Dec-94	1.51	3.8	0.609	0.16	11.72	0.00	13
25-May-95	0.15	15.5	1.79	0.12	66.96	13.1	76.7
7-Jun-95	26.23	92	6.81	0.07	131.1	32.1	148.5
7-Sep-95	0.00	77.3	9.58	0.12	290.308	14.1	278
17-Oct-95	3.00	33.8	1.94	0.06	50.964	33.8	90.9
3-Nov-95	2.72	17.2	1.122	0.07	21.609	1.50	18.7
23-Jan-96	0.43	6.2	0.199	0.03	4.69	0.00	6.2
3-Feb-96	0.44	2.5	0.125	0.05	3.076	0.00	2.5
6-Jun-96	5.18	57.4	5.19	0.09	190.377	35.1	224.2
3-Aug-96	60.60	124	16.72	0.13	355.466	38.1	324.7
11-Sep-96	18.51	135.8	11.51	0.08	253.46	31.2	273.6
28-Nov-96	0.00	85.5	3.257	0.04	97.236	5.30	108.3
20-Jun-97	8.65	127.2	6.72	0.05	142.6	44.4	253.7
9-Jul-97	3.77	92	9.58	0.10	258.204	77.5	233.4
15-Aug-97	33.47	100.8	18.61	0.18	358.35	54.9	263.2
22-Sep-97	29.26	124.2	8.78	0.07	202.565	59.5	180.1
4-Aug-98	20.95	146.5	14.16	0.10	298.031	42.7	358.1
6-Sep-98	47.86	90.1	10.63	0.12	241.825	27.7	227

Continued

12-Oct-98	28.68	154.5	11.51	0.07	221.685	72.5	269.31
5-Jan-99	0.38	26.3	0.221	0.01	4.466	0.00	26.3
27-Apr-99	0.00	14.6	0.379	0.03	7.291	12.30	16.5
12-Jun-99	16.60	137.3	6.32	0.05	174.812	38.9	127.21
11-Jul-99	19.92	126.2	12.80	0.10	285.225	43.2	188.9
30-Aug-99	20.56	115.3	14.29	0.12	298.031	60.1	264.6
5-Sep-99	18.44	120.9	9.78	0.08	190.377	33.9	260.9
4-Oct-99	36.74	83.8	9.58	0.11	234.997	29.1	140.8
20-Nov-99	3.43	26.6	1.151	0.04	40.613	0.00	26.6
11-Dec-99	1.57	3.3	0.629	0.19	12.112	0.60	16.4
23-Jul-00	14.51	83.7	11.29	0.13	223.872	62.6	255.5
17-Aug-00	26.63	154.5	19.83	0.13	381.915	56.1	314.6
10-Oct-00	15.02	91.1	10.30	0.11	251.107	46.7	179.1
14-Dec-00	2.04	7.11	0.550	0.08	13.335	0.00	9.11
Mean		69.77	7.18	0.09	157.80	26.90	159.12
Median		72.95	6.77	0.09	147.73	26.70	148.00
Standard Deviation		49.76	6.21	0.05	128.55	24.00	131.89
Skewness		0.28	0.39	0.20	0.25	0.58	0.57
Range		183.30	19.73	0.22	436.07	95.90	546.40
Minimum		2.30	0.10	0.00	2.12	0.00	0.00
Maximum		185.60	19.83	0.22	438.19	95.90	546.40
Confidence interval (95.0%)		9.87	1.23	0.01	25.51	4.76	26.17

several peaks. Multiple peak events were excluded from this analysis in order not to complicate the identification of storm duration and total storm volume. The same method was used by [7] [8] [24]-[26]. Single event peak discharge can be modeled easier as described by [27]. The start of the runoff event is the rainfall available for runoff after infiltration and other abstractions have been accounted for.

The antecedent precipitation index (API) was calculated as a measure of the available soil moisture content (ASMC):

$$API_t = P_t + \sum_{i=1}^{N} K_{t-i} API_{t-i} \tag{1}$$

where P_t is the area averaged precipitation at day *t*, *N* the number of days prior to the start of the runoff event and K_t is the recession constant calculated as the product for three individual constants, *i.e.* $K = K_s * K_i * K_g$ where K_s = 1.0, K_j = 0.43 and K_g = 1.33 are recession constants associated with surface storage, inflow and ground water flow respectively.

Total event runoff volume is calculated by dividing the daily runoff by the watershed area to obtain runoff depth in mm. The runoff volume was considered to be the area under the hydrograph from the start of the event (defined above) until it reaches base flow level or until the next rise starts. Using the above definition of an event, the average duration of the storm events was 12 days. Since the rainfall data was in daily basis, there was sometimes challenge to identify an exact amount of rainfall amounts resulting in a particular runoff event. The begin flow for each event was calculated as the flow at which direct runoff starts. R/P was calculated using the accumulated runoff amount and corresponding accumulated area averaged rainfall over the runoff event.

Based on the above criteria, we selected 100 storm events with various parameters showing the hydrologic characteristic of the study area (**Table 1**) [11]. Used 51 storms for only a 10-year (1964-1973) period that included events with multiple peaks also. In other studies [25] used 75 events, [28] used 29 events, [7] used 23 events, [26] used 4 - 9 events for each watershed, and [24] used 55 storm events for various study areas. We, therefore, believe that analysis of 100 storm events is adequate for testing event based rainfall runoff relationship.

3.3. Regression Analysis

A simple linear regression analysis was used to determine the relationship between runoff and other variables. Equations of the linear regression lines and their parameters were tested for statistical significance at the 5% level (α = 0.05) using a two-tailed t-test. In addition, a standard stepwise regression analysis was used to examine the effects of different factors on the runoff.

3.4. The Galway River Flow Forecasting System (GFMFS)

The Galway Flow Modeling Forecasting System (GFMFS) is software packages developed at Department of Engineering Hydrology, National University of Ireland, Galway [29]. A brief descriptions of the GFMFS software package may be found in [30]-[44]. The GFMFS models may be run in *updating* mode or *simulation* mode, depending on the choice of model. In *updating* mode the models use the lagged observed discharge along with precipitation input to simulate the streamflow simulation hydrograph to the corresponding observed hydrograph. In contrast, non-updating (*simulation*) mode uses the input of precipitation and excluding the use of the recently observed discharge as model inputs.

The five major hydrological applications of the GFMFS packages are 1) Modeling by calibration and validation for simulation of continuous river flow, 2) Estimation of river flow *i.e.* generation of synthetic flow series, using inflow data and a calibration model. 3) Modeling by calibration and verification, for lead-time forecasting in absence of QPF (quantitative precipitation forecasts), 4) Modeling by calibration and verification, for lead-time forecasting using QPFs, 5) Real time flow forecasting using models and techniques chosen in step 1). and/or 3) or 4).

Modeling by calibration and validation for simulation of continuous river flow in step 1 was applied for this study. The models implemented in this study (from the GFMFS package) are six rainfall runoff models that depend only on rainfall and runoff relationships (single input) and one complex hydrological models that uses more than one rainfall input and several conceptual parameters in the model formulation. These models are the Simple Linear Model (SLM), Non-Parametric Simple Linear Model (NP-SLM), Linear Perturbation Model (LPM), Non-Parametric Linear Perturbation Model (NP-LPM) and Linearly Varying Gain Factor Model (LVGFM), a non-linear black box type artificial Neural Network model (ANN). The complex hydrological models accessed from GFMFS package include Soil Moisture Accounting and Routing Model conceptual model (SMAR, we tested the three variants, namely the SMARG, SMAR-NC1 and SMAR-NC2 versions, but only the SMARG is reported on here since the results were similar for the two other versions) (see **Table 2**).

3.5. Other Complex Hydrological Models

In addition to the above hydrological models we further apply a conceptual semi distributed (HBV) and a physically distributed (SWAT) model in the study. The HBV model [45]-[48] is a rainfall-runoff model, which includes conceptual numerical descriptions of hydrological processes at the catchment scale. The general water balance can be described as:

$$R_{day} - ET_a - Q_{surf} = \frac{\mathrm{d}}{\mathrm{d}t}\left[SW + W_{seep} + Q_{gw}\right] \tag{2}$$

where SW is the soil water content (mm), R_{day} is the daily precipitation, Q_{surf} is the amount of surface runoff/

Table 2. Descriptive statistics results the run off coefficient for R/P for wet and dry events and wet and dry conditions on both 5-day prior rainfall-values correspond to the significant difference in periods and conditions.

Parameters	n. (no. of events)	R/P ratio ranges	Mean R/P	SD (±)	COV	P-value
Wet period	69	0.05 - 0.22	0.11	0.04	0.34	0.25
Dry period	31	0.0 - 0.19	0.05	0.05	0.97	0.03
Wet condition (5-day prior)	73	0.0 - 0.22	0.1	0.05	0.44	0.01
Dry condition (5-day prior)	27	0.01 - 0.19	0.07	0.05	0.74	0.46

streamflow, ET_a is the amount of actual evapotranspiration, W_{seep} is the amount of water entering the vadose zone from the soil profile and Q_{gw} is the amount of ground flow.

The HBV model can be used as a semi-distributed model by dividing the catchment into sub basin. Each sub basin is then divided into zones according to altitudes and the elevation zones which are further divided into different vegetation zones (e.g. Lakes, forested and non-forested areas).

The model is normally run on daily values of rainfall and air temperature, and daily or monthly estimates of potential evaporation. Observed streamflow data were used for calibration of the model through optimizing the embedded parameters.

SWAT (Soil and Water Assessment tool, version SWAT2005) is a physically based, distributed parameter model which operates on daily time step and uses physiographical data such as elevation, land use and soil properties as well as meteorological data and, stream flow data for calibration. It is computationally efficient for use in large watersheds, and is capable of simulating the impact of land management practices [49].

The effects of spatial variations in topography, land use, soil and other characteristics of watershed hydrology is incorporated by dividing a basin into several sub-basins based on drainage areas of tributaries and is further divided the sub-basins into a number of hydrological response unit (HRUs) within each sub-basin, based on land cover and soils. Each HRU is assumed spatially uniform in terms of land use, soil, topography and climate. The subdivision of the watershed enables the model to reflect differences in evapotranspiration for various crops and soils. All model computations are performed at the HRUs level [50].

The fundamental hydrology of a watershed in SWAT is based on the following water balance equation [50].

$$\frac{\partial SW}{\partial t} = R_{day} - Q_{surf} - ET_a - W_{seep} - Q_{gw} \tag{3}$$

where SW is the soil water content (mm), R_{day} is the amount of precipitation on (mm), Q_{surf} is the amount of surface runoff/streamflow (mm), ET_a is the amount of actual evapotranspiration (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile (mm), and Q_{gw} is the amount of ground flow (mm). Detail descriptions of the different model components can be found in [51] [52]. Like HBV model SWAT used observed streamflow data for calibration purpose to optimize high to very high sensitive parameters.

Table 5 rank the models according to complexity from simple to complex. SLM is the simplest followed by the LPM in their non-parametric and parametric forms and the LVGFM. Non parametric and parametric assume the observations must be independent, the observations in non-parametric forms must be drawn from normally distributed populations, these populations must have the same variances however in parametric form variable distributions have been.

The three models (SLM, LPM and LVGFM) are system-linear model in structure, and an ordinary least squares solution is used for estimation of the pulse response function except for the parametric forms where the parameters were optimised. HBV and SWAT models are the most complex with a complicated mathematical procedure to be processed during simulation.

3.6. Combination of Outputs

A particular rainfall-runoff model may have been selected from among a number of competing alternative models, based, perhaps, on its accuracy, its familiarity to the user, its ease of use, the type of the catchment, and the available data. However, there may be a potentially danger in relying entirely on one substantive rainfall-runoff model (a sample of one) since it is unlikely to perform satisfactorily at all time or under all conditions (e.g. perhaps not all of its structural assumptions are valid or the conditions under which it is assumed to operate are not entirely fulfilled. The method of combination of outputs from each of the model applied for the study area are carried out in the concept that the individual model assumed to capture some physical characteristics of the study area. We use three different methods of combining outputs (MOCT): The Simple Average Method (SAM), the Weighted Average Method (WAM), and the Neural Network Method (NNM).

3.6.1. The Simple Average Method (SAM)

The simple average method (SAM) is the simplest method of combining the outputs of different individual models. Given the estimated discharges from N rainfall-runoff models, a combined estimate of the discharge of the i^{th} time period, using the SAM, is given by

$$\hat{Q}_{Ci} = \frac{1}{N}\sum_{j=1}^{N}\hat{Q}_{ji} \tag{4}$$

where $\hat{Q}_{Ci}$: is the combined estimate of the discharge of the i^{th} time period, N is the number of rainfall runoff models and $\hat{Q}_{ji}$ the average simulate discharge for time period I from rainfall-runoff model j.

3.6.2. The Weighted Average Method (WAM)

When some of the individual models selected for combination appear to be consistently more accurate than others, in which case the use of the simple average method for combination can be quite inefficient [53], the use of a weighted average would be considered.

The weighted average method (WAM) for combining the estimated model outputs, in the case of N rainfall-runoff models, may be expressed as [54]

$$Q_i = \sum_{j=1}^{N} a_j\hat{Q}_{ji} + e_i \tag{5}$$

where Q_i is the combined discharge and a_j is the weight assigned to the j^{th} model estimated discharge. e_i is the combination error term.

The above equation may alternatively be expressed in matrix notation as

$$Q = PA + E \tag{6}$$

where P is the input matrix defined by

$$\begin{bmatrix} \bar{Q}_{1,1} & \bar{Q}_{2,1} & \cdots & \bar{Q}_{N-1,1} & \bar{Q}_{N,1} \\ \bar{Q}_{1,2} & \bar{Q}_{2,2} & \cdots & \bar{Q}_{N-1,2} & \bar{Q}_{N,2} \\ \vdots & \vdots & & \vdots & \vdots \\ \bar{Q}_{1,k-1} & \bar{Q}_{2,k-1} & \cdots & \bar{Q}_{N-1,k-1} & \bar{Q}_{N,k-1} \\ \bar{Q}_{1,k} & \bar{Q}_{2,k} & \cdots & \bar{Q}_{N-1,k} & \bar{Q}_{N,k} \end{bmatrix}$$

$Q = \left(Q_1, Q_2, Q_3, \cdots, Q_{k-1}, Q_k\right)^{\mathrm{T}}$ is the output vector, $A = \left(a_1, a_2, a_3, \cdots, a_{k-1}, a_k\right)$ is the weight vector and $E = \left(e_1, e_2, e_3, \cdots, e_{k-1}, e_k\right)$ is the combination error vector, T denotes the transpose of the vector and k is the total number of observations.

The preceding equation can be perceived as a multiple linear regression model. Thus, it can be readily shown that the ordinary least squares estimate of the weight vector is given by;

$$A = \left(P^{\mathrm{T}}P\right)^{-1}P^{\mathrm{T}}Q. \tag{7}$$

In the WAM, the sum of the weights a_i is normally constrained to be equal to unity, that is

$$\sum_{i=1}^{N} a_i = 1. \tag{8}$$

The main rationale behind constraining the sum of the weights to unity is that if the models included in the weighted average are unbiased, *i.e.* having a zero mean output error term, then the weighted average combined forecast is likewise unbiased [53].

In the case where the sum of the weights is constrained to equal unity, it can be shown using the method of constrained least squares (CLS) that the estimate of the weights vector

$$\bar{A}_{cls} \tag{9}$$

is given by

$$\bar{A}_{cls} = \left[p^{\mathrm{T}}P\right]^{-1}\left(p^{\mathrm{T}}Q + \frac{1}{2}b\lambda\right) \tag{10}$$

where b is the unit vector (*i.e.* all of its scalar components are unity) having the same dimension as the parameters vector A and λ is the Lagrangian multiplier which is given by

$$A = 2\left(b^{\mathrm{T}}\left(p^{\mathrm{T}}p\right)^{-1}b\right)^{-1}\left(1 - b^{\mathrm{T}}\left(p^{\mathrm{T}}p\right)^{-1}p^{\mathrm{T}}Q\right). \tag{11}$$

Alternative techniques, other than least squares, for estimating the weights a_i have also been used, e.g. by considering the covariance of the forecast errors of the individual models being considered.

3.6.3. The Neural Network Method (NNM)

The neural network method (NNM) provides an alternative to the simple average (SAM) and the weighted average methods (WAM) for combining outputs from different models. Neural networks are applied, in the GFMFS package, in the context of providing a non-linear function mapping of the simulated flows. Using a multi-layer feed forward neural network [44].

4. Results and Discussion

4.1. Relationship between Precipitation and Runoff

A linear regression analysis revealed a significant (α = 0.05) correspondence between mean event runoff and mean event rainfall (Table 2). The coefficient of determination (R^2) was 0.62 and 0.33 for the wet (69 events) or dry (31 events) (Table 3). A dry event is defined as an event where precipitation is zero the day before the event started. Figure 2(a) and Figure 2(b) shows the scatter plot between the mean event runoff and mean event rainfall for the wet and dry case. The average runoff coefficient (R/P) was 0.11 and 0.05 for the wet and dry events respectively. R/P ranged from 0.01 to 0.19 with a coefficient of variation (CV, which is the ratio of the standard deviation to the mean) of 0.97 for the dry events. This was almost three times higher than during the wet events. The higher relative variability observed during the dry period may be explained by the soil being close to saturation for the wet events, thus the relative variability between the different events will be small. Thus, event averaged precipitation is well correlated with event averaged runoff in the wet case, but not in the dry case. The mean monthly water balance plot for the study period for the Gilgel Abbay watershed shows the cycle of rainfall and runoff in relation to PET as estimated by the Penman Monteith method (Figure 3). A seasonal cycle is also seen in PET rates which start increasing in September and peaks during the months of March. The plot in Figure 3 suggests that the difference between rainfall and runoff is close to the PET values during the wet periods with unlimited soil moisture calculated for the watershed (Figure 3). Thus, it is important to examine alternative relationships that include other important variables, such as PET or water table depth as a surrogate for the ASMC, and their interactions for understanding rainfall-runoff dynamics.

4.2. Relationship between the Antecedent Precipitation Index (API) and Runoff

Using the precipitation information only on the day before the beginning of the event to classify the event into

Table 3. Regression statistics results for runoff-rainfall relationships for wet and dry periods, and wet and dry conditions based on 5 prior rainfall.

Parameters	Regression equation	r^2	P-value	Intercept (P-value)	Slope (P-value)
Wet period	Runoff = 1.853P + 25.265	0.62	0.0	0.16	0.0
Dry period	Runoff = 0.024P + 0.15	0.33	0.0	0.45	0.0
Wet conditions (5-day prior)	Runoff = 0.156P + 4.026	0.38	0.0	0.0	0.0
Dry conditions (5-day prior)	Runoff = 0.062P + 0.463	0.31	0.0	0.0	0.0

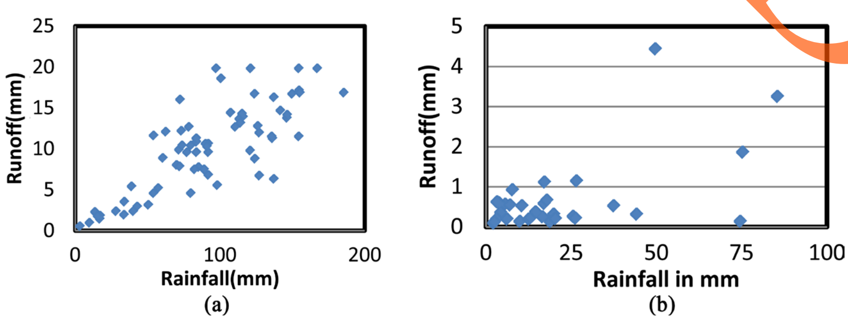


Figure 2. Event rainfall-runoff relationship for (a) wet (May-October = 69) and (b) dry (November-April = 31) periods.

wet and dry may means that we are not taking into account information about the soil moisture content prior to the event. A crude way of getting information about this is to use the API (Equation (3.1) to define wet and dry cases instead of the precipitation the day before the start of the event. **Table 3** shows the regression between the runoff and the 5-day API. API 5-day prior to event are correlated with event averaged runoff both for dry (27 events) and wet (73 events) cases. Results shows a significant ($R^2 = 0.38$) relationship between runoff and 5-day API ($R^2 = 0.38$ and $R^2 = 0.31$ for the wet and dry conditions, respectively, **Table 3** and **Figure 4**).

R/P is ranging from 0.01 to 0.22 for the 5-day wet conditions with a CV of 0.44 and a CV of 0.74 for the dry period with the ratios ranging from 0.01 to 0.19 (**Table 2**). These results suggested that seasonal event rainfall-runoff dynamics in the watershed may have been complicated due to other factors such as rainfall intensity and its aerial variability, spatial distribution (for watershed of this scale) of soil type and their properties, and depth to water table (*i.e.* soil water storage volume). These situations have been clearly examined through detail investigation of eight storm events among 100 ones.

Events selected either have very small or high R/P. For example, on day 17-Apr-80 a rainfall amount of 37.7 mm produced a runoff response of only 0.531 mm (R/P = 0.01), whereas for the storm event at day 2-Oct-94 17.3 mm produced 1.83 mm runoff (R/P = 0.11). The later event occurred directly following the return to base flow condition of the prior event and had a higher peak flow value, perhaps caused by surface runoff and shallow subsurface flow for a larger ASMC (already saturated conditions). For the event on day 17-Apr-80 with no previous rain 5 days prior, it is likely that the high ET rate during the dry period caused a large decrease in stream flow. Compare this with the event on day 2-Oct-94 where only 17.3 mm rain (5-day prior) produced a ratio of 0.11, whereas a ratio of 0.01 was generated for day 17-Apr-80 with no rain in the 5-day prior. Apparently the near-term soil moisture condition played a larger role in determining the runoff response during the dry period rather than a longer-term condition (30-day prior rainfall). The amount and rate of runoff will be dependent upon these key controlling factors (*i.e.* soil hydrologic properties, soil moisture storage, and rainfall) that vary spatially and temporarily [7]. However, we hypothesized that additional information on rainfall intensity, water table positions, and PET would help to more accurately determine the runoff and change in soil water storage processes.

4.3. Relationship between the Antecedent Precipitation Index (API) and Begin Flow

As described in Section 4.2 above, the equation of the simple linear regression model showed the 5-day API not significantly related to the begin flow during either the wet or dry period. Thus the 5-day API is unrelated to the begin flow as shown in **Table 4**.

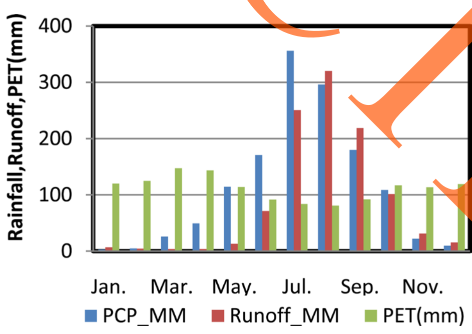


Figure 3. Mean monthly rainfall-runoff and PET for 1980-2000 period. PET was calculated using Penman monieth method.

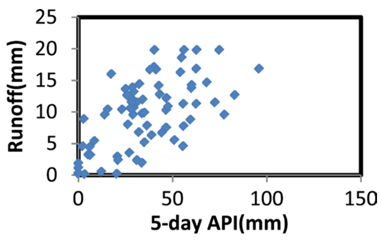


Figure 4. Rainfall-Runoff relationship for events wet (n = 73) based on 5-day API.

Table 4. Results of stepwise regression analysis evaluated for all rainfall events (n = 100), and wet and dry periods.

Variable	Begin flow	Rainfall	5-day rainfall
All storm events(n = 100)			
Runoff	$r^2 = 0.51$, P = 0.0	$r^2 = 0.76$, P = 0.0	$r^2 = 0.23$, P = 0.0
R/P	$r^2 = 0.26$, P = 0.0	$r^2 = 0.08$, P = 0.0	P > 0.07
Wet Period			
Runoff	$r^2 = 0.29$, P = 0.0	$r^2 = 0.62$, P = 0.0	$r^2 = 0.12$, P = 0.004
R/P	$r^2 = 0.09$, P = 0.01	P > 0.25	P > 0.69
Dry period			
Runoff	$r^2 = 0.41$, P = 0.0	$r^2 = 0.33$, P = 0.0	P > 0.57
R/P	P > 0.10	$r^2 = 0.13$, P = 0.05	P > 0.30

4.4. Multilinear Relationship between Begin Flow, API, Event Precipitation and Runoff

Results from the above analysis showed runoff was significantly related to rainfall amount and the API the initial flow rate (begin flow) (see Table 4). The 5-day API prior to the event had impact on runoff generation, but this was not strong. In the wet period, the runoff was correlated with initial flow due to previous rainfall condition and event rainfall amount. However, we did not find this was the case for the dry period at 5-day prior rainfall.

4.5. Model Results and Performance

In the above analysis we had seasonal relationship using event based analysis. From the result, it has been noted a big difference in relationship of rainfall runoff which are explained by various variables such as mean begin flow, API and soil moisture. The importance of doing simulation of various models in this section is that to derive the advantage of individual model outputs from their particular consideration of the study area. GFMFS software packages and other hydrological models have been applied to simulate rainfall-runoff relationship using observed daily rainfall and streamflow data for a period of 1980-2000.

The comparison among each model output is made using three evaluators: The coefficient of variation (R^2), the Nash Sutcliffe Efficiency (NSE) and the bias (simulation minus observations divided by the observations in %). The 1980-1992 data were used for model calibration and the remaining data from 1993-2000 used for validation.

4.5.1. Simulation Mode

The performance of the SLM is inferior to that of all other models. The LVGFM, which is a modification of the SLM, incorporating an element of linear variation of the gain factor (G_t, see appendix) with the catchment wetness index at each time step, performs consistently better than the SLM where the surface storage of the catchments might have affected the results. As Gilgel Abbay is characterized by strong seasonality, the LPM in simulation mode, with its inherent component of seasonal variation, outperforms the LVGFM and SLM. From Table 6 and Figures 5(a)-(i), we see that in simulation mode, the performance of the ANN model is clearly the best followed by LPM during calibration and validation with R^2 of 87.8% and 76.3%, respectively. This implicitly shows the non-linearity of rainfall-runoff relationships can be well be handled by systems type black box models without using complex conceptual or physically based models. The performance of the ANN model is R^2 89% and 85% during calibration and validation period, respectively. In the case of SMAR model, the parameters lumping applied to the study catchment which has diverse topographic variations may have influenced the performance of the model. Following LPM and ANN, the SMAR of SMARG variant explains the rainfall-evaporation-runoff relationships with 80.5% and 70.7% of R^2 during calibration and validation, respectively. As Table 5, the overall performance of the systems type black box models is comparable and in the case of ANN better than the conceptual or physically based hydrological models. Therefore, as far as estimation flow either in continuous or event based is concerned, systems type black box model with simple rainfall and runoff input can be adequate for water resources development purposes.

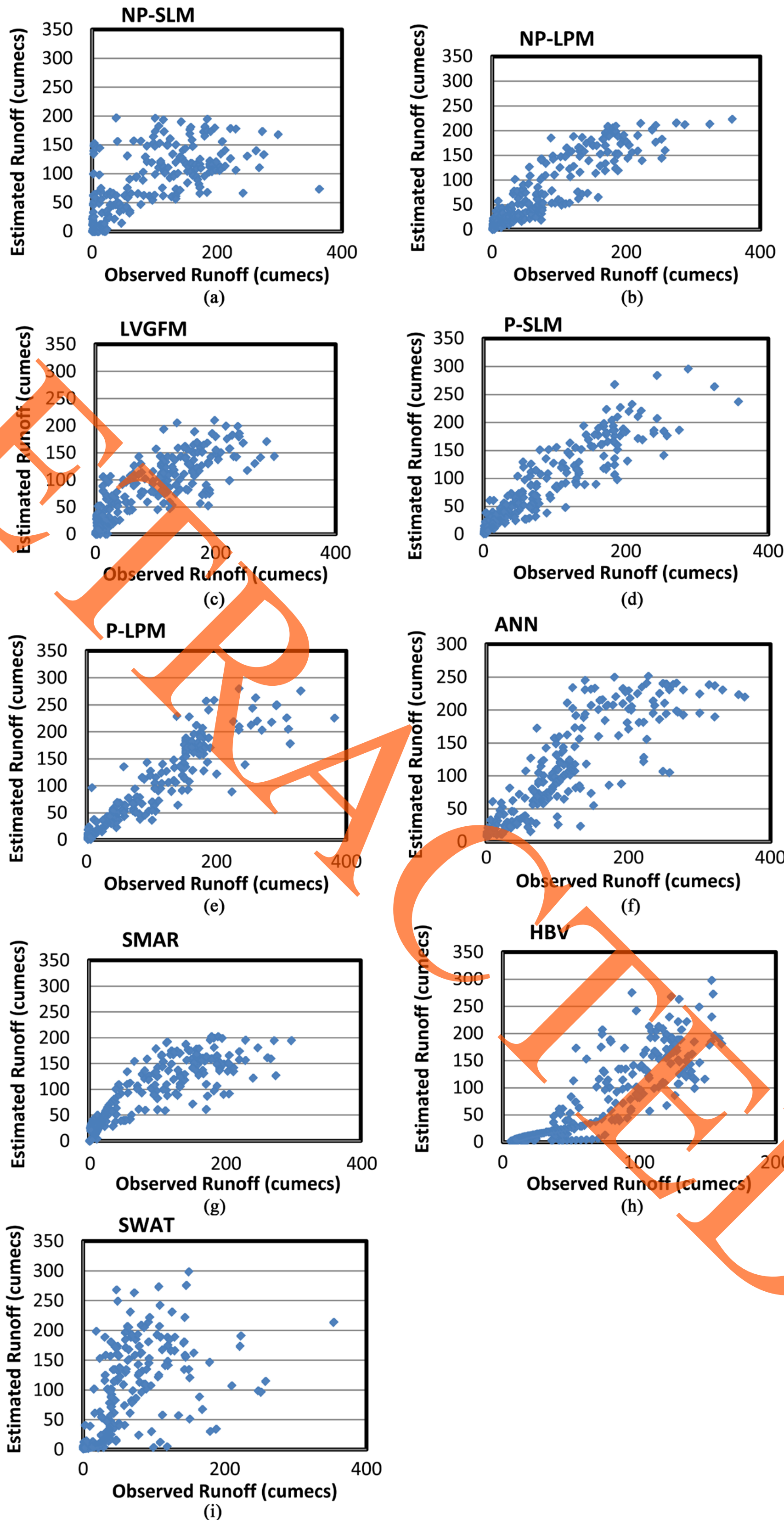


Figure 5. Scatter plots for various models [from (a) to (i)] for upper Gilgel Abbay river basin.

Table 5. List of models ranking from simple to complex in terms of increased mathematical procedures involved in the model to be processed.

Model	Type	Complexity ranking	mode	Description
NP-SLM	Empirical black-box	9	Simulation and non parametric	Non-parametric simple linear model. A linear time-invariant relationship between the total rainfall R_i and the total discharge
P-SLM	Empirical black-box	8	Simulation and parametric	Parametric simple linear model. The linear transfer function type representation of the transformation process of the input series to the output series for discrete data intervals
NP-LPM	Empirical black-box	7	Simulation and non parametric	Non-parametric linear perturbation model. The model uses the seasonal information of the observed rainfall and discharge series.
P-LPM	Empirical black-box	6	Simulation and non parametric	Parametric linear perturbation model. The linear transfer function type representation of the transformation process of the departures of the values of the input series from their respective seasonal means to the departure of the values of the output series from their respective seasonal means for discrete data intervals
LVGFM	Empirical black-box	5	Simulation and non parametric	Linearly varying gain factor model. The model is non-linear, can be viewed as a multiple linear regression model
ANN	Empirical black-box	4	Simulation	Artificial neural network model. The model is the multi-layer feed forward network consists of an input layer, an output layer and only one hidden layer between the input and the output layers.
SMAR	Physically inspired conceptual model	3	Simulation and non parametric	Soil moisture accounting and routing model. It is rainfall-evaporation-runoff model with three variants; SMARG, SMAR-NC1, SMAR-NC2
HBV	Conceptual model	2	Simulation	Hydrologiska Byrans Vattenbalans-Avedlning (Hydrological Bureau Water balance-section). It is considered as semi-distributed conceptual model and possible to run the mode separately for several sub basins and then add the contributions from all sub basins.
SWAT	Physical distributed model	1	Simulation	Soil and Water Assessment Tool. It is physically based distributed parameter model which operates on daily time step.

4.5.2. Updating Mode

In updating mode, LPM consistently performed the best of all other models. It accounted for more than 90% and 85% of the initial variance during calibration and validation period, respectively. Even, the simple models like P-SLM and P-LPM performs better than HBV and SWAT shown in Figures 5(a)-(i).

Generally, the updating models are better than the simulation mode models (with some exceptions) and the updating mode models has a lower reduction in R^2 and ENS in the validation period compared to the calibration period (Table 7).

4.5.3. Combining Outputs from Different Models

The method of combined outputs was used to the results of the five substantive models included in GFMFS software packages, both in simulation and updating mode. Three techniques for combining the estimated outputs of different models were conducted namely, the simple average method (SAM), the weighted average method (WAM) and the neural network method (NNM).

SAM, WAM and NNM account with R^2 values of 83.4, 90.4 and 90.42 percent during calibration and 79, 85.5 and 84.8 percent during validation period, respectively in simulation mode; and in the case of updating mode the values of R^2 are 90.2, 91.5 and 91.4 percent during calibration and 85, 85.3 and 85 percent during validation, respectively (Table 6 and Table 7). Therefore, combining the outputs of the systems type black box model has shown increased improvement in the accuracy of the results.

5. Summary and Conclusions

We believe application of complex conceptual or physically based models for simple flow estimation may not

Table 6. The model efficiencies (%) in simulation mode.

Model		Method	Calibration			Validation		
			R^2	Bias	ENS	R^2	Bias	ENS
NP-SLM		OLS	64.17	−7.81	0.65	51.00	−7.66	0.50
NP-LPM		OLS	86.94	0.02	0.87	77.98	−5.70	0.78
LVGFM		OLS	73.00	0.78	0.73	57.00	1.99	0.57
SMAR		OLS	80.49	−3.69	0.81	70.72	−4.44	0.71
ANN		OLS	89.70	2.35	0.90	85.00	3.44	0.85
HBV		Parametric	86.0	12.82	0.70	87.0	10.25	0.71
SWAT		Parametric	66.32	−0.02	0.62	59.4	−9.47	0.55
	SAM	Non-parametric		83.37			79.16	
MOCT	WAW	Non-parametric		90.41			85.53	
	NNM	Non-parametric		90.42			84.82	

Table 7. The model efficiencies (%) in updating mode.

Model		Method	Calibration			Validation		
			R^2	Bias	ENS	R^2	Bias	ENS
P-SLM		Parametric	89.81	−0.91	0.898	85.33	−0.91	0.85
P-LPM		Parametric	91.35	0.00	0.91	84.90	−2.49	0.85
	SAM	Parametric		90.21			85.06	
MOCT	WAW	Parametric		91.46			85.32	
	NNM	Parametric		91.42			85.01	

be always feasible especially in scarcely gauged locations in Africa. On that basis, we compared systems type black box rainfall-runoff models and other complex models that require inputs beyond rainfall such as SMAR, HBV and SWAT. The models were compared on the basis of long-term rainfall and stream flow data (1980-2000) and for 100 selected runoff events for the Gilgel Abbay watershed.

- Event runoff is largely a function of rainfall amount. The event rainfall-runoff relationships explained as much as 62% for the wet periods without incorporating the evaporative demands. Although the relationship between runoff and rainfall was significant (α = 0.05) for wet and dry periods, it was not as strong as expected. This suggests that about 38% of the runoff response in this watershed is influenced by other factors such as its intensity and duration, and to the near-term soil moisture conditions created by accumulated evapotranspiration and precipitation balances. Event rainfall-runoff relationships were also affected by 5-day prior rainfall under wet conditions, suggesting that soil moisture condition is an important element dictating the hydrologic dynamics of this watershed. However, this was not the case for the dry period indicating that the rainfall-runoff dynamics was more complex and variable in this system with shallow moderately drain soil. We argued that this variability is most likely related to rainfall characteristics such as intensity and duration. We confirm that event R/P were significantly higher during the wet period than for the dry periods. Although peak flow rate relationships with rainfall for both wet and dry periods were also significant, the wet period relationship was found to be stronger. It was also concluded that the rainfall amount and ASMC represented by the initial base flow rate were the main controlling factors for event runoff. The results of this study showed that all event variables (runoff, R/P, and peak flow rates) were controlled by rainfall amounts and available soil water storage. Future studies should further investigate other hydrologic indicators that affect the runoff response, such as spatial and temporal water table dynamics determined by balances of rainfall and ET. Information on depth to water table along with soil drainage porosity is necessary to determine available subsurface storage and, therefore, the ASMC at given times. Additionally, event rainfall intensity data are necessary not only to characterize the peak flow rates but also to accurately determine the rainfall amount responsible for event runoff regeneration and duration of storm events at different seasons and periods.

- Using continuous simulation models described in Section 3.5 and 3.6, we compared systems type black box and complex hydrological models in Gilgel Abbay catchment. Though the performance of the naïve SLM is clearly inferior to that of all other models (from systems type black box models), models such as the LPM and the ANN perform better than the complex hydrological models such as SMARG, HBV and SWAT. For instance it is shown in **Table 6** that the performance of LPM and ANN (both systems type black box) models evaluated with NSE criteria gives better hydrograph response than the complex models such as HBV and SWAT. Therefore it confirms that simpler models (that takes only rainfall as input) can surpass their complex counterparts in performance for continuous simulation and reproducing of hydrographs or flow estimation. There is a strong justification, therefore, for the claim that increasing the model complexity, thereby increasing the number of parameters, does not necessarily enhance the model performance. It is suggested that, in practical hydrology, the simpler models, may still play a significant role as effective simulation tools, and countries with scarce hydrological data should revitalize application of such systems type black box modelling schemes that depend only on rainfall and runoff data sets which could be easily available.

As a concluding statement, results of this study site may be of great importance for regional water management and water quality studies, for that matter designing the water related structures such as detention ponds and restoration efforts. These data will also provide useful insight to explain the variability in storm runoff response observed for the dry period, for example. Additionally, future rainfall-runoff event analysis study at this site should take advantage of current monitoring of rainfall intensity data, water table depths, solar radiation, and other hydro meteorological data, as well as modeling studies for accurately estimating soil moisture and actual ET that would help to explain the variability in runoff generation.

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