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Development of Rainfall Disaggregation Model in the Awash River Basin, Ethiopia

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Abstract. This study aims at developing a model that can generate synthetic hourly rainfall data from the existing daily rainfall data of Awash river basin. Fifteen minutes rainfall data collected from national meteorological agency for 13 active stations and daily data collected from 54 stations were considered. Stochastic rainfall disaggregation and Hyetos temporal precipitation model was tested using the available fifteen minutes data. Three regions with close climate condition and rainfall pattern were identified and tested to be homogeneous in the stochastic method. Both methods are tested by using statistical comparison of variance, skew-ness, probability of dry period, and Lag-1 ACF. The result of the stochastic method showed very good performance in preserving the probability of zero rainfall and the daily rainfall total. But it has limitation in disaggregating rainfall magnitudes with high return period. Statistical comparison of Hyetos model indicated very good agreement with the original data. Especially the daily total statistical properties were well preserved. The comparison of the two methods showed that Hyetos is better in preserving the statistical property. Generally the methods are capable in preserving statistical properties and the daily total rainfall depth. Therefore, Hyetos model is pertinent for only temporal disaggregation, whereas the stochastic method is applicable for both spatial and temporal disaggregation in the basin.

Keywords: Rainfall · Disaggregation · Stochastic · Hyetos

1 Introduction

1.1 Background

The need for higher resolution of temporal and spatial distribution of rainfall data has become higher in most of water resources assessment studies all over the world. Recently, the use of satellites for producing the quality of high resolution rainfall data both temporally and spatially was popular and possible [1]. But the access to such data in most cases was hardly possible to obtain at low cost anywhere and anytime [2]. Still rainfall data collection of finer time scale is possible by the use of different types of recording rain gauges. The number and distribution of such instruments in our country

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is not developed [3]. Therefore this calls for a scientific approach to fulfill the need of such data by extracting from the ones we have.

Stochastic models have a wide range of application in fields such as flood risk estimation, river flow forecasting and water resources engineering [4]. For areas where only daily rainfall records are available synthetic short-time period rainfall may be used as input for time varying infiltration models [5]. In a multitude of hydrological computation including rainfall-runoff and water balance modeling, flood forecasting and computer models of pollutant transport and many others, the access to high resolution temporal rainfall data is the crucial step [2].

Generating the higher temporal resolution rainfall from coarser time scale in our country context has not addressed very well. But there are few related studies such as by [6] which generated a maximum hourly rainfall data from existing daily rainfall records by regionalizing the rainfall stations of the basin. [7] showed the effect of temporal distribution of rainfall intensity in altering timing and magnitude of peak flood from a given catchment. To fulfill the gap of data shortage for such uses disaggregation models are vital approaches. But, model development for disaggregating daily rainfall data to hourly timescale is difficult with small record length of finer time scale record data.

Hardly available high temporal resolution data would have an impact in design water resource structure especially in developing countries such as Ethiopia. Most of these structures fail due to under estimation or are expressive due to over estimation peak flood, which is related to hourly rainfall distribution [6]. Irrigation and drainage design (IDD) manual [8] for the design of irrigation structures states the maximum hourly rainfall to be 50% of daily rainfall for areas less than 5 km^2 according to ministry of agriculture, with high uncertainty. The technique used in estimating design flood for such structures throughout is old and unreliable. In addition most drainage structure design is based on Ethiopian Road Authority (ERA) design manual [9] which divides the country in to five regional IDF curve. This would have uncertainty in higher rainfall variability across the country. [6] has indicated that these curves are satisfactorily reasonable for rainfall durations of one-half hour or more. The methods could over estimate or under estimate the maximum hourly rainfall magnitude [10]. Not only such methods need update but the effect of temporal rainfall variability needs to be addressed. Currently small numbers of recording stations are available in Awash River basin with small record length.

Even though the recording gauging stations with hourly time scale are unevenly scattered still the existing records are useful for disaggregating the daily rainfall data [1]. Extraction of hourly maximum from daily rainfall data is an important approach to capture the catchment response to rainfall and minimize error induced in lump [10]. Where, disaggregating daily rainfall to hourly and sub hourly time scale of rainfall data should be available. Hence these could be solved by developing a method for extracting hourly rainfall depth from available daily data. One way of doing would be by using available models of disaggregation by testing the performance of the models for our climate condition.

Therefore the aim of this paper was developing rainfall disaggregation model to generate synthetic data of hourly time scale from available daily rainfall data for Awash River basin. Particularly the original methodology developed by [11] with some modification. In addition a disaggregation model for temporal stochastic simulation of rainfall at fine time scales known as Hyetos, which was developed by the Department of Water Resources, Hydraulic and Maritime Engineering, National Technical University of Athens, was tested for generating hourly rainfall data from available daily rainfall data.

2 Research Methodology

2.1 Description of the Study Area

The Awash River basin (Fig. 1) is one of the main basins among the twelve basins of Ethiopia. It covers total area of 110,000 Km^2. Awash River basin extends from latitude 8° 30' N to 12° 00' N and 38° 05' E to 43° 25' E longitude. The mean annual rainfall in the basin varies from maximum of 1600 mm to minimum of 160 mm with annual average of 557 mm. The mean annual temperature varies from a minimum of 20.8 °C to the maximum of 29 °C in the basin [12]. The basin incorporates climate zones Arid and semi-arid in its most part. The basin is located mainly in the central highlands of Ethiopia, with water resource potential of 4.9 Bm^3 of surface flow [13]. The elevation in the basin ranges from 250 m to 4100 m a.m.s.l. showing with high variable range of topography.

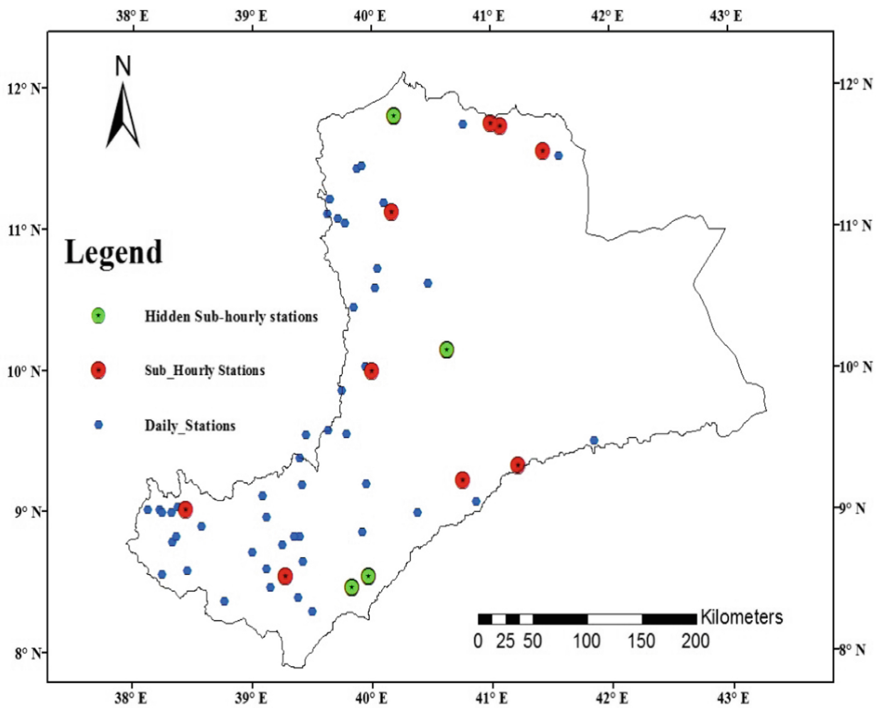

Fig. 1. Rainfall stations distribution in the Awash river basin

2.2 Rainfall Disaggregation Method

In this paper two main rainfall disaggregation methods were used to convert available daily rainfall record of Awash River basin in to hourly time scale. These methods includes: (i) Stochastic precipitation disaggregation method by [11] and (ii) Hyetos rainfall disaggregation model. Details of two methods are explained in the following sub sections.

Stochastic Method of Disaggregation

This method was developed by [11], whose overall process consists of creating event database (i.e. event rainfall depth with corresponding hourly depth) and constructing Cumulative Density Function (CDF) of event depth. Stochastic precipitation disaggregation method was selected because of limited data record. It was also known to perform well in preserving the intermittency and the characteristics of the rainfall process.

The procedure of disaggregation (Fig. 2) starts by setting ordinate ‘a’ from event CDF for month to be disaggregated of known daily rainfall depth (D_T), where $D(a) \leq D_T$. Then a random number (u_i) between 0 and ‘a’ was generated from uniform distribution and for the generated random number event depth Di was taken from the monthly CDF (Fig. 3b). This is the initial event depth, hence the process continues by subtracting Di from D_T until convergence condition (ε < Dt) was met. Where ε is assigned minimum threshold value of single, 1-h event for each month. Once the individual events Di are selected, the hourly depth, for these events are taken from the event database (Fig. 3a). For detail assumptions and procedure of the method readers are advised to view study by [11].

Two modifications have been applied on the method by [11]. The first modification was to adjust the method to properly fit our data limitation. The data were from the events which are from multiple stations within the basin. The second modification was the climate similarity between stations, which was approximated by regionalization in addition to comparison of station elevation and monthly rainfall record. Data from thirteen stations was utilized for this method, of which four stations are used as hidden stations for validation purpose.

Regionalization

This method considers climate proximity to cluster the stations in the basin. The aim was to form groups of sites that approximately satisfy the homogeneity condition. This suggests the sites with similar frequency distributions are statistically identical apart from a site specific scale factor [14].

Selection of Regionalization Parameters. For the purpose of disaggregation model three parameters which affect and related to rainfall variability have been chosen. The proposed parameters were elevation of the stations, geographical locations, and mean monthly maximum rainfall depth derived from sub hourly stations. But the last parameter for daily stations was the mean annual rainfall.

MINITAB statistical software was used to obtain the initial clustering of the daily and hourly stations. This statistical software has different types of clustering methods.

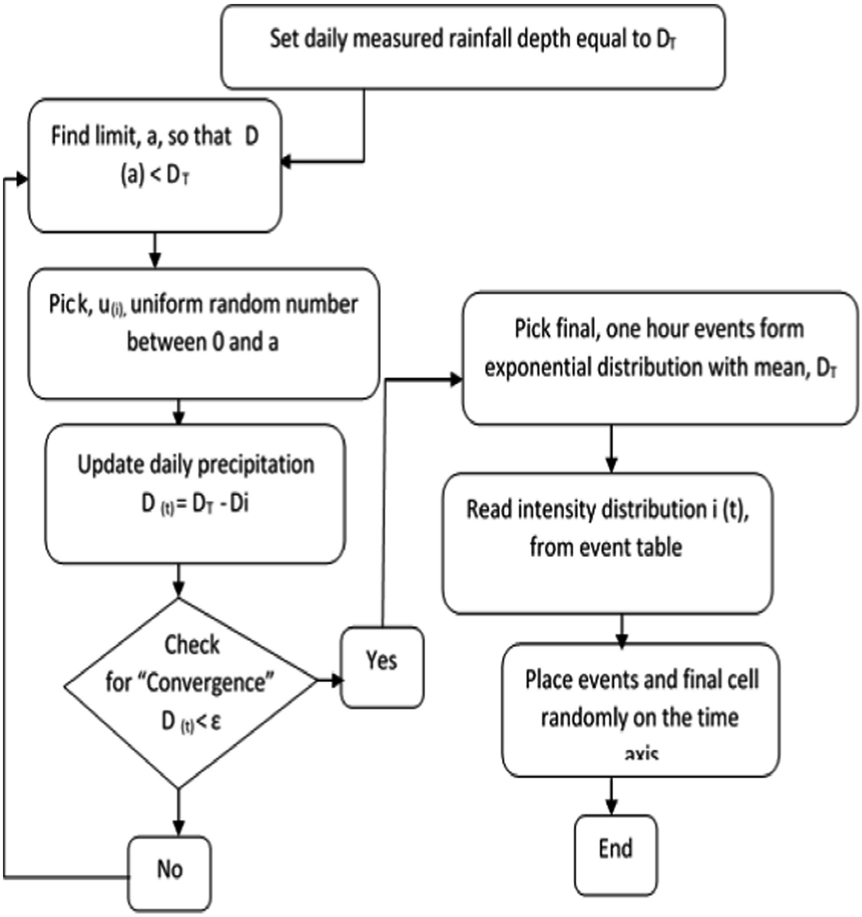

Fig. 2. Flow chart of disaggregation procedure (11)

(a)

Table of events		
n_i	i (t)	D_i
1	i_1 (t)	D_1
2	i_2 (t)	D_2
.	.	.
.	.	.
.	.	.
n	i_n (t)	D_n

(b)

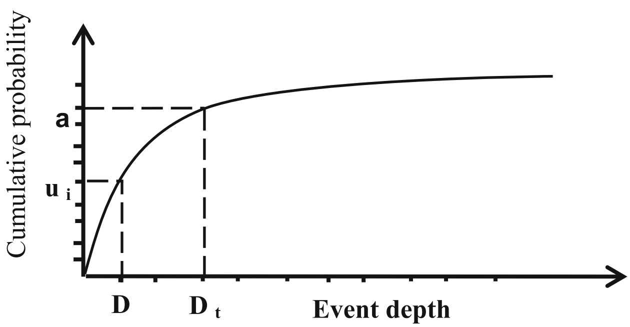

Fig. 3. Stochastic disaggregation procedure [11] [(a) Event table; (b) Event depth CDF;]

Among these clustering approaches K-means clustering mechanism was chosen and used for this study. The result of daily stations regionalization (Fig. 4) is in good agreement with elevation range.

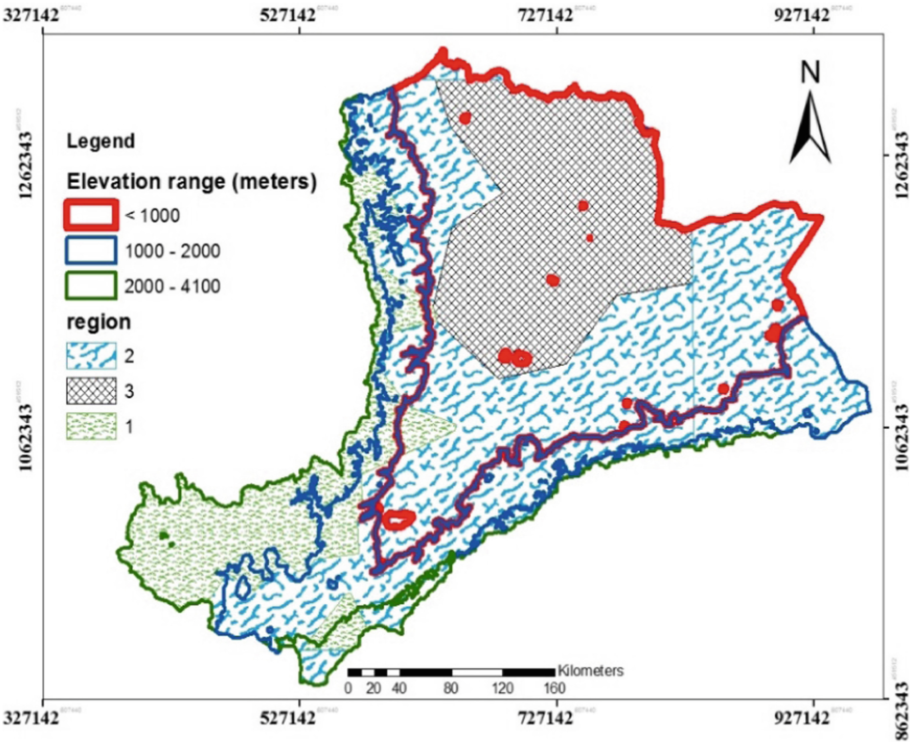

Fig. 4. Daily station regionalization output of Awash river basin

When comparing data at hand for this study with that of data utilized in the original work, it emphasizes the resulting disaggregation process was poor in dry months. This was because events recorded in dry months were smaller in number when compared to rainy months. Due to this reason three months i.e. July, August, and September were considered for this method.

The stochastic disaggregation procedure starts with finding events from the aggregated hourly rainfall data record. From stations in similar region hourly data were collected from months with no missing data. Once separate rainfall events collected in each event depth were calculated by summing observed hourly rainfall depths in each event. Then CDF's was calculated on monthly base using event depth.

Hyetos Rainfall Disaggregation Model

Based upon the Bartlett-Lewis process Hyetos rainfall disaggregation model combines a rainfall simulation model with proven techniques implemented for the purpose of adjusting the finer scale (hourly) to obtain the required coarser scale (daily) values [15]. The Bartlett-Lewis rainfall model is a continuous time model whereas the disaggregation operates on discrete time with two characteristic time scales, the higher level (e.g., daily) and lower-level (e.g., hourly) ones [15]. For detail assumptions and procedure of the method readers are advised to view study by [16].

Three stations (Table 1) with sufficient short duration data were chosen for use in this study. The stations namely Addis Ababa, Meiso, and Dubti were selected from different weather conditions in the basin so as to illustrate the applicability of the model in different weather conditions. In addition as the model requires monthly data for application, two months (with sufficient data record length) are selected from dry month and wet month for each of the stations. Test modes one and three are conducted on each continuous data, with separate validation period for application mode three. Due to shortage of data selected dry month for Meiso station is not necessarily from the driest, rather from "belg" season. Detail explanations and references of the Hyetos rainfall disaggregation model are available from the link http://www.itia.ntua.gr/en/softinfo/3/.

Table 1. Data used for Hyetos rainfall disaggregation model

Station name	Elevation (m)	Mean annual (mm)	Month for test mode I		Month for test mode III
			Dry month	Wet month	
Addis Ababa	2,277	1165	February	August	August
Meiso	1,338	792	April	June	June
Dubty	376	134	October	August	-

3 Result and Discussion

3.1 Disaggregation Result

Stochastic Method of Disaggregation Result

The results from the event data base event with duration of one hour were averaged to find the monthly threshold value. The event depths indicated in the monthly CDF of each region (Fig. 5). It was clearly observed that a rainfall characteristic that monthly threshold value the peak in august and decreases as we go to the dry months (Fig. 6). The observed data from each station, which was used in establishing the CDF and monthly convergence parameter (ε), ranges from three to seven years. This clarifies the representativeness of events, but it lacks to accommodate extreme event depths with higher return period.

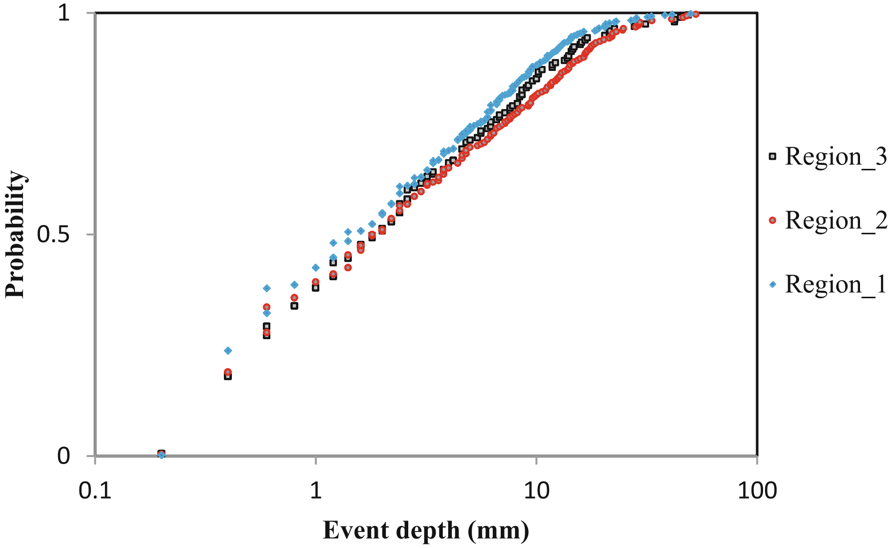

Fig. 5. August's CDF of event depth

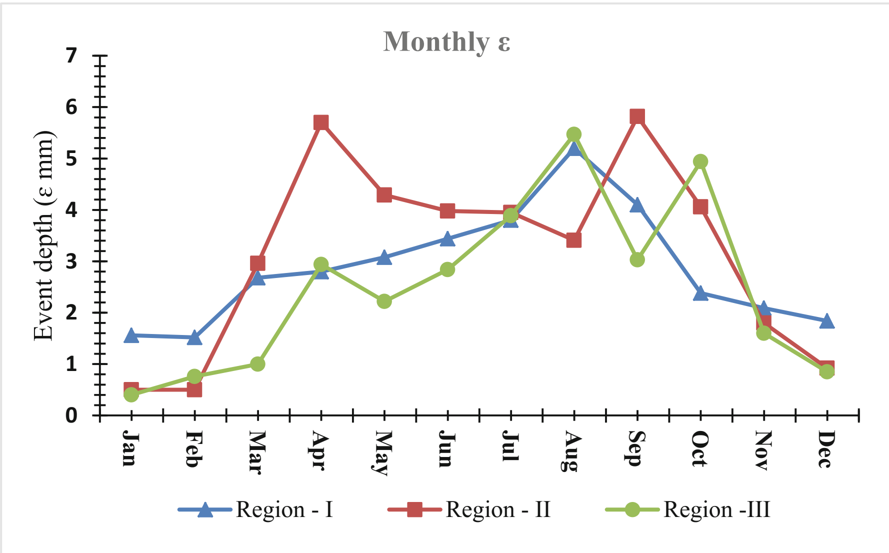

Fig. 6. Monthly convergence parameter

Stochastic method of rainfall disaggregation adapted in this study is different from other forms of disaggregation procedure especially from those methods which utilize frequency analysis. When compared to such methods it is advantageous since it provides full disaggregation of the daily rainfall depth and gives temporal variability also, rather than resulting in single intensity of rainfall depth for a given return period and duration. The process of using this method requires monthly event CDF and monthly convergence value. Therefore in this study the resulting methodology is presented in the form of monthly CDF with respective monthly convergence value. The monthly event CDF are developed for July, August and September month, plus the monthly convergence value presented in Fig. 6 is the result of this method for each region. Generally as presented in the methodology section this stochastic method of disaggregation is implemented by following the procedure outlined.

Three regions having three stations each (Table 2) for constructing event database was proven to be homogeneous based on the above parameters for use in the stochastic method of disaggregation. From region three a daily rainfall depth of 12 mm at Gewane station on 7/8/2015 was recorded, where the region's August month threshold value is 5.46; so as an illustration (Table 3) the disaggregation process resulted 4 events of 3 h, 4 h, 7 h and 1 h of the indicated depth.

Table 2. Sub hourly stations region with hidden stations

S/No	Station name	Remark	Homogeneous region
1	Erer		
2	Addis Ababa		
3	Sh/Robit		Region-1
4	Abomsa	hidden	
5	Woliso	hidden	
6	Meiso		
7	Awash Arba		Region-2
8	D/Fage	hidden	
9	Adama		
10	Semera		
11	Assaita		Region-3
12	Gewane	hidden	
13	Dubty		

The monthly convergence value needs to be calibrated for event depth greater than 20 mm. The reason behind this is because the model tends to relate the number of events or in other word number of Di with event depth. But this study was limited to conduct calibration of convergence value for larger values due to data limitation from different year.

Table 3. Disaggregation illustration for region-3

D_T (mm)	"a"	u_i	D_i	D_t	Selected hourly depth patern for each D_i from database of August of the region (mm/hr)						
12	0.846	0.521	2.2	9.8	1	0.2	1				
	0.811	0.578	2.8	7	0.2	1.8	0.6	0.2			
	0.746	0.725	6.8	0.2	3.8	0.2	0.6	0.2	0.4	0.4	1.2
			0.2		0.2						

After getting hourly rainfall depth for each Di event the starting time is taken randomly from a normal distribution constrained that no event should overlap. The illustration of disaggregation from region-1 and 2 (Table 4) showed the randomness of the method in spite of daily depth, in allocating different pattern of depth and duration.

Table 4. Disaggregation illustration for region-1 and 2

St. name	Day	D_T	"a"	u_i	D_i	D_t	Selected hourly depth patern for each D_i from database of August of the region		
Dalli fage (region-2)	5/8/2016	25.4	0.96	0.78	8.4	17	2.8	5	0.6
			0.91	0.83	11.2	5.8	0.4	8.8	2
			0.71	0.67	5	0.8	2.6	2.4	
					0.8		0.8		
Woliso (region-1)	27/8/2016	11.2	0.57	0.36	6.8	4.4	3.4	3.4	
					4.4		4.4		

Stochastic Method of Disaggregation Validation

In this study the stochastic model performs well with longer record year of shorter time scale. Besides, available data was less representative to rainfall depth with higher return period both in statistical representativeness and in predicting maximum hourly rainfall depth. Hence the model was poor in predicting intense rainfall occurring in short duration with large magnitude.

The validation process for this study was conducted by using separate stations in each region. For example the validation of region one using Woliso station for the month of August (Table 5) showed the method well conserved daily statistics more than the hourly statistics. Similarly result was observed on the other regions; that is the daily magnitude was well preserved, but the hourly predicted values were not in agreement with the observed value with some level of error. Especially the variance and skewness values are under estimated. The value of lag-1 Acf of observed and predicted hourly rainfall depth is over estimated. The reason for such variation between observed and predicted value is due to the problem of the model in disaggregating larger rainfall magnitudes.

Table 5. Statistical comparison of validation process

Probability of zero				Variance			
Observed		Predicted		Observed		Predicted	
Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily
0.90995	0.16129	0.9207	0.16129	0.41087	8.36928	0.21163	8.36928
Lag-1 ACF coeff.				Skewness			
Observed		Predicted		Observed		Predicted	
Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily
0.033767	0.030806	0.115606	0.030806	12.3464	1.8974	6.58969	1.8974

The hourly rainfall temporal distribution in the month of August at Woliso station clearly showed that the peak rainfall were under estimated whereas the lower magnitudes of rainfall were overestimated (Fig. 7). The other observation was the displacement of time of occurrence of disaggregated rainfall depth.

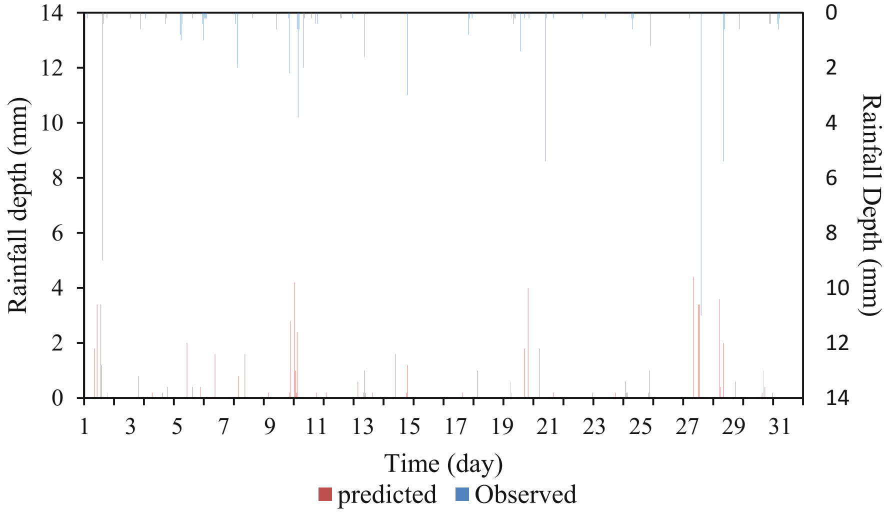

Fig. 7. Hourly rainfall distribution of observed and predicted rainfall depth for August month of at Woliso station

One of the purposes of disaggregation is enabling determination of peak events. Collecting the peak hourly events on daily base from both observed and predicted data of August month for Woliso station (Fig. 8) indicated a better prediction of hourly peak than taking 50% of the daily total which is the case presented by Irrigation Drainage Design Manual. But still the stochastic method of disaggregation needs adjustment by including ample fine time scale recorded data for a better prediction of higher depth of rainfall.

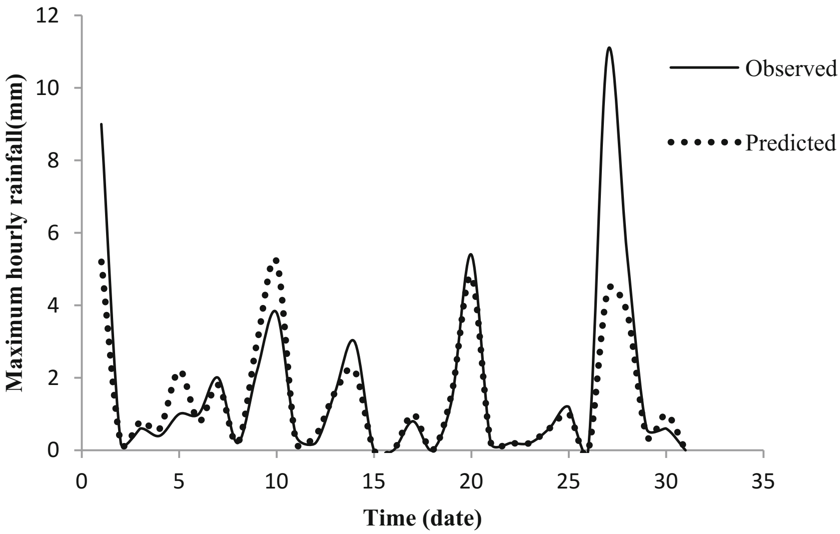

Fig. 8. Hourly maximum of August month at Woliso station

Hyetos Model Result

Hyetos model accesses available finer time scale rainfall data to calculate site specific model parameters in order to disaggregate daily rainfall depth. The BLM parameters were estimated for each station listed in the methodology section (Table 6). A principally similar model of Modified Bartlett-Lewis Rectangular Pulse Model (MBLRPM) was implemented in Upper Blue Nile River Basin and it was due to MBLRPM alone has poor result which suggested stochastic redistribution of the outputs of the model using Beta probability distribution function [3]. An adjusting procedure indicated in methodology section has proven the result of Hyetos model in this study.

Table 6. BLM parameter values

Station	Parameters	Month	
		8	2
Addis Ababa	α	97.99	3.07977
	κ	65.87	11.2771
	ϕ	25	0.2272
	λ (d–1)	2.25	0.1133
	μ_X (mm d^{-1})	95.94	93.025
	ν (d)	0.92839	0.000324

(*continued*)

Table 6. (*continued*)

Station	Parameters	Month	
		8	10
Dubty	α	3.24884	4.46
	κ	100	4.916
	ϕ	0.9864	1.477
	λ (d–1)	0.46623	0.0417
	μ_X (mm d^{-1})	10	110
	ν (d)	0.01066	0.0392
Station	Parameters	Month	
		4	6
Meiso	α	5.13323	17.414
	κ	1.65925	7.4219
	ϕ	0.02407	0.0608
	λ (d–1)	0.40659	0.3863
	μX (mm d^{-1})	16.5776	60
	ν (d)	0.02884	0.010118

Hyetos Model Validation

The model has shown to perform the disaggregation process by preserving the statistical property of original observed both at hourly and daily time scale. The comparison of disaggregated rainfall data for Meiso station on month six (Table 7) with obseved statistical property resulted poor comparison of variance and Lag-1 Acf than skewness and probability of zero. The comparison is conducted for all wet and dry periods. The daily statistical property is well preserved whereas on hourly time scale the Lag-1 autocorrelation coefficient shows over estimation when compared to the others. Compared to the case study performed on Heathrow airport rain gauge (London, UK) by Koutsoyiannis, Onof [15] generally the result of this study has slightly lower performance. Comparably better result was obtained on skew-ness and probability of dry period. Other case studies by [17] in Malaysia also indicated similar results. The result of Meiso station on month six had better predicted skew-ness than the previously mentioned studies.

Table 7. Validation result of Hyetos disaggregation model

Probability of zero				Variance			
Observed		Predicted		Observed		Predicted	
Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily
0.9681	0.667	0.9792	0.7	0.6785	20.766	0.732	20.887
Lag-1 autocorrelation coefficient				Skew-ness			
Observed		Predicted		Observed		Predicted	
Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily
0.1328	0.2852	0.1720	0.2820	16.092	2.6287	16.0869	2.631

3.2 Model Comparison

The result showed that both methods were capable preserving the daily total magnitude. On the other hand the stochastic method under estimate the rest values. The anticipated cause of this problem is related to under estimation of large rainfall magnitudes. Statistical comparison of both methods with observed magnitude of Meiso station for June 2010 (Fig. 9) was better conserved by Hyetos model.

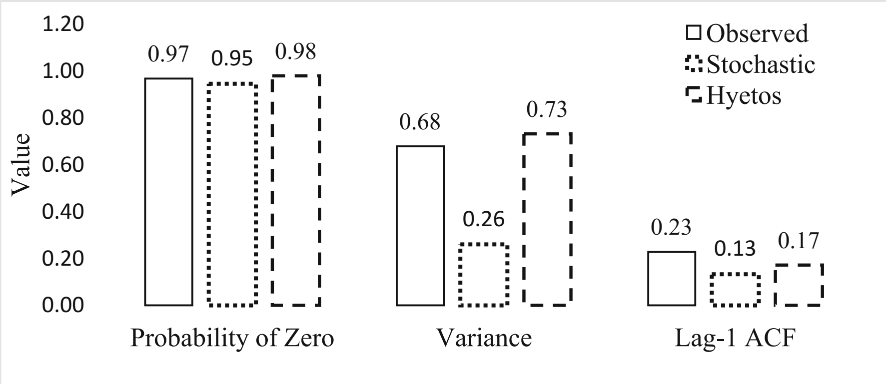

Fig. 9. Statistical comparison of models with observed

Skewness indicated similar pattern similar to the other comparisons. The probability of zero rainfall is the statistical property that is well preserved compared to the other. The comparison is performed by also altering the observed values i.e. by removing large rainfall depths. And it has been observed the performance of the stochastic method improves (particularly the skewness and variance). In general, comparison of the two methods showed that Hyetos is better, since the statistical property is from one station.

4 Conclusion

The stochastic method, which enables spatial disaggregation, has been found to be uncomplicated and stingy. Even though this method seems to have randomness in process it's showed to have good performance for small rainfall values. Acceptable performance was shown by the method for higher rainfall; this is due to data shortage to accommodate larger rainfall events from the recorded value. Hyetos model was tested on three climate conditions for rainy and dry seasons. Since the model was for specific site, stations having sufficient data from different climate conditions were selected. Hytoes model performance was consistent in preserving the statistical property on different data sets. In general it was understood that the specific disaggregation, where small records are available, can be extended by using Hyetos model. Whereas the problem of less and or shorter time scale in a given area can be alleviated by using the stochastic method.

References

1. Pluntke, T., et al.: Use of past precipitation data for regionalisation of hourly rainfall in the low mountain ranges of Saxony, Germany. Nat. Hazards Earth Syst. Sci. **10**(2), 353 (2010)
2. Güntner, A., et al.: Cascade-based disaggregation of continuous rainfall time series: the influence of climate. Hydrol. Earth Syst. Sci. Discuss. **5**(2), 145–164 (2001)
3. Engida, A.N., Esteves, M.: Characterization and disaggregation of daily rainfall in the Upper Blue Nile Basin in Ethiopia. J. Hydrol. **399**(3–4), 226–234 (2011)
4. Abdellatif, M., Atherton, W., Alkhaddar, R.: Application of the stochastic model for temporal rainfall disaggregation for hydrological studies in north western England. J. Hydroinform. **15**(2), 555–567 (2013)
5. Econopouly, T., Davis, D., Woolhiser, D.: Parameter transferability for a daily rainfall disaggregation model. J. Hydrol. **118**(1–4), 209–228 (1990)
6. Alem, A.M.: Developing a Regional Hourly Maximum Rainfall Extraction Method from Daily Maximum Rainfall for Part of Upper Blue Nile Basin Bounded by Amhara Region, Masters thesis. Bahir Dar University, Bahir Dar, Ethiopia (2015)
7. Knoesen, D., Smithers, J.: The development and assessment of a daily rainfall disaggregation model for South Africa. Hydrol. Sci. J. **54**(2), 217–233 (2009)
8. Ministry Of Agriculture: Irrigation and drainage design mannual, Ethiopia (2001)
9. Ethiopian Road Authority: Drainage design manual, Ethiopia (2013)
10. Pui, A., et al.: A comparison of alternatives for daily to sub-daily rainfall disaggregation. J. Hydrol. **470**, 138–157 (2012)
11. Socolofsky, S., Adams, E.E., Entekhabi, D.: Disaggregation of daily rainfall for continuous watershed modeling. J. Hydrol. Eng. **6**(4), 300–309 (2001)
12. Behailu, S.: Stream Flow Simulation For The Upper Awash Basin. Faculty of Technology Department of Civil Engineering, Addis Ababa University (2004)
13. Berhanu, B., Seleshi, Y., Melesse, A.M.: Surface water and groundwater resources of Ethiopia: potentials and challenges of water resources development. In: Melesse, A.M., Abtew, W., Setegn, S.G. (eds.) Nile River Basin, pp. 97–117. Springer, Cham (2014). https://doi.org/10.1007/978-3-319-02720-3_6
14. Hosking, J.R.M., Wallis, J.R.: Regional Frequency Analysis: An Approach Based on L-Moments. Cambridge University Press, Cambridge (2005)
15. Koutsoyiannis, D., Onof, C., Wheater, H.S.: Multivariate rainfall disaggregation at a fine timescale. Water Resour. Res. **39**(7) (2003)
16. Koutsoyiannis, D.: Rainfall disaggregation methods: theory and applications. In: Workshop on Statistical and Mathematical Methods for Hydrological Analysis, Rome (2003)
17. Hanaish, I.S., Ibrahim, K., Jemain, A.A.: Daily rainfall disaggregation using HYETOS model for Peninsular Malaysia. Matrix **2**, 1 (2011)