Study of the Bagmati River in Nepal as Religious Tourist Attraction: Quantile Regression approach for Assessment of Rainfall pattern over it

Rajendra Man Shrestha[1] and Ebha Shrestha[2]

Abstract:


Quantile regression is an emerging statistical tool used to explain the relationship between response and predictor variables. It provides more robust and efficient estimators, on the conditional median or other quantiles of the response variable, compared to OLS. This study aims to establish relationship between monthly rainfall data in the Bagmati River and some large-scale climate predictor variables using this technique over the period 1981-2000. Quantile regression model reveals the relationship between the monthly rainfall and each of seven predictor variables. Geopotential height 1, Mean sea level pressure 1, Precipitable water 1 showed a greater effect ranging from $q = 0.25$ *to* $q = 0.950$*. Each of these seven predictor variables has tendency to affect the rainfall uniquely to each other. Impact of climate change on these predictors may adverse effect on water tourism and religious tourism along the Bagmati River. Thus, the use of quantile regression is very important to determine the effect of the above seven predictors in a model to explain the monthly rainfall behavior over the river.*

Keywords: Quantile Regression, conditional quantile plots, relationship, robust, climate predictor variables, rainfall

Introduction

Nepal is rich in natural beauty. She possesses ecological diversity along with different traditional as well as cultural values, customs and rituals. Nepal is also famous as a country of temples. Hinduism and Buddhism are main religions of Nepal. Because of these attractions, tourists visit Nepal with increasing rate every year. Therefore, tourisms have been developing in several facets like mountaineering, trekking, Site-seeing, water tourism, nature walks, study and

1 Associate Prof. Padmakanya Multiple Campus, Tribhuvan University,
2 Student of School of Management, Kathmandu University, Nepal

religious tourism, etc. Water tourism is flourished by rafting, canoeing and kayaking in different rivers of Nepal.

Figure 1: *Pashupatinath Temple at Bagmati River bank*

Figure 2: *Hindu Pilgrims at Pashupatinath Temple*

Figure 1 displays Lord Pashupatinath temple at Bagmati River bank. *Hindu pilgrims* appear as the religious tourists at the same temple (Figure 2).

The topic of this paper mainly discusses to the Bagmati River along with its cultural and religious values of Pashupatinath temples and other historical monuments and temples with traditional customs. If the Bagmati River has run off with sufficient water, there is possibility of water tourism too. From many years to present, the river has been facing with water scarcity and severely affected by untreated sewage and solid waste. Its main source of water is rain and then a few natural springs. But natural springs are gradually decreasing due to rapid urbanization and high population, buildings and loss of forest and cultivated lands. Further the problem is aggravated by the impact of ever increasing climate change. It has been experienced by extreme climatic events that cause flash floods or severe drought in this river.

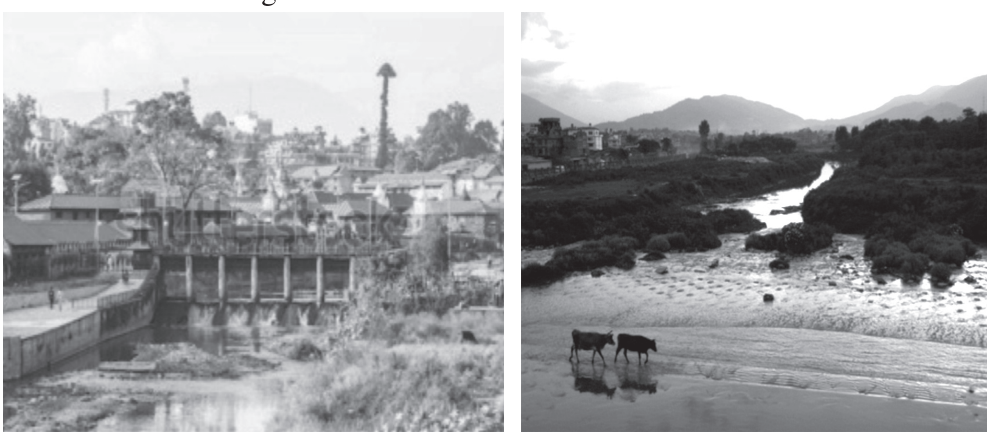

Figure 3: *Drought condition of the Bagmati River*

The Figure 3 depicts drought situation of the Bagmati River at Winter season

Therefore, this paper attempts to study the rainfall pattern, which is the main source of water to the Bagmati River using quantile regression approach.

Although the rainfall may be affected by natural climate variables, this study observes only main seven climate variables.

Climate variables

The seven climate variables are Geopotential height(GPH) (m) at 850 hpa, Relative Humidity (RH) in (%) at 850 hpa , Air Surface Temperature (AST) in Kelvin , Mean sea level pressure (pa), U- component of wind (Zonal wind)(UW) (m/s) at 850 hpa , V - component of wind (Meridional wind)(VW) (m/s) at 850 hpa and Perceptible water (PW) (mm). These variables are expected to affect the magnitude of the rainfall in atmospheric and oceanic circulation system.

Atmospheric as well oceanic circulations and their combinatorial systems are the complex natural system on the Earth. Weather and then climate of a region are cause of such system and further regular and periodic in nature in normal condition despite the fact that there are gradual natural changes taking in climate pattern ever since the evolution of the Earth (Shrestha et al., 2015a, 2015b, 2017). Precipitation or more precisely rainfall is very important hydrological phenomenon on the local region. It is globally accepted that the role of the rainfall is very important in maintaining and regulating the ecosystem as well as environment on the Earth. From the past few decades, the issues are raised on the impact of climate change on the rainfall pattern of the local region, the hemisphere and the world as a whole due to the effect of global warming. Burning of fossil fuel, pollution, forest fire, deforestation, other human activities are some causes for the global warming as they have been producing excessive greenhouses gases (IPCC, 2000, 2001). The Intergovernmental Panel on Climate Change and other previous researches have shown that climate hazards, including changes in precipitation cycles, reduced crop yields due to extreme weather event and changing local temperature are likely to decrease the food security of vulnerable population (IPCC, 2013). In Nepal, there was huge fluctuation in river run-off from season to season (Alam, 2004). Seasonal prediction of the rainfall becomes very important in Nepal for mitigating potential hazards due to landslides, flashfloods, droughts or water shortage at local regions (Sharma and Shakya, 2006). So the change in rainfall pattern may bring severe adverse effect in the river hydrology of Nepal. This paper intends to study about the rainfall pattern of the Bagmati River Basin in Nepal.

Statistical models used

To understand or identify the possible impact of climate change on the precipitation or rainfall, many papers have shown that General Circulation Models (GCMs) are currently the most credible tools and also provide estimation of climate variables (for example, air temperature, precipitation, relative humidity, etc.) on a global scale. But the direct use of GCM outputs is not suitable to assess the climate change at local region due to its course resolution in finer scale (Tareghian, R., and Rasmussen P. F., 2013). To study at the local level, several types of techniques are found to use in downscaling the GCM outputs at the local regions (Fealy, Sweeney, 2007). One of them widely used is Regression based Statistical Downscaling Model under several key assumptions (Fowler, H. J., and Wilby, R. L. (2007). Statistical Downscaling Model (Wilby et al., 2002) and Automated Statistical Downscaling are some examples of conventional regression models. Despite their popularity, these regression based conditional mean models have some limitations. If one takes interest in the quantiles of the conditional distribution rather than mean, the standard regression model becomes weak to provide the desired information. This is because the assumption of homogeneous variance may not be justified. Further, it is common practice that the regression residuals assume normal distribution. But this may not be valid assumption even after application of some normalizing transformation. This model is also very sensitive to outliers. Under such adverse as well as desired condition, the quantile regression is widely preferred by the researchers. Bremnes (2004), Friederichs and Hense (2007), Friederichs (2010), and Cannon (2011) are found to apply quantile regression for downscaling precipitation. But they have focused on the capability of quantile regression for forecasting and relationships with large-scale variables. Some more examples are also available. Weerts et al. (2011) used the quantile regression in analysis of annual streamflow distributions change over time of annual rainfall in Zimbabwe. Further, Tareghian and Rasmussen (2013) applied it for analysis of Arctic and Antarctica sea ice extent and for statistical downscaling of precipitation at five location in central and western Canada for the winter and summer seasons. Thus the present study is motivated by the importance of providing accurate estimates at the quantiles of the distribution of the rainfall amount determined by some large-scale climate predictor variables using NCEP/NCAR outputs (Kalnay et. al., 1996) over the Bagmati River Basin in Nepal. The following section deals with the materials and methods, results and discussion and finally conclusion.

Materials and methods

Study area

The Bagmati River basin (Figure 1) originates from the Shivapuri hills of the Mahabharata range and drains out of Nepal (Jha, 2002). Its main tributaries are Manohara, Bishnumati, Kulekhani, Kokhajor, Marin, Chandi, Jhanjh and Manusmara-located within the middle mountain of Nepal (26045’- 27049’ N-8502’- 85027’ E).They occupy an area of 3,604.44 km (referring to 25 stations). Babel et al. (2013) has mentioned that the elevation of the Bagmati River basin ranges from 80 m in Terai in the southern part of Nepal to 2900 m in the Mahabharata range in the north. Its length is about 51 km.

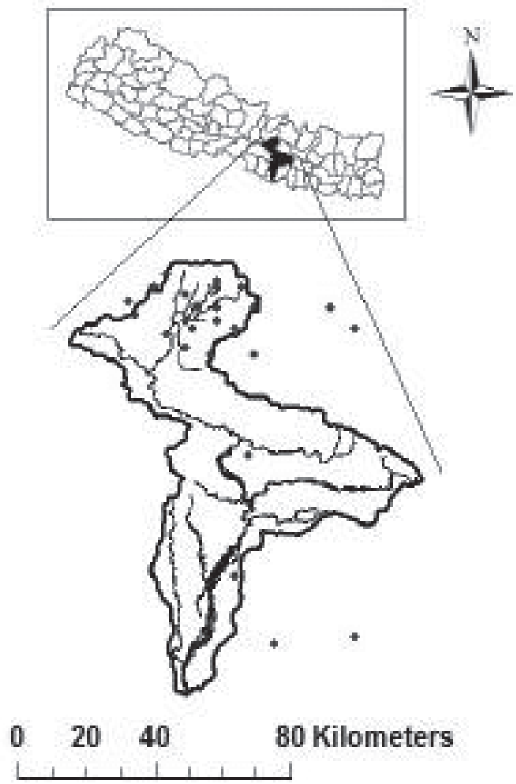

Figure 4: *Map of Nepal and the Bagmati River Basin with its tributaries and 25 meteorological stations*

Data

The present study has considered only 25 meteorological stations located in different parts of the basin for rainfall data. The data are obtained from the Department of Hydrology and Meteorology, Kathmandu, Nepal only for the time-period of January 1981- December 2008. As the study does not take consideration of spatial variation of the rainfall during these periods, the daily rainfalls of 25 stations are attempted to be aggregated into single time-series of the daily rainfall by incorporating all the stations. This single series is achieved using a weighted mean in Statistics, the weight being an area for each station demarcated within the basin using Thiessen polygon method in Arc GIS (ESRI, 2011). Therefore, the single series of the rainfall so obtained, named as area weighted daily rainfall (AWDR) is considered to represent the daily rainfall pattern of the Bagmati River basin during the mentioned periods. The daily data were aggregated to monthly data to study the monthly variation of the rainfall.

Climate predictor variables

A rainfall phenomenon is very complex system on the Earth and it is usually mentioned in several climate related papers. However, there are several potential climate variables considered as responsible for rainfall happening in nature. This paper has considered only seven climate predictors, which are supposed to be more responsible for the rainfall and commonly used in the papers. They are Geopotential height (GPH) (m) at 850 hpa, Relative Humidity (RH) in (%) at 850 hpa , Air Surface Temperature (AST) in Kelvin, Mean sea level pressure (pa), U-component of wind (Zonal wind) (UW) (m/s) at 850 hpa,

V-component of wind (Meridional wind) (VW) (m/s) at 850 hpa, and Precipitable water (PW) (mm). They were obtained from NCEP/NCAR reanalysis products source (Kalnay et. al., 1996) with spatial resolution of 25° N - 30° N in latitude and 82.5° E – 87.5° E in longitude for the period 1981-2008. Their grids encapsulate the Bagmati River basin. So, each predictor variable consists of 9 gridded monthly data for that period. Principal Component Analysis (PCA) was used to transform the seven predictors into respective nine principal components. They are Geopotential height1 (GPH1), Mean sea level pressure1 (MSLP1), Relative humidity1 (RH1), Relative humidity2 (RH2), Precipitable water1 (PRECIP1), U-component of wind1 (UWIND1), V-component of wind1 (VWIND1) and Air temperature at surface1 (TEMP1). All these components are measured in monthly basis and there were monthly data on them for the period of 1981-2008.

Methodology

Quantile Regression

Quantile regression extends ordinary least-square regression to quantiles of the response variable. In addition, it is an extension of median regression based. It was proposed by Koenker and Basset (1978). In quantile regression, a regression model is developed for selected quantiles of the conditional distribution of the response variable. It is a very flexible regression as it is not required to assume homogenous residual variance and to make any assumption about the error distribution like conventional linear regression. Further the quantile regression is also more robust to outliers.

Quantile regression deals with the determination of models for user-selected quantiles in the conditional distribution of the dependent or response variable. So, the linear quantile function used in this study is in the form of:

$Q_\tau(y/\boldsymbol{x}) = \boldsymbol{x}^T\boldsymbol{\beta_\tau}$ → [1], where **x** is a vector of predictor variables and $\boldsymbol{\beta}_\tau$ is a vector of parameters related to the τ^{th} quantile regression. The parameters may include an intercept or constant for the regression model such that the first element of **x** is 1. Now for a given set of observations ($\mathbf{x}_i$, y_i), i = 1, 2, 3, …, n, the parameter vector $\boldsymbol{\beta}$ is estimated by minimizing the loss function

$$\widehat{\beta_\tau} = \underset{\beta}{arg\ min} \sum_{i=1}^{n} \rho_\tau(y_i - \boldsymbol{x}_i^T\boldsymbol{\beta}) \rightarrow [2]$$

Where the function $\rho_\tau(.)$ is defined as

$$\rho_\tau(z) = |z|\{\tau\ .I\ (z > 0) + \ (1 - \ \tau).I\ (z < 0)\}, \quad \rightarrow [3]$$

where I (.) is the indicator function, which is one when the argument is true and zero otherwise. The loss function is non-negative taking a minimum value of zero only when z = 0.

In other words, if the model fits well, a plot of fitted versus actual values will show that τ percentage of observed values should be less than the fitted values, with 1 – τ percentage of the observed values greater than that of the fitted values (Yu et al., 2003)

The equation [2] is solved using most commonly preferred method, simplex algorithm in linear programming method and standard error of the estimates are calculated by inverse-rank method (Barrodale and Roberts, 1973, 1974). Data for 1981-2000 were considered for building model and data for 2001-2008 were taken for the model validation. Models were developed with selection of predictors based on AIC and BIC criteria.

Results and discussion

First of all, exploratory data analysis was performed to examine whether a dependent and all the independent variables fit to a Normal distribution. The results are displayed in Table 1.

Table 1: Preliminary Quantile Regression and Ordinary Regression Models with normality test

K-S Test Statistics	Variables	Spearman's rank correlation	OLS regression	Quantile regression at quantile					VIF
3.28*	Rainfall			0.10	0.25	0.50	0.75	0.95	
1.65**	GPH1	-0.80*	-59.42	-32.28	-106.95**	-145.63**	-100.88	-144.01	708.7
1.76**	MSLP1	-0.82*	74.29	30.72	123.33	171.14	115.40	191.86	1374.5
1.65**	RH1	0.51*	1.98	-25.35	-17.99	-22.28**	-30.02**	9.40	18.7
2.32*	RH2	0.79*	1.19	-16.40	-7.94	-17.35	-25.96	1.86	21.9
2.87*	PRECIP1	0.88*	199.47*	123.20*	144.88*	168.23*	250.64*	263.87*	50.2
2.179*	TEMP1	0.75*	-18.92	-23.09	6.29	24.73	-1.42	46,71	165.3
0.839	UWIND1	-0.22*	-4.47	-4.224	-0.499	-2.92	1.25	21.57	4.6
1.568*	VWIND1	0.84*	-12.58	6.08	-3.13	5.48	-0.009	-16.26	10.2
0.553	VWIND2	0.27*	-4.49	-2.12	-4.13	0.772	3.00	1.02	2.2
	Constant		141.56*	69.87*	100.30*	127.95*	184.89*	253.97*	
	F-statistic		112.76*						
	R square		0.815	0.404	0.518	0.635	0.695	0.748	
Note: Standard error estimated by bootstrapping method with 1000 replications in quantile regression									
*Significant at 1%, ** significant at 5% and *** significant at 10%.									
Spearman's rank correlation is between the rainfall and each predictor.									

According to the Kolmogorov-Smirnov (K-S) Test, all the variables did not fit to the normal distribution as the test-statistics possessed the significant p-values at 5% level besides UWIND1 and VWIND2. These results indicated not to apply the Ordinary least regression to model weighted monthly rainfall on GPH1, RH1, RH2, PRECIP1, TEMP1, UWIND1, VWIND1 and VWIND2. However, for the comparison purpose and to compute the multi-collinearity statistics, the OLS regression was run. Spearman's rank correlation analysis depicted that weighted monthly rainfall was positively and significantly correlated with RH1, RH2, PRECIP1, TEMP1, VWIND1 and VWIND2 but negatively correlated with GPH1, MSLP1 and UWIND1. In addition, the strength correlation was varying across them. It was observed that some predictor variables had opposite sign in the OLS regression like MSLP1, TEMP1, VWIND1, etc. This was mainly due to severity of collinearity effect in the model. For example MSLP1 has VIF of 1375.5. Besides UWNID1 and VWIND2, all have the VIF more than 10. Because of this situations quantile regression model have also adverse effect in the sign of the coefficients of the predictors at the quantiles of 10, 25, 50, 75 and 95. Further, all the models have most of the regressor possessing the insignificant effect. Thus, the models presented at Table 1 became unsuitable to determine the real effect of the predictor variables in the weighed rainfall. The following steps display the quantile regression model with selected predictor variables.

There are two types of final quantile regression models presented in Table 2.a and Table 2.b. Table 2.a includes precipitable water1 along with other predictors but Table 2.b has excluded it. This is done because of similar effect of precipitable water and Relative humidity.

Table 2.a: Final Quantile Regression Models at 5 different quantiles

Variables	Validated Quantile regression model with inclusion of precipitable water1 at quantile				
Rainfall	0.10	0.25	0.50	0.75	0.95
GPH1	-11.85*	-73.30*	-75.07*	-73.41*	-70.05*
MSLP1		68.86*	70.37*	75.12*	85.51*
RH1	-7.03*				
RH2					
PRECIP1	101.78*	118.04*	140.84*	197.48*	277.37*
TEMP1	-24.52*				
UWIND1					15.93*
VWIND1					-19.72*
VWIND2	-4.77*				
Constant	67.45*	101.74*	120.74*	187.62*	251.26*
*Significant at 1%, ** significant at 5% and *** significant at 10%.					

Table 2.a revealed that GPH1 has gradual decrease in effect on the rainfall while going from quantile 10 to 95. But Precip1 has, in contrast has a rapid increase in effect on the rainfall while going from quantile 10 to 95. MSLP1 has similar behavior but with slow rate than Precip1. RH1 and TEMP1 were only included in the 10th quantile model. Uwind1 and Vwind1 were included in the 95th quantile regression model. They have moderate opposite effect on the rainfall. The scenario effect has a little different in Table2.b as shown below.

Table 2.b: Final Quantile Regression Models at 5 different quantiles

Variables	Validated Quantile regression model without inclusion of precipitable water1 at quantile				
Rainfall	0.10	0.25	0.50	0.75	0.95
GPH1	-30.57*	-232.25*	-26.81*	-485.46*	-857.76*
MSLP1		270.74*	339.73*	584.74*	1072.25*
RH1	45.75*	46.90*	58.89*	92.90*	99.00*
RH2	49.26*	49.90*	54.14*	89.83*	74.02*
TEMP1		98.29*	119.99*	211.36*	382.09*
UWIND1					
VWIND1				-33.20*	
VWIND2					
Constant	67.25*	91.79*	123.61*	185.97*	274.44*
*Significant at 1%, ** significant at 5% and *** significant at 10%.					

Table 2.b revealed that GPH1 has more severe decrease in effect on the rainfall while going from quantile 10 to 95. But this time MSLP1 has a more rapid increase in effect on the rainfall while going from quantile 10 to 95. Similarly RH1 and RH2 have positive effect with slow rate in all quantile level than Precip1. TEMP1 has also positive effect with higher rate in all quantile level. VWIND1 has less negative impact on the rainfall at 75th quantile.

The different sign for some predictors may be due to collinearity effect. These two tables have thus presented that the rainfall may increase or decrease at 5 quantile level or lower level, medium level or higher level due to effect of several 7 climate predictors. If there is impact on climate change on these predictors, there will be either drought situation of the river, or may show heavy flood in the river.

Figure 5: Flood in the Bagmati River in Monsoon season

Figure 4 reveals the flash floods in the Bagmati River. This flood can damage settlements in its banks and many villages and their settlements may come under inundation in the Terai region. However, the tourism is mainly focused at Pashupatinath Temple and its territory. This seems independent of floods and drought events. If the water tourism is to be developed along with the religious tourism, the river will be the main attraction. So, the river should be full of water at normal level without any pollution. Many devotees also take bath in the river for their religious rituals and customs. Climate change may affect the river making unbalanced river situations, i.e.; sometimes huge floods or sometime severe droughts.

Figure 6: *Devotees are taking bath at Sali River, one of tributaries of Bagmati River*

Conclusion

Quantile regression models are more robust models compared to the ordinary least square (OLS) models. They do not consider several assumptions of the OLS regression. The models possessed the varying effect of 7 predictors on the monthly rainfall. Specially, GPH1, MSLP1 and PRECIP1 have shown such pattern. The change due to global warming on those predictors may bring drought or flash floods in the Bagmati River. Either situations may be very serious in tourism development regarding the religious as well as cultural and water tourism on this river. So actions should be taken on time for the River making important tourist attractions both as a religious tourism and water tourism.

In order to revive the Bagmati River, the government has already started different projects. One of them is The Bagmati River Basin Improvement Project.

Figure 7: *The dam site is being cleared in Dhap*

According to the Bagmati River Basin Improvement Project, it has plans to construct two artificial dams in the upper stretch of the Bagmati. The Dhap and Nagmati dams will be built in the Shivapuri National Park. They will collect rainwater in the monsoon and release it in a controlled manner in the dry season. The construction of the Dhap dam (See Figure 6) began in April. Covering an area of around 13 hectares, It will hold 850,000 cubic metres of water and release it at a rate of 40 litres per second during the dry season. The larger Nagmati will hold 8,000,000 cubic metres of water and release it at a rate of 400 litres per second. This activity expects the Bagmati River will gradually take its original shape. Then religious may flourish soon along with water tourism.

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