ISSN 0097-8078, Water Resources, 2017, Vol. 44, No. 2, pp. 331–341. © Pleiades Publishing, Ltd., 2017.

WATER QUALITY AND PROTECTION: ENVIRONMENTAL ASPECTS

Characterization and Prediction of Stormwater Runoff Quality in Sub-Tropical Rural Catchments[1]

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Received June 1, 2015

Abstract—Due to scarcity of local data on stormwater pollution levels and rainfall-runoff generation process, very few attempts have been made towards the management of stormwater in sub-tropical rural catchments. An attempt has been made in the present study to characterize and predict the stormwater runoff characteristics using regression modeling from five rural catchments in north-west India. Stormwater samples and flow data were collected from 75 storm events. Samples were analyzed for pH, total suspended solids (TSS), 5-day biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), total kjeldhal nitrogen (TKN), total phosphorous (TP), nitrate-nitrogen (NO_3^-–N), total coliform count (TC), fecal coliform count (FC), Zn, Cu and Fe. It was found that size of the catchment and the land use practices influenced the stormwater quality even in predominantly rural areas, otherwise thought to be homogeneous. The results obtained were related with the antecedent dry days (ADD) and average rainfall. ADD was found to be positively correlated with pollutant loads whereas average rainfall showed negative correlation. The study highlights the importance of ADD in causing greater mean pollutant concentrations except for TKN, TP and NO_3^-–N. Regression models were developed for the studied catchments to estimate mean pollutant concentrations as a function of rainfall variables. Results revealed that measured pollutant concentrations demonstrated high variability with ADD and average rainfall in small rural catchments, whereas in large catchments, factors like land use, extent of imperviousness etc. resulted in low predictability of measured parameters.

Keywords: antecedent dry days, mean pollutant concentrations, regression model, rural catchment, stormwater quality, village pond

DOI: 10.1134/S0097807817020129

INTRODUCTION

In numerous studies conducted in different countries, urban stormwater runoff has been recognised as an important non-point pollution source for receiving water bodies [1, 4, 6, 26, 30, 31]. In recent years, some studies have also highlighted the stormwater runoff from rural highways as a significant contributor to water quality degradation [8, 19]. Stormwater runoff from rural areas can be laden with pollutants and forms the considerable quantity of non-point water source for rural streams and ponds [23]. For effective stormwater management strategies, watershed planners need information about the quality and quantity of stormwater runoff reaching the receiving water bodies like ponds in rural areas [2, 7].

Different models like regression, stochastic, and deterministic simulations have been used to determine the quality in terms of mean pollutant concentrations and loads in stormwater runoff [14]. Regression analysis has been applied by many researchers to predict and characterize rainfall and pollutant characteristics, and to show the relationship between these two variables [1, 5, 11, 13, 16–18, 20, 21, 24]. Hamilton and Luffman (2009) have achieved relative success in using multiple linear regression analysis ($R^2 = 0.565$) to predict the concentration of E. coli using precipitation, discharge, and turbidity as predictors. Madarang and Kang (2014) concluded that sufficient number of storms is a necessary condition for developing a reliable regression model and to overcome the over-fitting problem.

Maniquiz et al. (2010) established that rainfall parameters like total event rainfall and average rainfall intensity are possible predictors of pollutant loads. Irish et al. (1998) and Brezonik and Stadelmann (2002) found that loads for each constituent are dependent upon a unique subset of variables. Gan et al. (2008) determined that antecedent dry period and depth of rainfall are main rainfall factors influenc-

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Table 1. Characteristics of study catchments

Rural catchment	Catchment location	Catchment area, ha	Catchment population	Land use, %			
				impervious cover	grass cover	crop cover	tree canopy
Majari	31°11′20.40′ N 75°58′12″ E	3.83	783	90	8	0	2
Samrai	31°10′43.30″ N 75°37′57.26″ E	11.47	1879	87	11	0	2
Sodhian	31°05′38.87″ N 76°01′37.90″ E	6.77	1040	72	20	6	2
Mandiala	31°33′ N 74°50′42″ E	7.71	1420	82	15	0	3
Tayabpur	31°23′48.29″ N 75°18′50.34″ E	2.52	540	65	25	6	4

ing the quality of highway runoff in rural areas. Chow et al. (2013) concluded that multiple regression models are useful for estimating event mean concentration (EMC) values of most pollutants and reinforced the importance of antecedent dry days (ADD) for causing greater EMC values for most of the pollutants. However, some other studies found negative correlation between EMCs of parameters like TSS, SRP and TP against ADD [2, 25]. The quality of runoff has also found to be impacted by the geographic and physical factors such as the type and intensity of land use, degree of imperviousness, tree cover, soil type and slope [9, 16]. Wang et al. (2013) found considerable fluctuations in mean pollutant concentrations of stormwater runoff from different urban land uses. In a sub-tropical country like India, rural catchments usually do not have any provision for stormwater drainage and due to the natural slope almost whole of the stormwater accumulates in the village ponds thus impairing an important source of water. Although, the application of regression models in urban runoff quality determination have started over the past decade, very limited studies have been conducted in exclusively rural areas. Even in rural areas, most of the research on non-point source pollution has been concentrated in temperate regions where the rainfall-runoff generation processes are quite different from subtropical environments. Thus, this study aims to achieve the following goals: (1) to characterize the stormwater runoff quality from different rural catchments; (2) to construct regression models of mean pollutant concentrations from rural stormwater runoff using antecedent dry days and average rainfall as predictors.

MATERIALS AND METHODS

Study Area

Five rural watersheds were selected in Doaba region of Punjab state in north-west India to serve as catchments for the present study. The region lies in the sub-tropical belt and the climate is determined by the extreme hot and cold conditions. The temperature ranges from 0 to 45°C (min/max) in the chosen area of study. The annual average rainfall ranges from 650 to 900 mm, of which 75% of rainfall falls in three months of summer. The selected rural catchments are covered by four rainfall stations of India Meteorological Department (IMD), namely, Nawanshahar, Kapurthala, Phagwara and Nakodar, which are the closest rainfall stations, approximately 2–3 km from the study areas. The five catchments represent a wide range of population sizes, catchment areas of the pond and land uses (Table 1). Majari village (Nawanshahar) is located along the state highway and having small area serving as catchment for the studied pond. Samrai (Phagwara) is a large village having at least four identified outlets for village catchment area. Sodhian (Nawanshahar) is a mid-sized village with only one pond for collection of almost whole of the stormwater generated in the catchment. Mandiala (Nakodar) is a large catchment village having one pond to collect the stormwater generated. Tayabpur (Kapurthala) is a small catchment village with one pond serving as an outlet for whole of the catchment stormwater (Figs. 1 and 2).

For information on the watershed characteristics and identification of the catchment area of ponds, physical survey of the catchments, interviews with local people and the survey maps provided by the Department of Water Supply and Sanitation, Government of Punjab were used. Google Earth Pro was used for demarcating the catchments and assessing the area contributing to the runoff and the data pertaining to rainfall events have been obtained from IMD.

Sample Collection and Analysis

In this study, a total of 20 independent rainfall events were monitored for each of the five catchments

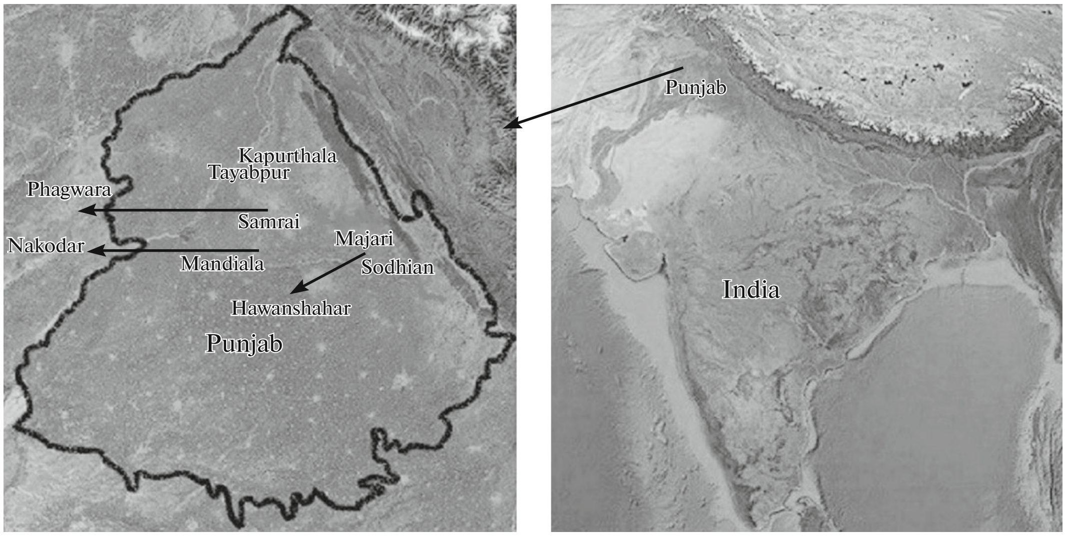

Fig. 1. Location map of Punjab state and study areas.

during July 2011 to September 2014. Out of these 20 rainfall events, 15 were used for model development while remaining 5 were used for its validation. The ADD and rainfall depth data procured from IMD is represented in the form of box plots (Fig. 3). Stormwater samples were manually collected at regular intervals from the inlet point of the ponds during the rainfall event, i.e. from the start of rainfall event till it subsides. Specifically, one sample was collected every 5 min within 30 min after the runoff started, every 10 min during a period of 30 to 60 min, and thereafter every 30 min till the end of the rainfall [30]. For every time interval one liter stormwater sample was collected in glass bottles. The monitored rainfall depths range from 5.2 to 102 mm and ADD was between 4 and 28 days. A minimum gap of 4 days between any two successive storm events being sampled was maintained as per the guidelines specified in Caltrans Stormwater Monitoring Protocol Guidance Manual [10]. Velocity-area method was used to determine the flow rates during the sample collection. All stormwater samples were brought to the environmental laboratory of Guru Nanak Dev Engineering College and analyzed for pH, total suspended solids (TSS), 5-day biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), total kjeldhal nitrogen (TKN), total phosphorous (TP), nitrate-nitrogen (NO_3^-–N), total coliform count (TC), fecal coliform count (FC), and heavy metals: Zn, Cu and Fe. The samples were collected and analyzed according to Standard Methods for Examination of Water and Wastewater [28].

Data Analysis

Correlations between mean pollutant concentrations and storm characteristics were determined using Pearson correlation analysis. Multiple regression analysis was used to develop the regression models using MiniTab version 17. Regression analysis was undertaken keeping pollutant concentration as dependent variable, and ADD and average rainfall as two independent variables. The general multiple linear regression (MLR) equation used to develop estimation equations for mean pollutant concentrations is shown as:

$$\textit{Mean pollutant concentrations or Load} \\ = a \pm b\,(\text{ADD}) \pm c\,(\text{Avg. Rainfall}),$$

where a is a constant, dependent on other variables like land use etc.; b and c are the dependent parameter constants; and ADD (days), average rainfall (mm) are the input variables.

The developed regression equations were first calibrated and then validated to confirm the accuracy of the regression equations obtained and assess their ability to predict the concentration of pollutants. Chi square tests were applied to evaluate the goodness of fit at level of significance.

The value of chi square (X^2) obtained for a particular pollutant parameter is compared with the tabulated value of chi squared distribution for $\alpha = 0.05$ significant level at $n - 1$ degrees of freedom. If the calculated value is less than the tabulated value, the null hypothesis gets accepted which means that the hypothesis stating that the regression equations obtained can predict the concentrations of the pollutants with 95% accuracy and 5% standard error holds true and valid.

The developed regression models were used for the assessment of stormwater quality in all the rural catchments under three different sets of conditions, i.e. worst case, average case and best case conditions. These conditions are defined by exploring rainfall data of last 10 years provided by IMD.

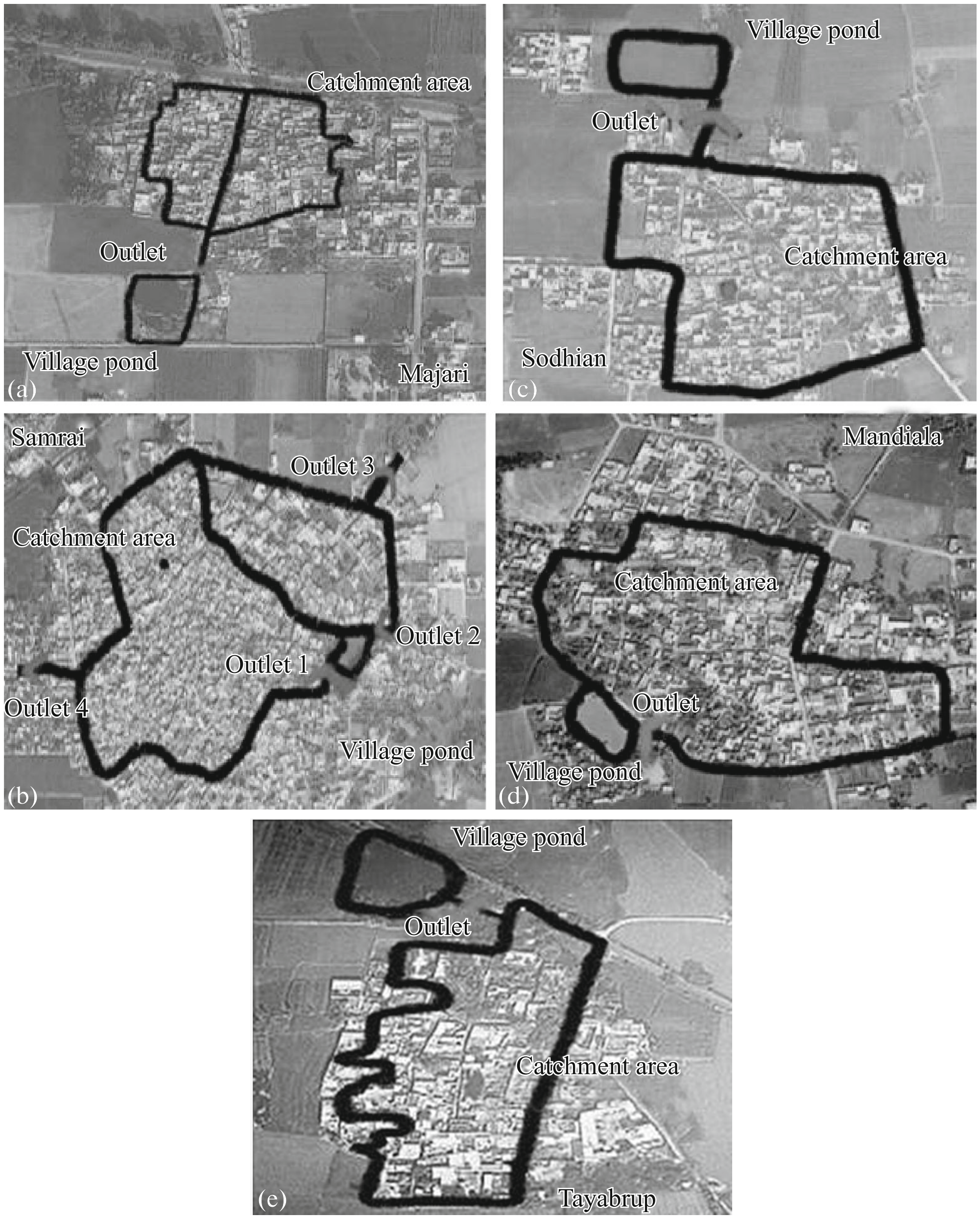

Fig. 2. Catchments of villages (a) Majari, (b) Samrai, (c) Sodhian, (d) Mandiala, (e) Tayabpur.

RESULTS AND DISCUSSION

Stormwater Runoff Characterization

The results of the major runoff quality parameters determined in present study are tabulated in Table 2. The comparison of average concentrations of stormwater quality parameters among the studied catchments revealed that the largest rural catchment, Samrai, has recorded the highest mean concentrations for TSS, BOD_5, COD, TKN, NO_3^-–N and Zn. The second largest rural catchment, Mandiala showed the highest average concentrations of TP, TC, FC and Fe. High standard deviations (Std. Dev.) for stormwater runoff parameters in studied catchments demonstrate large temporal fluctuations in mean pollutant concentrations. The standard deviations for stormwater parameters are highest in Samrai catchment followed by Mandiala, Sodhian and the smaller catchments of Majari and Tayabpur. Different land use practices in the catchments and the catchment size might be responsible for generating pollutants in different concentrations.

Similar studies have also been reported from other parts of the world but mostly these studies have been implemented in urban areas or on urban edge areas. By comparing the results of these studies with the present work, it can be concluded that the mean pollutant concentrations of organic constituents are higher in the stormwater generated from rural catchments than the results of Patiala, India [1] and USA [27]. This can be attributed to the fact that in the present study, samples were taken from the inlet point of ponds through drains feeding wet weather flow (during rainfall event). Mean pollutant concentrations of Zn and Cu in present work were much lower than the study results of Patiala, India and USA. Runoff from the catchments in USA is less polluted as compared to the others. Due to the predominantly urban nature of watershed in Paris [15], the water quality of stormwater runoff was closely related to the layout of land uses, drainage system and environmental background. In general, pollutant concentration values of all the parameters were much higher in Paris than this study's results. Mean value of organic constituent COD (315 mg/L) in present study was much lower than the results of Iran (561 mg/L) [29]. Whereas, the concentrations of TKN and TP observed in our study were on higher side than that of Iran.

Correlation Analysis and Regression Model Development

The relationship between mean pollutant concentrations with ADD and average rainfall was analyzed using Pearson correlation analysis. Only significant correlation i.e. $p < 0.05$ are shown in Table 3. ADD was found to be positively correlated with pollutant loads whereas average rainfall mostly showed negative correlation. In Majari and Tayabpur catchments, ADD demonstrated strongest correlations with TSS, BOD_5, COD, $NO_3^-{-}N$, TP, Zn, Cu and Fe. In other rural catchments, ADD was observed to be strongly correlated with TSS, BOD_5 and COD. This shows that with the increase in ADD periods the mean pollutant concentrations tend to increase. This outcome corroborates the findings of other researchers [2, 5, 8]. Similar relationship with ADD was not observed for TKN at Majari, Samrai and Tayabpur catchments and for TP at Majari, Samrai and Sodhian catchments. Similarly, $NO_3^-{-}N$ also showed significant relationship with ADD only at Majari catchment. These findings suggest that concentrations of TKN, TP and $NO_3^-{-}N$ are more influenced by site specific characteristics like land use, type of pavements, etc. instead of ADD.

Average rainfall was found to be moderately correlated with mean pollutant concentrations at Majari and Tayabpur catchment. Negative correlation was observed with BOD_5, $NO_3^-{-}N$ and Zn at Majari and with TKN, TP and Fe at Tayabpur. In Samrai, Sodhian and Mandiala catchments, moderate to strong negative correlations were observed between mean pollutant concentrations and average rainfall. This finding can be attributed to more runoff generation during large storms that dilutes the pollutant concentrations [2, 8]. Interestingly, TSS was positively correlated with rainfall amount at Majari, Sodhian and Tayabpur catchments. This implies that more

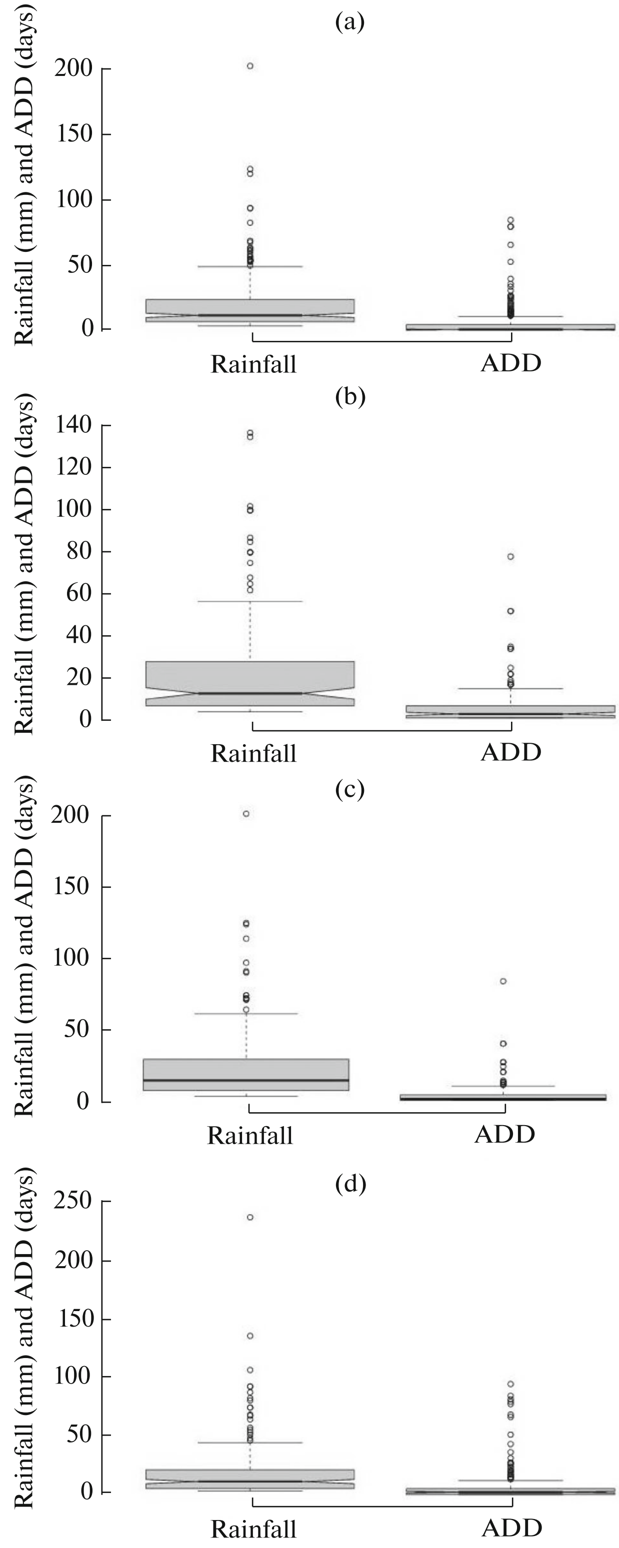

Fig. 3. Box plots of rainfall stations (a) Nawanshahar, (b) Kapurthala, (c) Phagwara, (d) Nakodar.

Table 2. Summary of stormwater quality in rural catchments

Catchment	Parameters, mg/L (except pH) (TC—Total Coliforms/100 mL, FC—Fecal Coliforms/100 mL)											
	pH	TSS	BOD_5	COD	TKN	NO_3^-–N	TP	TC	FC	Zn	Cu	Fe
Majari												
n	170	170	170	170	155	170	170	160	160	155	155	155
min	7.34	145	61	228	8.27	3.87	0.75	14000	2000	0.027	0.008	0.872
max	8.24	287	140	400	13.31	6.82	2.65	245000	48400	0.102	0.032	1.964
mean	7.77	206	102	305	10.99	5.25	1.42	109000	17500	0.07	0.02	1.45
Std. Dev.	0.34	53	27	59	1.78	1.02	0.74	79000	16900	0.03	0.01	0.40
Samrai												
n	180	180	180	180	165	180	180	170	170	165	165	165
min	6.86	140	65	230	7.84	3.70	0.55	118000	13200	0.086	0.009	0.655
max	8.25	495	276	576	18.42	13.25	4.21	843000	82500	0.236	0.028	1.823
mean	7.52	225	115	315	12.35	6.46	2.44	410000	37200	0.15	0.02	1.42
Std. Dev.	0.53	134	80	130	3.79	3.49	1.37	281000	23600	0.05	0.01	0.44
Sodhian												
n	155	155	155	155	155	155	155	145	145	155	155	155
min	7.66	68	45	148	8.40	2.48	1.80	229000	19800	0.073	0.010	0.762
max	8.05	258	190	465	13.98	9.56	3.30	645000	79100	0.152	0.024	1.165
mean	7.88	133	96	231	11.21	5.27	2.43	393000	59600	0.12	0.02	0.97
Std. Dev.	0.15	72	54	117	2.22	2.53	0.57	143000	21000	0.03	0.01	0.16
Mandiala												
n	168	170	170	170	155	170	170	158	158	160	160	160
min	7.38	75	48	175	7.40	3.60	0.85	210000	35700	0.082	0.008	0.921
max	8.34	407	238	521	15.95	11.20	4.57	878000	94500	0.183	0.024	2.541
mean	7.83	211	108	290	10.38	5.96	2.85	468000	71500	0.14	0.01	1.59
Std. Dev.	0.35	110	70	125	3.32	2.79	1.49	250000	21700	0.04	0.01	0.53
Tayabpur												
n	175	175	175	170	160	170	170	160	160	160	160	160
min	7.34	136	73	242	7.41	4.33	1.54	217000	18900	0.064	0.007	0.925
max	8.17	254	143	376	12.23	6.90	3.10	550000	48900	0.127	0.030	1.935
mean	7.74	184	102	303	10.20	5.68	2.47	380000	32500	0.09	0.02	1.52
Std. Dev.	0.32	48	26	52	1.77	0.91	0.66	121000	12600	0.02	0.01	0.38

runoff volume results in higher TSS concentrations. Meanwhile, negative correlation was witnessed between TSS and average rainfall at Mandiala catchment, whereas, in Samrai catchment, relationship was found to be not significant. Such variations in observations make it imperative to perform site specific studies while determining the variation of pollution loads with rainfall parameters.

Regression models can help predicting the pollution concentrations, which largely depends on both build-up and wash-off processes. The build-up depends on the ADD, land use and wind speed. Wash-off is a function of event rainfall volume, rainfall intensity and duration of rainfall [18]. Due to the practicality of determining the rainfall variables in a rural area, two major rainfall factors, i.e. ADD and the average rainfall have been evaluated to develop regression models in the present study. Table 4 presents the multiple linear regression results for estimating the mean pollutant concentrations. The parameters for those, the regression showed coefficients of determination (R^2) less than 0.5 for all the catchments were dropped. R^2 values for some of the parameters are greater than 0.8, hence suggesting that the equations and data are well matched. The calibration of the regression equations were performed by applying chi

Table 3. Correlation of pollutant concentrations with rainfall variables for rural catchments (Significant correlations at $p <$ 0.01 are shown in bold)

Catchment	Parameters								
	TSS	BOD_5	COD	TKN	NO_3^-–N	TP	Zn	Cu	Fe
					Majari				
ADD	0.77	0.85	0.82	–	0.71	–	0.53	0.54	0.68
Avg. Rainfall	0.54	–0.53	–	–	–0.57	–	–0.60	–	–
					Samrai				
ADD	0.56	0.75	0.58	–	–	–	0.65	0.52	0.61
Avg. Rainfall	–	–0.54	–0.58	–0.59	–0.68	–	–0.55	–0.52	–0.58
					Sodhian				
ADD	0.72	0.76	0.59	0.56	–	–	0.55	–	0.70
Avg. Rainfall	0.57	–0.58	–	–	–0.66	–0.63	–0.60	–	–0.54
					Mandiala				
ADD	0.55	0.58	0.60	0.58	–	0.62	0.67	0.54	0.56
Avg. Rainfall	–0.53	–	–0.57	–0.70	–0.54	–0.55	–	–	–0.53
					Tayabpur				
ADD	0.73	0.81	0.75	–	–	0.59	0.55	0.61	0.69
Avg. Rainfall	0.56	–	–	–0.54	–	–0.53	–	–	–0.59

square test on the same 15 storm events which were used for the development of regression models. The chi square values were compared with the tabulated values at $n - 1$ degrees of freedom (df), i.e. 14 for all the rural catchments. For most of the cases, the null hypothesis was valid, as the chi square values obtained were less than the tabulated value (23.68 at df = 14) at the level of significance set at $\alpha = 0.05$ (Table 4). To validate and to test the predictive power of the calibrated regression models, chi square tests were again applied on the five additional storm events and the goodness of fit was evaluated at the level of significance set at $\alpha = 0.05$ (Table 4). The null hypothesis was found to be valid for most of the parameters, as the chi square values obtained were less than the tabulated value (9.49 at df = 4). The standard error of estimate (SEE) ranges from good (SEE = 0.004) to poor (SEE = 40).

Among all the parameters TSS, BOD_5, COD, NO_3^-–N, TKN along with heavy metals (Zn, Fe and Cu) showed a strong dependence on ADD and washoff resulting from the amount of rainfall. Total Phosphorus demonstrated a weak reliance on these independent variables. Rainfall variables evaluated in this study were unable to explain the variability in total coliform and fecal coliform count. This finding may be attributed to the dependence of coliform bacteria on TSS and temperature as determined by Chen and Chang (2014).

In general, ADD positively influenced the concentrations of the pollutants, i.e., more the dry days, higher the pollutant concentration, whereas, amount of rainfall was observed to be negatively related with the pollutant concentration. A large variation in the mean pollutant concentrations was observed between different sites. This outcome can be attributed to a complex interaction among factors like drainage area, extent of development, land use and amount of impervious area. It was observed that in the smaller catchments such as Tayabpur and Majari, the measured pollutant loads demonstrated high variability with ADD and average rainfall which is evident from high values of coefficients of determination (R^2) of the measured parameters (Table 4). The variation in the coefficients of determination of measured end points in these smaller catchments was also found to be low. These observations showed that due to homogeneity of smaller catchments the mean pollutant concentrations are less prone to be influenced by the variables other than ADD and average rainfall. In contrast, Samrai and Mandiala catchments have large areas and therefore demonstrated low variability of measured pollutant parameters with ADD and rainfall, which is apparent from the low values of coefficients of determination (Table 4). Low predictability of large rural catchment models is the result of more variable pollutant sources and the influence of variables like rainfall pattern, type of pavements, land use practices, vehicular movement etc. The results of village Sodhian also corroborated the outcome that with increase in size of the catchment the variability of pollutant concentrations decreases against rainfall variables.

Table 4. Multiple linear regression results for mean pollutant concentrations and goodness of fits statistics for study catchments (R_d–Avg. Rainfall) (SEE refers to standard error of estimate)

Catchment	a	ADD b	R_d c	R^2	SEE	Calibration		Validation	
						X^2	Null Hypoth.	X^2	Null Hypoth.
				Majari					
TSS	29.37	19.24	0.70	0.91	39	29.45	Reject	15.29	Reject
BOD_5	57.11	1.78	–0.74	0.96	13	9.89	Accept	2.94	Accept
COD	147.06	6.43	–1.57	0.97	23	10.57	Accept	2.23	Accept
TKN	4.76	0.06	–0.08	0.41	3.35	38.93	Reject	17.82	Reject
NO_3^-–N	3.25	0.584	–0.053	0.98	0.54	3.14	Accept	1.24	Accept
TP	2.88	0.064	–0.052	0.43	0.70	34.68	Reject	19.64	Reject
Zn	0.164	0.007	–0.003	0.87	0.02	0.05	Accept	1.28	Accept
Cu	0.012	0.002	–0.0003	0.91	0.004	0.14	Accept	0.56	Accept
Fe	2.13	0.090	–0.026	0.96	0.126	1.78	Accept	0.78	Accept
				Samrai					
TSS	305.50	4.87	–1.73	0.78	28	19.53	Accept	6.88	Accept
BOD_5	99.48	3.73	–0.64	0.93	5	5.09	Accept	4.56	Accept
COD	245.42	6.88	–1.26	0.67	27	14.09	Accept	8.67	Accept
TKN	5.78	0.83	–0.07	0.66	2.47	3.23	Accept	1.40	Accept
NO_3^-–N	8.45	0.654	–0.067	0.56	3.78	7.69	Accept	4.69	Accept
TP	2.52	0.053	–0.048	0.35	0.80	38.90	Reject	16.87	Reject
Zn	0.042	0.011	–0.0001	0.67	0.028	0.07	Accept	3.35	Accept
Cu	0.026	0.001	–0.0003	0.77	0.005	0.53	Accept	0.42	Accept
Fe	1.869	0.014	–0.015	0.69	0.304	2.55	Accept	3.57	Accept
				Sodhian					
TSS	27.72	3.30	0.056	0.85	15	11.56	Accept	7.42	Accept
BOD_5	104.29	1.56	–1.20	0.95	6	4.55	Accept	1.63	Accept
COD	246.51	4.96	–2.60	0.73	24	20.12	Accept	11.48	Reject
TKN	8.32	0.366	–0.005	0.53	2.38	3.11	Accept	3.47	Accept
NO_3^-–N	7.29	0.32	–0.098	0.67	1.71	12.04	Accept	14.60	Reject
TP	4.63	0.082	–0.054	0.95	0.21	0.25	Accept	1.78	Accept
Zn	0.10	0.01	–0.003	0.80	0.033	0.18	Accept	2.54	Accept
Cu	0.016	0.001	–0.0002	0.43	0.006	24.54	Reject	10.50	Reject
Fe	1.46	0.001	–0.013	0.82	0.106	2.15	Accept	1.17	Accept
				Mandiala					
TSS	252.86	4.09	–2.45	0.65	40	33.12	Reject	24.34	Reject
BOD_5	94.30	2.46	–0.92	0.60	17	19.17	Accept	7.88	Accept
COD	279.39	5.42	–2.58	0.72	32	22.45	Accept	7.25	Accept
TKN	13.17	0.45	–0.12	0.95	0.63	1.68	Accept	2.66	Accept
NO_3^-–N	7.09	0.51	–0.082	0.79	0.73	2.18	Accept	2.76	Accept
TP	2.11	0.44	–0.049	0.77	0.66	1.50	Accept	3.55	Accept
Zn	0.015	0.01	0.0002	0.69	0.019	0.15	Accept	1.67	Accept
Cu	0.022	0.001	–0.0003	0.55	0.006	0.24	Accept	0.67	Accept
Fe	2.65	0.073	–0.028	0.57	0.54	3.31	Accept	1.74	Accept
				Tayabpur					
TSS	56.49	2.93	0.54	0.91	17	5.97	Accept	7.76	Accept
BOD_5	128.50	1.37	–0.95	0.98	4.42	3.44	Accept	4.12	Accept
COD	256.32	3.79	–1.79	0.94	21	7.16	Accept	6.48	Accept
TKN	13.58	0.09	–0.076	0.95	0.59	0.87	Accept	5.75	Accept
NO_3^-–N	5.87	0.22	–0.077	0.39	4.12	25.65	Reject	14.40	Reject
TP	3.55	0.16	–0.042	0.94	0.24	1.32	Accept	1.49	Accept
Zn	0.127	0.003	–0.001	0.93	0.01	0.09	Accept	1.55	Accept
Cu	0.025	0.002	–0.0002	0.89	0.003	0.38	Accept	0.98	Accept
Fe	2.10	0.033	–0.015	0.98	0.08	1.75	Accept	1.16	Accept

Table 5. Independent variables combinations for prediction of stormwater quality

Rainfall Station	Independent variables	Worst case*	Average case**	Best case***
Nawanshahar	ADD, days	85	25	4
	Avg. Rainfall, mm	22	43	71
Kapurthala	ADD, days	78	21	4
	Avg. Rainfall, mm	28	60	93
Phagwara	ADD, days	85	20	4
	Avg. Rainfall, mm	30	63	112
Nakodar	ADD, days	95	33	4
	Avg. Rainfal, mm	24	58	75

* Maximum ADD and minimum effective rainfall.
** Average ADD and average effective rainfall.
*** Minimum ADD and maximum effective rainfall.

Table 6. Predicted stormwater quality parameters for best, worst and average case conditions (Values in parentheses indicate results for average case)

Catchment → Parameter	Majari	Samrai	Sodhian	Mandiala	Tayabpur
TSS, mg/L	145–287* (206)	131–667 (293)	45–309 (112)	75–407* (211)	118–299 (150)
BOD_5, mg/L	12–192 (70)	43–397 (134)	25–210 (92)	35–306 (122)	45–208 (100)
COD, mg/L	61–659 (240)	131–792 (303)	82–611 (259)	107–733 (309)	105–502 (229)
TKN, mg/L	–	1.26–74.23 (17.97)	6.23–38.33 (15.32)	5.98–53.42 (21.19)	6.87–18.47 (10.91)
NO_3^-–N, mg/L	1.82–51.72 (15.57)	3.56–62.03 (17.31)	1.60–32.16 (11.02)	2.98–53.76 (19.23)	–
TP, mg/L	–	–	1.12–10.41 (4.35)	0.18–42.35 (13.65)	0.28–14.85 (4.39)
Zn, ppm	0–0.69 (0.21)	0.074–0.97 (0.25)	0–0.884 (0.221)	0.07–0.97 (0.356)	0.046–0.333 (0.13)
Cu, ppm	0–0.175 (0.05)	0–0.102 (0.03)	–	0.003–0.11 (0.037)	0.007–0.035 (0.017)
Fe, ppm	0.64–9.21 (3.26)	0.25–2.61 (1.204)	0.54–1.26 (0.93)	0.84–8.91 (3.43)	0.84–4.25 (1.89)

* Values from the analysis results.

Stormwater Quality Assessment

The three different sets of conditions for which the stormwater quality assessment was carried out are shown in Table 5. The maximum rainfall was taken from the upper 95% confidence level of 10 year rainfall values. All other conditions are the actual values obtained from 10 year meteorological data. Table 6 enlists the results of various stormwater quality parameters obtained for the above set of conditions. The values in parentheses indicate the results of stormwater quality parameters for average conditions. Best case is represented by minimum ADD and maximum effective rainfall i.e. minimum values, whereas worst case is represented by maximum ADD and minimum effective rainfall conditions i.e. maximum values. Therefore, the predicted values of stormwater quality parameters for best case in Table 6 are less than the minimum values of actual stormwater quality presented in Table 2, whereas predicted values for worst case conditions are higher than the real time maximum values. The values have been obtained for those parameters for which R^2 value is more than 0.5 and regression model is successfully calibrated. In cases where the calibration of regression models failed, the maximum, minimum and average values are reported from the characterization results. It has been found that for R^2 values less than 0.5, the regression equations provide misleading results due to weak relationship between measured parameter and independent variables. It has been observed that in isolated cases of metal pollutants especially Cu and Zn, the regression equations predicted negative values in best case conditions which were assumed to be zero while reporting the results. The predicted results of regression models will aid in making the decisions on selecting the stormwater treatment schemes especially under worst case conditions without actually carrying out the analysis for those conditions.

CONCLUSIONS

This research is the stepping stone for designing watershed level village pond based integrated stormwater and wastewater treatment systems to manage and treat the huge volumes of stormwater generated. The following conclusions can be drawn from this study:

1. The two largest catchments of Samrai and Mandiala show the highest mean pollutant concentrations in stormwater runoff. Significant variation in the stormwater quality of large and small catchments is witnessed. These findings suggest that even in rural areas which are considered to be homogeneous in nature, size of the catchment and the land use practices influence the stormwater quality to a large extent. Therefore, site specific studies are important to determine the stormwater quality even in predominantly rural areas.

2. Present study emphasizes the importance of ADD in causing greater mean pollutant concentrations in rural catchments which is also highlighted by other researchers in urban areas. Except TKN, TP and NO_3^-–N, ADD influences the mean pollutant concentrations of all other pollutants. Average rainfall is found to be negatively correlated with mean pollutant concentrations, however the extent of influence is limited for most of the pollutants.

3. Multiple regression models are useful for predicting the mean pollutant concentrations of most of the pollutants, except pH, TC and FC. ADD and average rainfall to a large extent covered most of the variability in pollutant loads, still, there is a need to consider the impact of variables like land use in the development of models for large rural catchments. These findings contradict the outcome of some other studies in temperate regions that show negative relationship between EMC and ADD. Nevertheless, developed regression models can be a useful tool in making crucial decisions on treatment alternatives for stormwater management without analyzing every rainfall event. In case of worst case conditions, regression models can provide reliable stormwater quality results without waiting for the worst case conditions actually to occur.

ACKNOWLEDGMENTS

The authors are grateful to Testing and Consultancy Cell, Guru Nanak Dev Engineering College, Ludhiana for partially funding the testing and analysis work. The authors would also like to thank India Meteorological Department for providing the all important meteorological data.

REFERENCES

1. Arora, A.S. and Reddy, A.S., Development of multiple linear regression models for predicting the stormwater quality of urban sub-watersheds, *Bull. Environ. Contamin. Toxicol.*, 2014, vol. 92, no. 1, pp. 36–43.
2. Brezonik, P.L. and Stadelmann, T.H., Analysis and predictive models of stormwater runoff volumes, loads, and pollutant concentrations from watersheds in the twin cities metropolitan area, Minnesota, USA, *Water Resour.,* 2002, vol. 36, no. 7, pp. 1743–1757.
3. Chen, H.J. and Chang, H., Response of discharge, TSS, and E. coli to rainfall events in urban, suburban, and rural watersheds, *Environ. Sci.: Processes Impacts*, 2014, vol. 16, pp. 2313–2324.
4. Chow, M.F. and Yusop, Z., Characterization and source identification of stormwater runoff in tropical urban catchments, *Wat. Sci. Technol.*, 2014, vol. 69, no. 2, pp. 244–252.
5. Chow, M.F., Yusop, Z., and Shirazi, S.M., Storm runoff quality and pollutant loading from commercial, residential, and industrial catchments in the tropic, *Environ. Monit. Assess.*, 2013, vol. 185, no. 10, pp. 8321–8331.
6. Davis, B.S. and Birch, G.F., Catchment-wide assessment of the cost-effectiveness of stormwater remediation measures in urban areas, *Environ. Sci. Policy*, 2009, vol. 12, no. 1, pp. 84–91.
7. Driver, N.E. and Troutman, B.M., Regression models for estimating urban storm-runoff quality and quantity in the United States, *J. Hydrol.*, 1989, vol. 109, nos. 3–4, pp. 221–236.
8. Gan, H.Y., Zhuo, M.N., Li, D.Q., and Zhou, Y.Z., Quality characterization and impact assessment of highway runoff in urban and rural area of Guangzhou, China, *Environ. Monit. Assess.*, 2008, vol. 140, nos. 1–3, pp.147–159.
9. Graves, G., Wan, Y., and Fike, L., Water quality characteristics of stormwater from major land uses in South Florida, *J. Am. Wat. Res. Assoc.*, 2004, vol. 40, no. 6, pp. 1405–1419.
10. *Guidance manual: Stormwater Monitoring Protocols*, California Department of Transportation (CALTRANS), Report No. CTSW-RT-00-005, 2000.
11. Ha, S.J. and Stenstrom, M.K., Predictive modeling of storm-water runoff quantity and quality for a large urban watershed, *J. Environ. Eng., ASCE*, 2008, vol. 134, no. 9, pp. 703–711.

12. Hamilton, J.L. and Luffman, I., Precipitation, pathogens, and turbidity trends in the little river, Tennessee, *Phys. Geogr.*, 2009, vol. 30, no. 3, pp. 236–248.
13. Han, Y.H., Lau, S.L., Kayhanian, M., and Stenstrom, M.K., Characteristics of highway stormwater runoff, *Wat. Environ. Res.*, 2006, vol. 78, no. 12, pp. 2377–2388.
14. Irish, L.B., Barrett, M.E., Malina, J.F., and Charbeneau, R.J., Use of regression models for analyzing highway storm-water loads, *J. Environ. Eng., ASCE*, 1998, vol. 124, no. 10, pp. 987–993.
15. Kafi, M., Gasperi, J., Moilleron, R., Gromaire, M.C., and Chebbo, G., Spatial variability of the characteristics of combined wet weather pollutant loads in Paris, *Water Resour.*, 2008, vol. 42, no. 3, pp. 539–549.
16. Kayhanian, M., Suverkropp, C., Ruby, A., and Tsay, K., Characterization and prediction of highway runoff constituent event mean concentration. *J. Environ. Manag.*, 2007, vol. 85, no. 2, pp. 279–295.
17. Khan, S., Lau, S.L., Kayhanian, M., and Stenstrom, M.K., Oil and grease measurement in highway runoff-sampling time and event mean concentrations, *J. Environ. Eng., ASCE*, 2006, vol. 132, no. 3, pp. 415–422.
18. Kim, L.H., Kayhanian, M., Lau, S.L., and Stenstrom, M.K., A new modelling approach in estimating first flush metal mass loading, *Wat. Sci. Technol.*, 2005, vol. 51, nos. 3–4, pp. 159–167.
19. Legret, M. and Pagotto, C., Evaluation of pollutant loadings in the runoff waters from a major rural highway, *Sci. Total Environ.*, 1999, vol. 235, nos. 1–3, pp. 143–150.
20. Ma, J.S., Characteristics of pollutants in highway runoff: regression, representativeness, and first flush, *Ph.D. Thesis*, Los Angeles: University of California, 2002, p. 195.
21. Ma, J.S., Kang, J.H., Kayhanian, M., and Stenstrom, M.K., Sampling issues in urban runoff monitoring programs: Composite versus grab, *J. Environ. Eng., ASCE*, 2009, vol. 135, no. 3, pp. 118–127.
22. Madarang, K.J. and Kang, J.H., Evaluation of accuracy of linear regression models in predicting urban stormwater discharge characteristics, *J. Environ. Sci.*, 2014, vol. 26, no. 6, pp. 1313–1320.
23. Mallin, M.A., Johnson, V.L., and Ensign, S.H., Comparative impacts of stormwater runoff on water quality of an urban, a suburban and a rural stream, *Environ. Monit. Assess.*, 2009, vol. 159, nos. 1–4, pp. 475–491.
24. Maniquiz, M.C., Lee, S., and Kim, L.H., Multiple linear regression models of urban runoff pollutant load and event mean concentration considering rainfall variables, *J. Environ. Sci.*, 2010, vol. 22, no. 6, pp. 946–952.
25. Passeport, E. and Hunt, W., Asphalt parking lot runoff nutrient characterization for eight sites in North Carolina, USA, *J. Hydrol. Eng., ASCE*, 2009, vol. 14, special issue: Impervious Surfaces in Hydrologic Modeling and Monitoring, pp. 352–361.
26. Qin, H.P., Khu, S.T., and Yu, X.Y., Spatial variations of storm runoff pollution and their correlation with landuse in a rapidly urbanizing catchment in China, *Sci. Total Environ.*, 2010, vol. 408, no. 20, pp. 4613–4623.
27. Smullen, J.T., Shallcross, A.L., and Cave, K.A., Updating the U.S. nationwide urban runoff quality date base, *Wat. Sci. Technol.*, 1999, vol. 39, no. 12, pp. 9–16.
28. *Standard Methods for the Examination of Water and Wastewater*, 21st ed., Washington, D.C.: Am. Public Health Association, Am. Water Works Association, Water Environ. Federation, 2005.
29. Taebi, A. and Droste, R.L., Pollution loads in urban runoff and sanitary wastewater, *Sci. Total Environ.*, 2004, vol. 327, nos. 1–3, pp. 175–184.
30. Wang, S., He, Q., Ai, H., Wang, Z., and Zhang, Q., Pollutant concentrations and pollution loads in stormwater runoff from different land uses in Chongqing, *J. Environ. Sci.*, 2013, vol. 25, no. 3, pp. 502–510.
31. Zgheib, S., Moilleron, R., Saad, M., and Chebbo, G., Partition of pollution between dissolved and particulate phases: what about emerging substances in urban stormwater catchments?, *Water Resour.*, 2011, vol. 45, no. 2, pp. 913–925.