Determination of Infiltration Model Parameters Using Basic Soil Physical Properties

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Determination of infiltration model parameters using basic soil physical properties

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Abstract

Quantification of infiltration rate is a time-consuming process because of its variability and challenges in the accurate estimation of infiltration model parameters. In this study predictive equations for parameters of Horton, Kostiakov, Modified Kostiakov and Philip infiltration models were developed using basic soil-properties. The model-parameters were initially determined applying non-linear Levenberg Marquardt algorithm (LMA) on field-observed infiltration data and were subsequently determined by predictive equations developed after applying regression analysis to investigated soil-properties. Regression analysis was carried-out using stepwise-regression (SR) where all the measured soil-properties were used, and by applying principal component analysis (PCA) prior to multiple linear-regression for reducing number of predictors. The results revealed that developed equations using stepwise regression and the ones developed after applying PCA were able to explain 40- 78% and 10- 50% of variation respectively. The performance evaluation of developed regression equations at two information levels along with LMA for prediction of infiltration model-parameters was carried out by computing an overall performance index (OPI), which combines relative weight of different statistical indicators, namely, Coefficient of Determination (R^2), Nash–Sutcliffe Efficiency (E_{NS}), Willmott's Index of Agreement (W), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Performance evaluation revealed, LMA with highest OPI-value is most suitable to ascertain parameters of studied infiltration models. However, for selected models using parameters determined at two information levels, it was observed that there exists no significant difference in OPI-value of computed infiltration rates suggesting that equations developed after PCA can be used successfully for determination of infiltration model-parameters.

Keywords: Infiltration model Parameters; Soil physical properties; Levenberg Marquardt algorithm; Principal Component Analysis; Stepwise regression; lesser Himalayas.

Declarations

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Author Abdul Qayoom Dar managed the literature searches.

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Introduction

Infiltration is an important process of the hydrologic cycle, governed by gravity, suction and pressure forces exerted by the soil in absorbing water from the outer soil's surface down its profile. Accurate estimation of infiltration rate is essential as it is one of the significant factors deciding the ability of soil to absorb water and initiation of runoff in a landscape (Bayabil et al. 2019). Further, quantification of infiltration may be potentially helpful to the hydrologists, irrigation and agricultural engineers, and soil scientists for accurate determination of soil moisture status, runoff, sediment and solute transport, estimation of artificial groundwater recharge, design of irrigation and drainage systems, water balance modelling etc. (Parhi et al. 2007; Ma and Shao 2008). Consequently, soil and water scientists dedicated a great deal of attention to infiltration studies, resulting in the development of a large number of computational infiltration models. These models can be classified as physically based infiltration models such as that of Philip (1957), Green and Ampt (1911), Smith-Parlange (1978), semi-empirical models such as those of

Horton (1940), Holtan (1961) and empirical models such as those of Kostiakov (1932), Modified Kostiakov (Smith 1972). However, identification of suitable infiltration models for the real-world data is a complex process as it is not always evident which model is more apt for a given condition (Mishra et al. 2003). From the viewpoint of field applicability of different infiltration models, accurate parameter estimation is very important (Deep and Das 2008). The appropriate determination of infiltration model parameters could assist in more realistic infiltration simulation, and aid in designing optimum irrigation facilities, predicting runoff occurrence time and amount (Moore et al. 1981). Numerous studies on determining infiltration models parameters and selection of the best fit model for evaluating the infiltration characteristics have been reported in the literature (Machiwal et al. 2006; Duan et al. 2011; Dagadu and Nimbalkar 2012; Syedzadeh et al. 2020). The finding of these studies revealed that under different regions, different models are feasible for prediction of the infiltration rate. In general, infiltration being dependent on soil and water characteristics, type of vegetative cover, climatological variables etc. (Kale and Sahoo 2011), is a complex process and due to the heterogeneity in soil physical and chemical properties (Syedzadeh et al. 2019) varies temporally and spatially. Thus, there is a need to compare the infiltration models at the regional level in order to choose the best fit model for evaluating the rate of water movement into the soil. Moreover, for the generation of precise predictive results, accurate determination of infiltration model parameters is essential.

The assessment of infiltration model parameters, however, is troublesome because of the absence of any physical meaning of several parameters of the developed infiltration models and their inability to be determined directly (Shao and Baumgartl 2014). Several researchers have used various techniques, namely, graphical technique (Dagadu and Nimbalkar 2012); simple regression model (Abdulkadir et al. 2011; Ogbe et al. 2011), and Levenberg-Marquardt algorithm (LMA) (Mazloom and Foladmand 2013; Oyedele et al. 2019) to quantify the infiltration model parameters from the field data. All the parameter estimation techniques rely on the field measured infiltration data, and often the actual data is not available in practice. Due to high variability of infiltration rate spatially and temporally (Mishra et al. 2003), it requires a large number of in-situ measurements, sample collection and analysis for determination of infiltration model parameters. Consequently, efforts have been made to indirectly determine the model parameters. One such effort is the Pedo-transfer function (PTF) approach (Bouma 1989) linking the soil hydraulic characteristics to readily accessible soil properties. Most of the studies in this regard, however,

have concentrated to develop regression equations for prediction of moisture retention and hydraulic characteristics (Grinevskii and Pozdnyakov 2009; Amanabadi et al. 2019; Dharumarajan et al. 2019). However, a very few researchers have also made efforts to develop the regression equations using PTF analysis for the prediction of infiltration model parameters, for example under rain forest in Guyana (Van de genachte 1996), the University of Queensland, Pinjarra Hills, Australia (Shao and Baumgartl 2014), and in several regions of Iran (Dashtaki et al. 2016). The findings of these studies with respect to developed regression equations using easily measured soil properties differ significantly on account of spatial heterogeneity resulting from anthropogenic activities, geological and pedological processes, suggesting that the result can be implemented exclusively at local scales.

Reconnaissance of literature revealed that a very few research (Van de genachte 1996; Shao and Baumgartl 2014; Dashtaki et al. 2016) has been carried out to develop the explicit regression equations using PTF analysis for the prediction of infiltration model parameters, and to the best of the author's knowledge no such studies have been carried out in the western Himalayan region of India. It has also been observed that extrapolating the regression equations developed using PTF approach to a different region is problematic (Tomasella and Hodnett 2004; Minasny and Hartemink 2011; Patil and Singh 2016). The western Himalayan region due to heterogeneous topographical characteristics, varied landscape and diverse geomorphic units is subjected to spatial variability of soil physical characteristics. It is thus of paramount importance to analyze variation in infiltration characteristics in this region as it is the significant input for estimation of many important hydrological processes like flood prediction and groundwater recharge estimation etc. Further, prediction equations for the infiltration model parameters with a large number of independent variables require cumbersome laboratory analysis for determination of soil physical properties. Principal Component Analysis (PCA) offers an alternative to identify the smaller set of variables containing most of the information in the original set of variables and has been used by several researchers (Rezaei et al. 2006; Gergen and Harmanescu 2012; Carlon et al., 2001; Shin and Lam, 2001). Rezaei et al. (2006) used PCA to identify minimum data set for soil quality assessment in range lands of Tehran, Iran. Gergen and Harmanescu (2012) applied PCA to characterize the heavy metal contamination of vegetables in Banat Country, South-west of Romania. Although it has been observed that PCA has been applied in a vast number of studies but a thorough search of the relevant literature yielded no related article on application of PCA to

simplify the data set for the estimation infiltration model parameters. Therefore, keeping above points in consideration, the present study in an urban sub-basin of the western Himalayan region of India has been undertaken to (i) measure the infiltration rate throughout the study area for determination of the parameters of selected infiltration models of Horton (H), Kostiakov (K), Modified Kostiakov (MK) and Philip (P); (ii) examine various soil properties and quantify their relationship with the infiltration parameters by developing predictive regression equations; and (iii) develop the predictive equations for the infiltration parameters with minimal data sets using the Principal Component Analysis (PCA) .

Materials and Methods

Study area description

The present field research was conducted in an urban sub-basin of lesser Himalayas, part of Dal Lake catchment, Jammu and Kashmir, India. The study area is part of the Indus Water Resource Region of the Jehlum basin (Fig. 1) encompassing an area of 32.19 km^2. It is spread over the geographical coordinates of 34º04′ to 34º10′N latitude and 74º48′ to 74º53′ E Longitude with elevation ranging from about 1580 to 4390 m above the mean sea level (MSL). The climate of the sub-basin is temperate with monthly mean maximum and minimum temperature varying between 31°C in July/August and -4°C in January, with an annual average of 11°C (Badar et al. 2019). Annual precipitation in the study sub-basin varies from 650-1000 mm with an average annual precipitation of 780 mm (Rasool and Kumar 2019). The undulating topography, diverse geomorphology and land use of the study area make basin hydrology more complicated. The major land uses in the study area comprises of urban settlements, grasslands, shrubland, agriculture fields with thin vegetation, floating garden etc. The urban settlements, mostly in the plain area, is densely populated and anthropogenic activities are rampant.

Site Selection and Experimental investigation

In order to select the sites for performing infiltration experiments and collect soil samples to determine various soil properties, a field survey was carried out. The sites were selected using purposive stratified methods of random sampling taking into account the land use and soil type. As reaching the sites for collecting field samples was also one of the constraints in undulating terrain, while selecting sampling sites transportation accessibility was also taken into account.

Information regarding land use land cover (LULC) and soil type were taken from available literature (Rasool et al. 2020). The area under shrubland, farmland and built-up land covered 8.3, 12.6 and 43.95% area of the sub-basin, respectively, while the remaining portion of the sub-basin is mainly under water-bodies, wetlands and aquatic vegetation. The study region mainly consisted of clay (40.9 %) and sandy clay (55.4 %) soils and only a small portion of the area (3.6 %) is under loamy sand soils. Hence, we considered only clay and sandy clay textured soils for our study. A total of 23 locations were selected considering different soil types and land covers. A portable Global Positioning Systems (GPS) receiver was utilized to acquire the geographical coordinates of the respective experimental sites, and the selected sites were plotted using Arc GIS (Fig. 1).

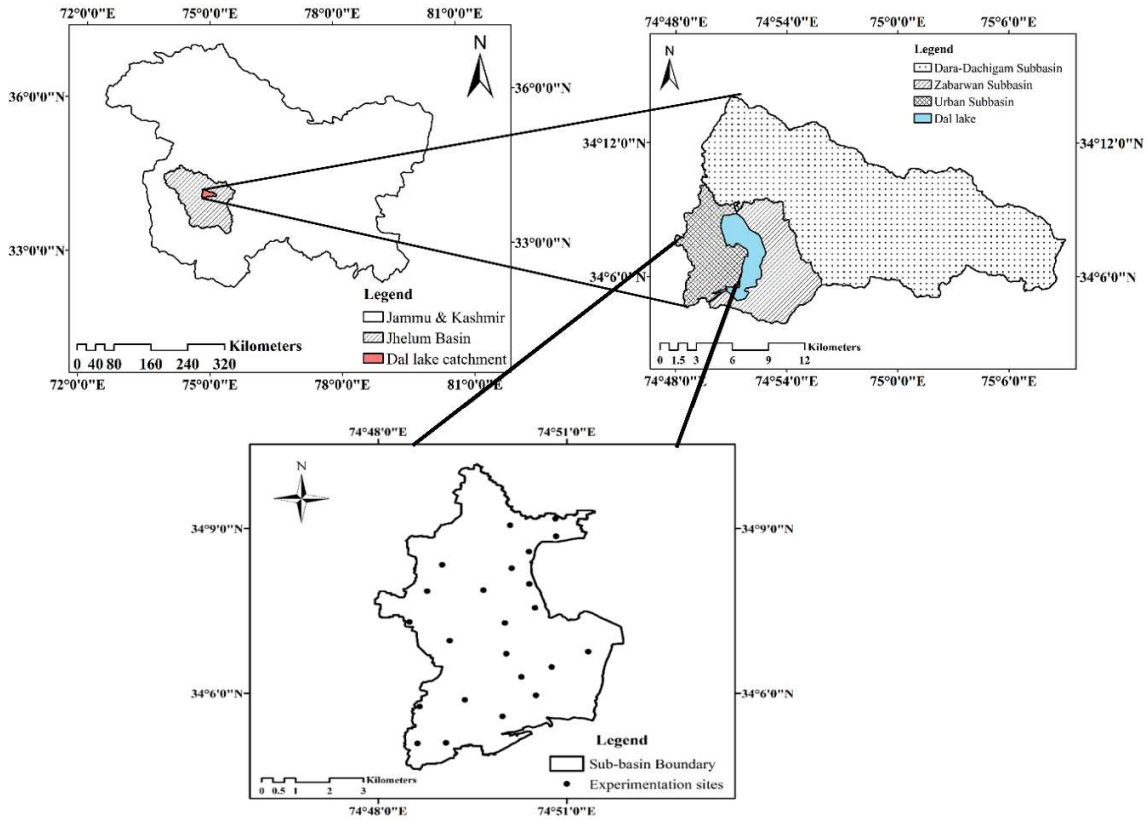


Fig. 1 Study area along with selected experimentation sites

At each of the selected sites, the samples were collected from an average depth of 25 cm and the collected samples were designated, stored in plastic bags and were taken to the laboratory for analysis. The particle size distribution of disturbed soil samples was estimated using the hydrometer method (Gee and Bauder 1986). For this purpose, disturbed samples in the laboratory

were air-dried, ground, passed through the 2 mm sieve and assayed in the laboratory. The undisturbed samples were used to ascertain antecedent moisture content using the gravimetric method. Organic carbon, saturated hydraulic conductivity (K_s), and soil water pressure heads at field capacity and permanent wilting point were determined using Walkley and Black wet oxidation method (Walkley and Black 1934), falling head method (Dingman 2002), and Pressure plate apparatus, respectively. The bulk density (ρ_b) was estimated by the core cutter method (Blacke and Hartge 1986a). Soil porosity was computed applying Equation (1):

$$\eta = \left(1 - \frac{\rho_b}{\rho_{sp}}\right) * 100 \qquad (1)$$

Where, ρ_{sp} is the particle density and was determined using the pycnometer method (Blacke and Hartge 1986b).

The geometric mean and geometric standard deviation of soil particle diameter were determined using the expressions (Shirazi and Boresma 1984) given below in Equation (2) and Equation (3):

$$d_g = \exp(0.01 \sum_{i=1}^{n} f_i \, ln \, M_i) \qquad (2)$$

$$\sigma_g = \exp(0.01 \sum_{i=1}^{n} f_i \, ln^2 \, M_i - a^2)^{0.5} \qquad (3)$$

Where, d_g is the geometric mean of soil particles; σ_g is the geometric standard deviation of soil particles; n is the number of soil textural fractions, f_i is the proportion of total soil mass with a diameter equal to or less than M_i and M_i is the mathematical mean of two successive limits of particle size.

Field experiments were conducted using the double-ring infiltrometer with 30 cm inner diameter and 60 cm outer diameter rings to measure the infiltration rate. The infiltrometer was carefully penetrated, using the falling weight type hammer, up to the depth of 15 cm into the soil. Water was filled in both the rings carefully without disturbing the soil surface, and steady head /water level was maintained in both the rings during the measurements. The rate of fall of the water level in the inner cylinder was measured at different time intervals, the measurements of water level were continued till the infiltration rate attained a steady value. The infiltration experiments were replicated three times at each of the selected sites to account for measurement variations and accurate determination of infiltration rate in the study region.

Infiltration models evaluated

The movement of soil moisture in the unsaturated soil profile is described by a nonlinear partial differential equation derived by Richards (Richard 1931) based on Darcy's law. The Richards equation has been applied to various complex situations (Ying et al. 2010) but the equation is non-linear, without any closed-form analytical solutions. However it can be solved using numerical techniques with predefined boundary conditions, initial conditions and then solving the equation for thin layers for small-time changes to obtain the distribution of water pressure and water content in the soil (Dingman 2015). Numerical solution of the Richards equation necessitates various measurements to be made to explain satisfactorily variations in soil properties that occur both vertically in the soil profile and from spot-to-spot in the field (Skaggs and Khaleel 1982). As the numerical solution of the Richards' equation is computationally intensive and requires extensive input (Ali et al. 2016; Ali and Islam 2018), infiltration models with simplified data requirements are preferred for field application. In this study four infiltration models, namely, Horton (H), Kostiakov (K), Modified Kostiakov (MK) and Philip (P) were selected. These four infiltration models selected based on their practical utility and wide use in various studies (Mishra et al. 2003; Machiwal et al. 2006). All the selected models chosen are based on empirical parameters and reflect the in-situ conditions (Wilson 2017) and thus predict the infiltration rates more accurately (Turner 2006). The infiltration models assessed for obtaining the model parameters are briefly presented in **Table 1**. The parameters of infiltration models demonstrate the effect of physical properties of soil on the infiltration rate in addition to initial moisture content and vadose zone conditions (Ogbe et al. 2011). Thus, to minimize the difference between the fields measured and model-predicted infiltration rates, accurate estimation of model parameters is an important step. In this study, using observed infiltration data, parameters of the infiltration models were determined using non-linear Marquardt algorithm of Statistical Package for Social Sciences 20.0 release software (SPSS 2011). This optimization method has been extensively used for the parameter estimation of the infiltration equations, as this technique has the ability to address the constraints of other parameter estimation techniques (Deep and Das 2008). The value of the parameter f_c for the Horton and Modified Kostiakov infiltration model, was determined experimentally and was used as model parameter in the field data to assess the predictability of infiltration models.

Table 1 Infiltration Equations and fitting parameters of models evaluated

Model name	Infiltration-rate Equation	Parameters
Horton (1940)	$f_p = f_c + (f_o - f_c)e^{-K_h t}$	f_p = the infiltration rate (cm hr^{-1}), f_c = the final steady state infiltration capacity, f_o = the initial infiltration capacity, K_h = Horton's decay coefficient specific to the soil characteristics and vegetation cover (T^{-1}), t = time from the start of infiltration (hr.), α (α>0) and β (0< β<1) = Kostiakov empirical constants α′(α′>0) and β′ (0< β′<1) are Modified Kostiakov empirical constants without physical meaning depending on the soil type, initial moisture content, rainfall rate and vegetative cover, S = the Sorptivity (cm $hr^{-1/2}$) and A= a parameter related to saturated hydraulic conductivity and represents the effects of soil suction and gravity head respectively
Kostiakov (1932)	$f_p = \alpha t^{-\beta}$	
Modified Kostiakov (1972)	$f_p = f_c + \alpha' t^{-\beta'}$	
Philip (1957)	$f_p = \frac{1}{2}\mathrm{S}t^{-.5} + A$	

Predictive Regression Equations for Infiltration parameters

Prediction using linear regression

For the derivation of predictive regression equations for the parameters of selected infiltration models, the observed/estimated parameters (measured or determined using LMA) of the assessed model were used as dependent variables and all the investigated soil properties were used as independent variables. In order to derive the appropriate PTFs to predict the infiltration model parameters, the regression models were derived using the procedure of stepwise regression using the SPSS. The stepwise regression (SR) method involves developing regression models in steps adding a predictor to the model at each step. In order to prevent the procedure from getting into an infinite loop, the variables were added and removed at 0.05 and 0.10 significant levels (Dashtaki et al. 2016). The efficiency of the developed equation was assessed by the coefficient of determination (R^2). Since R^2 increases with the addition of predictor at each step irrespective of the fact that if the added variables have increased the power of regression equation and the equation with highest R^2 may appear to present a perfect fit only because it contains more variables. Therefore in addition to R^2, adjusted coefficient of determination (R^2adj) determining the fitting of the multiple regression equations for the sample data was used. The R^2adj is computed using the below expression given in Equation (4):

$$R^2{}_{adj} = 1 - (1 - R^2)\left[\frac{n-1}{n-(K+1)}\right] \qquad (4)$$

Where R^2 is the coefficient of determination, n is the sample number and K is the number of independent variables in the regression equation.

The value of R^2adj increases only if the predictor added at each step enhances the model predictability obtained in the previous step and increase the power of regression equation, otherwise with the addition of more variables the value of R^2adj decreases. Thus, in stepwise regression, the predicted infiltration equation for the infiltration parameters with the highest R^2adj and having a feasible value of R^2 is considered to be the best performing equation.

Prediction using Principal Component Analysis prior to regression analysis

The prediction equations generated using the stepwise regression for the infiltration model parameters in general utilizes a large number of independent variables to capture the most of the soil physical properties for greater accuracy, It has been reported that a large set of correlated variables is difficult to interpret and apply in further analysis compared to a small set of uncorrelated variables (Dunteman 1989). In order to reduce the number of variables recognized as considerably important in equations developed using stepwise regression for infiltration model parameters, factor reduction utilizing Principal Component Analysis (PCA) (Jolliffe 1986) was performed using SPSS. The PCA is an approach to reduce the number of variables by transforming an original set of variables into a considerably smaller set of uncorrelated variables that are linear functions of original variables having a large number of independent variables (Dunteman 1989). It aims to formulate a smaller set of variables containing most of the information in the original set of variables. In order to select a subset using PCA from a large data set, there are several strategies, and we adopted the strategy similar to that of Andrews and Carroll (2001) and Rezaei et al. (2006). In this strategy, it was assumed that the infiltration parameters were best represented by the Principal Components (PCs) with Eigenvalues >1. Within each PC, only highly weighted factors receiving weighted loading values (either positive or negative) within 10% of the highest weight were retained. Furthermore, within each PC in order to reduce the redundancy among more than one highly weighted variables, the correlation analysis was performed among the variables. The Pearson correlation coefficient was used to find out correlations among the different soil properties. The variables having a correlation coefficient greater than 0.7 were considered highly correlated (Andrews and Carroll 2001). To choose the variables among the well correlated

variables, the absolute value of the correlation coefficients were summed up. In general, the variable with the highest correlation sum was assumed to best represent the group. In order to evaluate at what extent the reduced data set precisely represent the infiltration parameters, multiple linear regression (MLR) analysis was performed in SPSS using standardized infiltration parameters and standardized PCs as dependent and independent variables respectively. The equations were then translated and expressed in terms of original infiltration parameters and controlling variables. The coefficient of determination (R^2) was used to appraise the efficiency of the developed equations. Finally, the validity of the predictive equations generated by applying stepwise regression and PCA was assessed. For assessing the validity of the developed predictive regression equations for the infiltration model (H, K, MK and P) parameters, the parameters were computed using the developed equations and the same were substituted in the aforementioned infiltration models and the infiltration rates were calculated.

Evaluation of parameter estimation technique

Eventually, statistical analysis was carried out to check the closeness between the observed (field-measured) and predicted (determined using LMA, stepwise regression and PC analysis) infiltration rates. For this purpose, five statistical indicators, namely, Mean Absolute error (MAE), Root of the mean square error (RMSE), Nash–Sutcliffe Efficiency (E_{NS}), Willmott's index of agreement (W) and Coefficient of determination (R^2) were used (Leagates and McCabe 2009) Equation (5-9):

$$MAE = \frac{\sum_{j=1}^{n}(\left|(i_p)_j - (i_m)_j\right|)}{n} \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{\left[(i_p)_j - (i_m)_j\right]^2}{n}} \tag{6}$$

$$E_{NS} = 1 - \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}}((i_m)_j - (i_p)_j)^2}{\sum_{\mathrm{j}=1}^{\mathrm{n}}(i_m)_j - (\overline{i_m})_j)^2} \tag{7}$$

$$W = 1 - \frac{\sum_{j=1}^{n}\left[(i_p)_j - (i_m)_j\right]^2}{\sum_{j=1}^{n}\left[\left|(i_p)_j - (\overline{i_m})\right| + \left|(i_m)_j - (\overline{i_m})\right|\right]^2} \tag{8}$$

$$R^2 = \left[\frac{\sum_{j=1}^{n}\left[(i_m)_{j-}(\overline{i_m})_j\right]\left[(i_p)_{j-}(\overline{i_p})_j\right]}{\left[\sum_{j=1}^{n}\{(i_m)_j - (\overline{i_m})_j\}^2\right]^{0.5}\left[\sum_{j=1}^{n}\{(i_p)_j - (\overline{i_p})_j\}^2\right]^{0.5}}\right]^2 \tag{9}$$

where, $i_m, i_p, \overline{i_m}$ *and* $\overline{i_p}$ are values of measured, predicted, mean measured and mean predicted infiltration rates respectively, j is the number of the j_{th} infiltration measurement in a set of soil infiltration measurement for soil with a total of n infiltration reading, and n is the number of infiltration rate measurement.

The parameter estimation technique with lower values of MAE and RMSE and higher values of the R^2, E_{NS} and W was selected as best performing with good agreement between measured and predicted infiltration rates. However, when multiple indicators are used, sometimes it becomes very difficult to assess the overall performance and rank of the superiority of one model over the other models (Ali et al. 2016). Hence, to assess the overall performance and rank of the techniques, an overall performance index (OPI) is determined using the expression (Ali et al. 2016) given below in Equation (10).

$$OPI = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{m} RW_j \qquad (10)$$

Where, RW_j is the relative weight of a quantitative statistic and is estimated as a ratio of the assigned weight (equal weight of 0. 20 assigned to all five statistical indicators) to the rank of the parameter estimation technique for infiltration rate estimates, j = 1, 2….. m, where m is the number of statistical indicators for evaluating the technique performance (here, m = 5), i = 1, 2, 3... N, N is the indices for a total number of samples considered in this study. It is to be noted here that while ranking the infiltration parameter prediction techniques based on the values of statistical indicators, techniques with equal values of a given statistical indicator were assigned equal ranks.

Results and Discussion

Soil Physical Properties Analyzed

Overview of the basic statistics (mean, standard deviation, coefficient of variation) of soil physical properties in the study area is given in **Table 2**.

The mean value of textural components revealed that sand (44.4%) and clay (42.17%) are the major soil components followed by silt (11.17%). In order to elucidate the total variation or heterogeneity of the given variables, the coefficient of variation (CV) was determined. The criterion proposed by (Nielsen and Bouma, 1985) was exercised to categorize the parameters into low (CV< 0.1), moderate (CV 0.1-1) and high (CV>1) variable classes. From the values of CV

(Table 2), it was inferred that on the whole, the textural fractions of sand, silt, and clay have moderate variability with CV> 0.1.

Table 2 Descriptive statistical analysis of soil properties

Soil Properties	Minimum	Maximum	Mean	Standard Deviation	Coefficient of variation
Sand (%)	30	50	44.43	4.71	0.11
Silt (%)	8	16	11.17	2.36	0.21
Clay (%)	35	54	42.17	3.87	0.10
ρ_b (g/cm3)	1.39	1.6	1.49	0.06	0.04
η (%)	33.04	48.33	41.58	4.9	0.12
OC (%)	1.22	3.34	2.45	0.73	0.29
d_g (mm)	0.01	0.05	0.04	.009	0.23
σ_g (mm)	22.55	27.51	25.86	1.3	0.05
MC (%)	30.42	31.46	30.9	.33	0.01
FC (%)	33.5	42.7	37.52	1.96	0.05
WP (%)	22.4	32.1	26.38	2.00	0.08
K_s (cm/hr.)	0.001	0.243	0.087	0.072	0.83

The moderate variability might be due to the presence of more than one soil texture in the study area and also as a consequence of pedogenic processes affected by the micro topographical variations (Vasu *et al.* 2017). The CV values of soil physical properties revealed that η, OC and d_g have moderate variability with a CV of 0.12, 0.29 and 0.23 respectively, across the sub-basin. In the present sub-basin since most of the area is under the urban settlements, there is intensive human intervention and severe soil erosion. The soil erosion, in turn, resulted in the drastic changes in textural fractions of soil thus resulting in the moderate value of variability for η, OC and d_g. However in the given sub-basin with a CV < 0.1, ρ_b, σ_g, MC and FC, have low variability. Low variability of ρ_b has also been reported by Wang and Shao (2013) and Duffera et al. (2007). On the contrary, there was high variation in K_s (CV=0.83). The underlining reason for the high variability of K_s in the study area is clay mineralogy, tillage practices, pore-size distribution and pore continuity, moisture availability, particle size distribution and organic carbon content or biotic activity (Sarki et al. 2014). High variability of K_s is well supported by many authors (Wang and Shao 2013; Shukla et al. 2004). Spatial variability in soil physical properties indicates the need to conduct infiltration studies to account for soil heterogeneity within a given sub-basin.

Infiltration parameters estimated

The parameters of different infiltration models were determined using the non-linear Marquardt algorithm by fitting selected infiltration models to the observed data of 23 sites. In order to get an overview of the infiltration parameters in the given study area, the value of the infiltration parameters computed by fitting the selected infiltration models to the observed infiltration rates and are presented in **Table 3**.

Table 3 Value of infiltration model parameters

Infiltration Models	Model Parameters	Mean	Standard Deviation	Coefficient of Variation
Horton	f_o	32.56	18.16	0.56
	K_h	3.54	0.98	0.28
Kostiakov	α	6.75	4.31	0.64
	β	0.45	0.1	0.22
Modified Kostiakov	α'	4.13	2.05	0.50
	β'	0.58	0.06	0.10
Philip	S	12.15	6.55	0.54
	A	1.63	2.29	1.4

From the statistical measure of dispersion (CV) of the model parameters, it was revealed that parameter A of the Philip model displays the highest variability in comparison to other parameters. The high variability may be due to the fact that the parameter is related to saturated hydraulic conductivity (Dashtaki et al. 2016), which also has a high variation (CV=1) in the study area. From the CV values in Table 3, it is observed that the Parameters β and β' has lower variability than α and α' in Kostiakov and Modified Kostiakov models of infiltration. In general, the variance observed for model parameters vary significantly but the values are within acceptable ranges. The results obtained in this study are analogous to the findings of previous researchers (Shao and Baumgartl 2014; Dashtaki et al. 2016).

Predictive regression equations for Infiltration Parameters

For the accurate estimation of infiltration rate, it is important that the parameters of infiltration models are computed accurately. In order to achieve this objective, the infiltration model parameters were computed using two different approaches, namely, stepwise regression and PCA. The computed parameters were then substituted in the selected infiltration models and statistical analysis was carried out to assess the performance of different infiltration models developed using the model parameters obtained through different techniques.

Prediction models using Stepwise regression

The predictive equations were developed for the parameters of Horton, Kostiakov, Modified Kostiakov and Philip model for the given sub-basin (**Table 4**). On the basis of the results obtained in step-wise regression, it is clearly observed that among the soil properties used in developing regression equations, different soil properties were retained and eliminated for prediction of the different infiltration parameters. The independent variables retained and their relationship with different infiltration parameters are presented in Table 4.

The soil textural fractions were retained in most of the regression equations and have substantial effects on the different parameters. These results are in line with those of (Shao and Baumgartl 2014), who also reported that the soil texture fractions have a significant impact in the prediction of infiltration parameters in the Veterinary Science Farm of the University of Queensland, Pinjarra Hills, in eastern Australia. However, from the results (Table 4) it is observed that the equations developed for the parameters of f_o (H), α, β (K), α′ (MK) and S, A (P) were able to explain greater than 50% of the variation (with $R^2_{adj} > 0.5$) reflecting the fact that soil properties retained for these parameters played a crucial role and their inclusion in the equations is required for their accurate prediction. Whereas equations developed for the parameter K_h (H) and β′ (MK) explained up to 40% of the variation (with $R^2_{adj} = 0.4$) representing that the retained soil properties are not enough to predict the parameters precisely due to the fact that they are not sufficient inputs to characterize the pore structure of soils (Pachepsky et al. 2006) and hence, could not improve the parameter derivations.

Table 4 Derived predictive equations for the infiltration model parameters using Stepwise Regression

Parameter regression equations	**R^2** (R^2 adj)
Horton	
$f_o = 5.98\text{Sand} - 6.04\text{Silt} + 4.28\text{Clay} + 94.158\rho_b + 2.97\eta + 94.52\text{MC} - 15.8\sigma_g - 94.12\text{Wp} + 97.04\text{FC} - 4287.4$	0.84(0.74)
$K_h = 0.31\text{Sand} - 4.2\text{Silt} - 2.7\text{Clay} - 2.0\text{OC} - 1223.6d_g - 6.03\sigma_g - 1.9K_{sat} - 1.8\text{MC} + 0.17\eta + 406.7$	0.62(0.40)
Kostiakov	
$\alpha = 0.94\text{Clay} + 604.3d_g + 0.64\eta + 14.19\text{MC} + 13.69\text{FC} - 13.32\text{WP} - 684.79$	0.84(0.78)
$\beta = 0.03\text{Sand} - 14.4d_g - 0.045\sigma_g + 0.42\text{MC} - 1.43\rho_b - 9.85$	0.70(0.61)
Modified Kostiakov	
$\alpha' = 5.94\rho_b + 2.22K_{sat} + 2.67\text{OC} - 10.94$	0.63(0.57)
$\beta' = -0.01\text{Sand} - 0.04\text{Silt} - 0.09\sigma_g + 0.009\eta - 0.1K_{sat} - 0.1\text{OC} + 2.65$	0.53(0.40)
Philip	

$S = 2.35\text{Sand} + 3.2\text{Clay} + 23.13\rho_b + 1.05\eta + 38.17\text{MC} + 612.5d_g - 3.1\sigma_g - 35.07\text{Wp} + 36.24\text{FC} - 1864.97$	0.80(0.70)
$A = -0.118\text{Sand} - 18.12\text{Silt} - 14.85\text{Clay} - 36.44\rho_b + 0.4\eta + 8.45\text{MC} - 6189.3d_g - 22.4\sigma_g + 0.31\text{Wp} + 0.24K_{sat} + 1416.53$	0.78(0.60)

Broadly the predictive equations generated using the retained variables were able to explain the variation ranging from 40- 78% for different infiltration parameters (Table 4), and the results are in line with those of Dashtaki et al. (2016). Dashtaki et al. (2016) also reported that the selected predictors in their studies describe the entire variation of soil water infiltration with R^2_{adj} ranging from 0.19 to 0.82 due to absence of a quantitative index of soil structure as infiltration process is strongly influenced by soil macropores.

The soil particle size distribution, bulk density and organic carbon are not sufficient inputs to characterize the pore structure of soils (Pachepsky et al. 2006) and hence, could not improve the PTF derivations (Dashtaki et al. 2016). On the whole, from the calculated values of R^2_{adj} of the prediction equations developed using soil properties it may be concluded that the equations are efficient enough to determine the parameters of different infiltration models. Moreover, the predictive equations developed using regression analysis have a coefficient of determination (R^2) ranging from 0.62-0.84 and the results accord with those of (Shao and Baumgartl 2014), who reported that the infiltration parameter equations developed using various controlling factors having R^2 in the range of 0.44-0.93 were feasible enough for the prediction of various infiltration parameters. Thus from R^2 values obtained in this study, it may be concluded that developed equations using regression analysis would perform well in estimating the target infiltration parameters of selected models in the study area.

Prediction models developed using PCA prior to regression

The prediction equations developed by stepwise regression analysis resulted in a reduction in the number of independent variables used for the prediction of infiltration parameters of the selected models and has undoubtedly resulted in better prediction with a high coefficient of determination. However, in order to save effort and time and to further reduce the number of independent variables in predicting different parameters and select only the most important variables, PCA was carried out before regression analysis. The factor loading matrix for parameter A of Philip model is given in **Table 5a**.

The number in the matrix represent the contribution of each variable to the principal component. On the basis of criterion adopted (PC's having eigenvalues > 1), only the first three PCs were retained (Table 5a). It is clearly observed that the selected PCs with the proportional variance of 0.405, 0.324 and 0.166 by PC1, PC2 and PC3, respectively, were able to explain more than 89% of the cumulative variation (Table 5a). Under the selected PCs for the parameter A, PC1 has Sand, clay, D_g and WP while as PC2 has ρ_b, η and MC as the highly weighted variables, while under PC3 only silt content was retained. In order to reduce the redundancy the interrelations among selected variables were determined and a correlation matrix was calculated (Table 5b). As shown in Table 5b, statistically significant (P< 0.01) correlations exist amongst the soil physical properties. In order to represent the first PC textural fraction of clay was considered because of its highest correlation sum (**Table 5b**) and ease of measurement. As the most significant element from PC2 to be included in the determination of parameter A, moisture content was retained due to its highest correlation sum. However, within PC3 only the textural fraction of silt obtained high weightage and was retained to represent the third PC.

Table 5(a) Principal component loading matrix for parameter A of Philips infiltration model

Soil properties	**Principal Components**		
	PC1	**PC2**	**PC3**
Sand	**0.947***	0.266	0.095
Clay	**-0.934**	0.023	0.321
Bulk Density (ρ_b)	0.133	**-0.877***	0.332
Porosity (η)	-.0433	**0.825**	0.041
MC	0.171	**-0.873**	0.410
Dg	**0.960**	0.115	-0.106
GSD	0.447	0.576	0.618
WP	**-0.888**	0.228	0.349
Silt	-0.374	-0.582	**-0.699***
K_{sat}	0.023	0.476	-0.520
Eigen Values	**4.05**	**3.24**	**1.66**
Cumulative variance	0.405	0.729	0.895

Table 5(b) Correlation coefficients and Correlation sums of highly weighted soil properties within the PCs

PC1 variables	Sand	Clay	Dg	WP
Sand	1	0.848*	0.933*	-0.738*
Clay	0.848*	1	-0.942*	0.944*
Dg	0.933*	-0.942	1	-0.839*
WP	-0.738*	0.944	-0.839*	1
Correlation Sum	**3.52**	**3.73**	**3.71**	**3.52**
PC2 variables	BD	Porosity	MC	
BD	1	-0.757*	0.965*	
Porosity	-0.757*	1	-0.768*	
MC	0.965*	-0.768*	1	
Correlation Sum	**2.72**	**2.53**	**2.73**	

* Significant at the 0.01 level.

*As per the methodology adopted, weighted loading values (either positive or negative) within 10% of the highest weight were retained.

Likewise, for all the parameters of infiltration models, PCs were calculated. The independent variables retained after the application of factor reduction using PCs for different infiltration parameters are presented in **Table 6a.** It can be clearly observed from Table 6a, that for all the parameters PC1 and PC2 were identified while PC3 was defined only for a few of the parameters, including f_o, K_h, β and A. Despite the fact that similar independent variables were used for determination of the parameters of infiltration models, different numbers of PCs were identified and the factors loading for each PC varied indicating that parameters are physically different. The independent variables retained in different PCs have different units of measurement, therefore MLR was performed for the standardized infiltration parameters on the basis of defined PCs (Table 6a).

Table 6(a) Regression equations developed on the basis of Principal components

Parameter regression equations based on PCs	PC1	PC2	PC3
Horton			
$\text{Z score } (f_o) = -0.018PC1 - 0.701PC2 - 0.257PC3 + 3.907 \times 10^{-15}$	FC, WP	Silt, σ_g	Silt, σ_g, MC
$\text{Z score } (K_h) = -0.135PC1 - 0.10PC2 - 0.1PC3 - 1.837 \times 10^{-16}$	Sand, D_g	η, MC	OC, K_{sat}
Kostiakov			
$\text{Z score } (\alpha) = -0.058PC1 - 0.822PC2 + 6.786 \times 10^{-15}$	Clay, FC, WP	MC	
$\text{Z score } (\beta) = -0.58PC1 + 0.396PC2 - 4.332 \times 10^{-15}$	Sand, D_g	MC, ρ_b	
Modified Kostiakov			
$\text{Z score } (\alpha') = 0.057PC1 - 0.665PC2 + 9.086 \times 10^{-16}$	K_{sat}	ρ_b	
$\text{Z score } (\beta') = -0.132PC1 - 0.084PC2 - 0.052PC3 + 1.224 \times 10^{-15}$	Silt, σ_g	K_{sat}	H
Philip			
$\text{Z score } (S) = -0.177PC1 + 0.687PC2 + 3.15 \times 10^{-15}$	Clay, FC, WP, D_g	ρ_b, MC	
$\text{Z score } (A) = 0.209PC1 + 0.699PC2 - 0.05PC3 + 3.25 \times 10^{-15}$	Clay, Sand, WP, D_g	ρ_b, MC, η	Silt

The equations were then transformed and interpreted in terms of unstandardized parameters which are actually the independent variables retained in different PCs (**Table 6b**).

Table 6(b) Predicted regression equation for the parameters developed after PCA

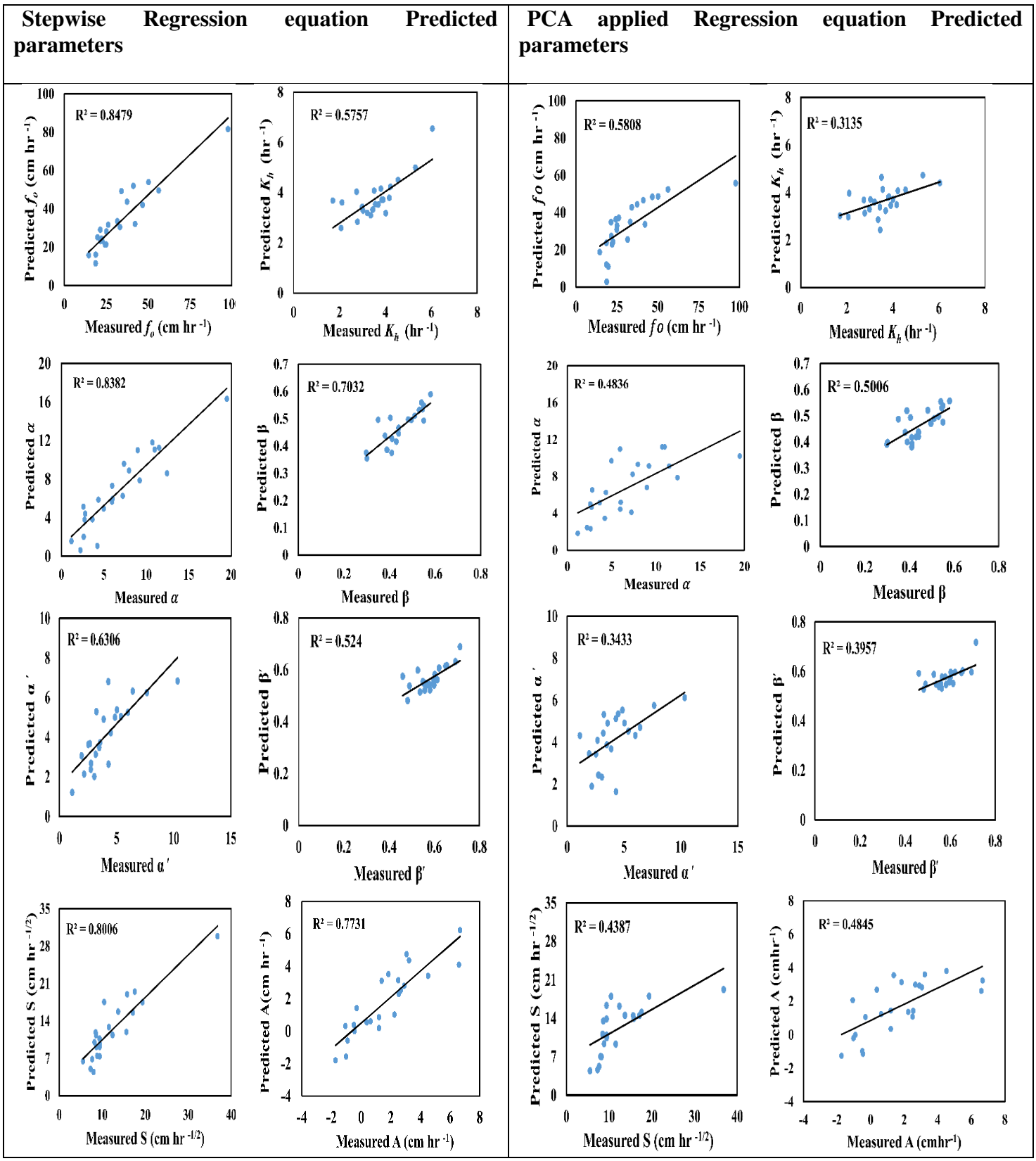
Parameter regression equations with PCA	R^2(R^2 adj)
Horton	
$f_o = -8.47\text{Silt} - 4.27\ \text{FC} - 37.1\text{MC} - 11.28\sigma_g + 1729.05$	0.60 (50)
$K_h = -0.03\text{Sand} + 120d_g + 0.2\eta - 2.4\text{OC} - 2.6\text{MC} - 2.4K_{sat} + 78.8$	0.33 (0.10)
Kostiakov	
$\alpha = -0.64\text{WP} - 9.04\text{MC} + 303.76$	0. 50 (0.43)
$\beta = -0.01\text{Sand} + 0.15\text{MC} - 4.03$	0.50 (0.45)
Modified Kostiakov	
$\alpha' = 0.33K_{sat} - 20.9\rho_b + 35.67$	0.40 (0.30)
$\beta' = -0.04Silt + 0.01K_{sat} - 0.002\eta - 0.08\sigma_g + 3.3$	0.40 (0.26)
Philip	
$S = -0.599\text{Clay} - 57.82\rho_b + 123.51$	0.44 (0.40)
$A = -3.5\text{MC} - 0.12Clay - 0.34\text{Silt} + 119.42$	0.50 (0.41)

From the results presented in Table 6(b) it is clearly observed that for the parameters f_o (H), α, β (K), and S, A (P) the predicted equations were able to explain greater than or equal to 40% of variation representing soil properties retained were sufficient in their prediction and thus may be expected to have an acceptable prediction capacity. Moreover, the developed equations have lesser number of independent variables so will be less laborious and time consuming. The ρ_b and K_{sat} were identified as significant predictors for the parameter α′ of MK model as they explained 30% of the variation. However, for the parameters β′ of MK model, the developed regression equation was able to explain only 26% of the variation. Unfortunately the predictive regression equation for the parameter K_h (H) despite having a maximum number of soil properties was able to explain only 10% of the variation. On the whole, the soil properties retained after applying PCA were able to develop regression equations for different infiltration parameters explaining variation ranging from 10- 50%. The decreased variation in the equations may be attributed to the fact that the retained independent variables were not able to describe the variance thereof (Dashtaki et al. 2016) and thus there is need to consider other parameters like soil properties representing the pore structure of soils (Pachepsky et al. 2005), vegetation, topography etc (Shao and Baumgartl 2014). However, to check the acceptability of regression equations for the prediction of infiltration parameters R^2 was computed and it is clearly observed that predicted equations developed by applying PCA prior to regression (table 6b) have acceptable R^2 values ranging from 0.33 to 0.60, and are likely to perform well, in estimating the parameters of infiltration models.

Performance assessment of derived equations

In order to check the validity of techniques used to develop regression equations for infiltration model parameters, the scatter plots were set between the predicted model parameters values determined using PTF approach against the values estimated from observed data using non-linear Levenberg Marquardt algorithm (LMA) (Fig.2).

From the Fig 2, it is clearly observed that the dots in the parameters computed using simple stepwise regression equations (Table 4) are closer to the parameters determined from the observed data using LMA and lie relatively closer to 1:1 line, whereas the parameters computed using a regression equation developed after factor reduction can be seen with more dispersion from the LMA determined parameters. The same can also be observed from R^2 values displayed in the plots. In general, the predicted equations for the parameters developed using stepwise regression (Table 4) were found to perform better than that of regression equations developed after applying PCA (Table 6b).



In order to check the difference between the parameters estimated by two techniques a paired sample t-test was carried out (**Table 7**). From the paired sample t-test (Table 7) it is clearly

observed that there is no statistically significant difference (P>0.05) between the values of different parameters of each of the selected infiltration models computed by two different techniques.

Table 7 Paired sample t-test on comparing infiltration model parameter determination methods

Infiltration Model	Parameters determined using SR and applying PCA prior to regression	P-Value
Horton	f_o	0.952
	K_h	0.356
Kostiakov	α	0.978
	β	0.765
Modified Kostiakov	α′	0.923
	β′	0.074
Philip	S	0.931
	A	0.536

Thus regression equation developed by both the approaches can be used to predict the parameters of infiltration models. However the regression equations developed after PCA requires lesser number of the independent variables, thus requiring lesser time and effort for determination of model parameters.

Fig. 2 Measured vs. observed selected parameters of infiltration models

The regression equations developed with reduced number of independent variable after PCA were thus considered more feasible to apply in real life problems, particularly while applying to larger areas, basins, sub-basin where heterogeneity exists. In order to assess the suitability of regression equations presented in Table 4 and 6b with respect to LMA for the estimation of model parameters of the selected infiltration models, the performance assessment was carried out by comparing field-measured infiltration rates with the predicted ones (determined by substituting the Parameters estimated using LMA, Stepwise Regression and PCA applied regression equations). The computed value of the statistical indices of ENS, RMSE, MAE, R^2 and W of the selected parameter estimation techniques for the infiltration models of Horton, Kostiakov, Modified Kostiakov and Philip for the soil textures of clay and sandy clay under different land covers are presented in Table 8, 9, 10 and 11, respectively.

It is clearly observed that for the Horton model (**Table 8**) the parameter estimation technique of LMA with an OPI of 0.960 for clay soils and 0.938 for sandy clay soils ranked first followed

by the regression equations developed using SR with OPI of 0.487 for clay and sandy clay soils, while the equations developed applying PCA prior to regression ranked third with an OPI of 0.397 and 0.408 for clay and sandy clay respectively. A closer look in the ENS, RMSE, MAE, R^2, and W values (Table 8) revealed that the regression equations developed using SR and those developed after applying PCA resulted in almost equal values of R^2, and W in most cases, but SR developed equations resulted in improved MAE and RMSE values in most cases. These results suggest that the choice of a particular parameter estimation would get affected by the application of a different statistical indicator for performance evaluation. Moriasi et al. (2007) also suggested the application of a combination of graphical techniques and dimensionless and error-index statistics for evaluating model performance.

For the Kostiakov model, it is clearly evident from **Table 9** that LMA resulted in better ENS, RMSE, MAE and W values, thus, the parameter estimation technique of LMA (Table 9) with the respective OPI values of 0.687 and 0.656 for the clay and sandy clay soils ranked first. Under the soil texture of clay, unlike for the Horton model, the prediction equations developed prior to PCA have the OPI value greater than that of equation developed simply by stepwise regression and ranked second. However, for the sandy clay soils prediction equations developed using SR with OPI of 0.633 may perform better than the PCA applied equations.

Similar to the Kostiakov model, in case of the MK model (**Table 10**)LMA resulted in better ENS, RMSE, MAE and W values, and this is followed by the prediction equations developed using SR (Table 10). Contrary to the Kostiakov model, in cases of MK model higher ENS values were obtained with the SR developed equations as compared to PCA applied predicted equations in most cases. Thus in general LMA with an OPI of 0.873 (clay) and 0.885 (Sandy clay) for the MK model (Table 10) ranked first. It is observed that for the clay soils SR applied equations (OPI= 0.553) ranked second and regression equation developed prior to PCA (OPI=0.406) ranked third. Similarly, for sandy clay soils, prediction equations developed using SR and PCA ranked second and third with an OPI value of 0.495 and 0.461 respectively.

For the Philip model (**Table 11**), all the parameter estimation techniques resulted in equal values of R^2. However, LMA with the most feasible value of statistical indices having an OPI of 0.933 and 0.954 for clay and sandy clay soils respectively ranked first. Furthermore, prediction equations developed using SR resulted in lower RMSE and MAE values as compared to that of PCA applied predicted equations. Thus it can be concluded that the equation developed simply by

stepwise regression with an OPI of 0.570 and 0.577 for clay and sandy clay soils ranked second while PCA applied regression equations with an OPI of 0.543 and 0.521 ranked third.

Table 8 ENS, RMSE MAE, R^2 and W of three parameter estimation techniques for Horton Model

SOIL TYPE	Horton Model	Levenberg-Marquardt algorithm					Stepwise Regression					PCA applied prior to regression				
	Sites	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W
CLAY SOILS	A1	0.98	0.97	0.83	0.98	0.995	0.91	2.03	1.43	0.96	0.98	0.85	2.66	2.17	0.95	0.96
	A2	0.98	0.80	0.55	0.987	0.996	0.91	1.99	1.59	0.99	0.97	0.65	3.89	2.65	0.98	0.94
	A3	0.99	1.28	1.01	0.988	0.997	0.71	6.00	4.88	0.99	0.91	0.72	5.94	4.96	0.98	0.91
	SC1	0.99	0.27	0.18	0.999	1	**0.22**	6.62	4.64	0.99	0.89	0.75	3.72	2.58	0.99	0.96
	SC2	0.99	0.58	0.47	0.996	0.999	0.97	1.41	1.05	0.99	0.99	0.99	0.78	0.66	0.99	0.99
	SC3	0.988	0.41	0.311	0.989	0.997	0.98	0.53	0.37	0.99	0.99	**0.44**	2.87	2.32	0.97	0.91
	BU1	0.99	0.55	0.42	0.989	0.997	0.71	2.76	1.87	0.99	0.89	0.77	2.45	1.60	0.98	0.92
	BU2	0.99	0.52	0.36	0.992	0.998	0.95	1.25	0.87	0.99	0.98	**-0.65**	6.99	4.88	0.99	0.50
	BU3	0.98	0.91	0.71	0.979	0.991	0.92	1.75	1.14	0.98	0.98	0.88	2.18	1.52	0.98	0.98
	BU4	0.99	0.53	0.44	0.993	0.998	0.67	3.48	2.40	0.99	0.94	**-0.11**	6.35	4.45	0.99	0.86
	OPI	0.960					0.487					0.397				
SANDY-CLAY SOILS	A4	0.994	0.96	0.66	0.990	0.999	0.99	1.42	1.04	0.99	1.00	0.99	1.16	0.86	0.99	1.00
	A5	0.997	0.64	0.48	0.996	0.99	0.98	1.94	1.37	1.00	0.99	0.90	3.97	3.38	0.98	0.98
	A6	0.996	1.03	0.69	0.992	0.996	0.92	3.19	2.24	0.98	0.98	0.97	1.96	1.42	0.98	0.99
	A7	0.99	0.89	0.66	0.989	0.997	0.96	1.53	0.97	0.99	0.99	0.92	2.31	1.37	0.98	0.97
	SC4	0.81	11.19	8.59	0.836	0.951	0.75	12.86	8.53	0.84	0.92	**0.41**	19.66	13.51	0.83	0.77
	SC5	0.996	0.89	0.65	0.995	0.999	0.96	2.64	1.69	1.00	0.99	0.99	1.33	0.81	0.99	1.00
	SC6	0.997	0.56	0.40	0.996	0.999	0.91	2.94	2.02	1.00	0.98	0.85	3.80	2.79	0.99	0.97
	BU5	0.992	0.54	0.42	0.992	0.998	0.85	2.25	1.58	0.99	0.97	**0.44**	4.41	3.29	0.99	0.79
	BU6	0.98	0.94	0.66	0.978	0.994	0.90	1.86	1.32	0.97	0.98	0.77	2.87	2.04	0.98	0.96
	BU7	0.94	1.39	0.97	0.948	0.986	0.79	2.70	1.82	0.95	0.96	**0.31**	4.86	3.12	0.94	0.90
	BU8	0.97	1.07	0.79	0.976	0.986	0.97	1.16	0.86	0.98	0.99	0.97	1.16	0.89	0.98	0.99
	BU9	0.99	0.60	0.44	0.992	0.998	0.94	1.64	1.15	0.99	0.99	0.71	3.57	2.42	0.99	0.95
	BU10	0.97	1.09	0.94	0.966	0.991	**0.17**	5.37	4.37	0.90	0.73	0.87	2.14	1.62	0.93	0.97
	OPI	0.938					0.487					0.408				

Note: figures in bold indicate the least feasible value of ENS of the three selected parameter estimation techniques

Table 9 ENS, RMSE MAE, R2 and W of three parameter estimation techniques for Kostiakov Model

Soil Type	**Kostiakov Model**	**LMA**					**SR**					**PCA applied prior to regression**				
	Sites	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W
CLAY SOILS	A1	0.85	2.60	2.21	0.901	0.957	0.81	2.92	1.89	0.901	0.96	0.82	2.88	1.91	0.909	0.96
	A2	0.86	2.47	1.77	0.96	0.957	0.84	2.65	2.16	0.979	0.94	**-0.95**	9.23	8.48	0.973	0.76
	A3	0.89	3.65	2.92	0.931	0.972	0.54	7.58	6.64	0.912	0.88	**0.38**	8.83	7.83	0.913	0.83
	SC1	0.88	2.57	1.89	0.959	0.965	0.78	3.50	2.11	0.948	0.96	0.79	3.40	1.91	0.945	0.96
	SC2	0.88	3.02	2.01	0.935	0.969	0.92	2.42	1.58	0.930	0.98	0.93	2.41	1.62	0.933	0.98
	SC3	0.66	2.23	1.65	0.973	0.875	0.93	1.01	0.93	0.972	0.98	0.95	0.87	0.84	0.976	0.98
	BU1	0.79	2.38	1.70	0.937	0.928	**-0.56**	6.43	4.88	0.939	0.54	0.83	2.10	1.53	0.940	0.94
	BU2	0.81	2.38	1.70	0.916	0.939	0.60	3.44	2.50	0.910	0.86	0.73	2.82	2.01	0.911	0.91
	BU3	0.91	1.87	1.43	0.982	0.953	0.96	1.21	0.98	0.977	0.99	0.84	2.51	2.29	0.954	0.96
	BU4	0.79	2.75	1.99	0.939	0.93	0.73	3.12	2.64	0.952	0.94	0.83	2.48	2.09	0.955	0.96
	OPI	0.687					0.500					0.647				
SANDY-CLAY SOILS	A4	0.87	4.41	3.3	0.99	0.962	0.84	4.95	3.74	0.962	0.95	0.58	8.03	6.61	0.960	0.87
	A5	0.83	5.17	3.38	0.914	0.95	0.71	6.64	4.91	0.907	0.91	0.78	5.88	3.98	0.919	0.93
	A6	0.933	4.29	3.05	0.915	0.958	0.89	3.74	2.63	0.913	0.97	0.53	7.81	6.11	0.915	0.85
	A7	0.89	2.63	1.85	0.965	0.968	0.90	2.60	2.18	0.944	0.98	**0.36**	6.46	5.69	0.946	0.82
	SC4	0.862	9.54	5.93	0.95	0.95	0.73	13.36	9.36	0.951	0.90	**-0.02**	25.89	19.55	0.948	0.61
	SC5	0.85	5.24	3.68	0.963	0.95	0.77	6.56	4.44	0.966	0.92	0.80	6.10	4.14	0.966	0.93
	SC6	0.845	3.83	2.63	0.938	0.95	0.93	2.56	2.16	0.941	0.98	0.91	2.94	2.01	0.940	0.97
	BU5	0.79	2.74	2.15	0.897	0.93	0.88	2.08	1.51	0.897	0.97	0.67	3.40	2.25	0.900	0.93
	BU6	0.83	2.51	1.98	0.97	0.94	0.87	2.19	1.70	0.970	0.97	**-0.04**	6.13	5.29	0.976	0.85
	BU7	0.88	2.02	1.37	0.983	0.96	0.80	2.60	1.67	0.983	0.97	0.95	1.36	1.18	0.984	0.99
	BU8	0.86	2.43	1.98	0.952	0.927	0.90	2.12	1.73	0.952	0.97	0.93	1.69	1.24	0.957	0.98
	BU9	0.87	2.42	1.82	0.955	0.96	0.90	2.09	1.52	0.949	0.97	**-0.32**	7.66	6.52	0.956	0.82
	BU10	0.84	2.39	2.22	0.864	0.954	**-0.87**	8.05	6.62	0.859	0.55	0.74	3.02	2.51	0.850	0.93
	OPI	0.656					0.633					0.546				

Note**:** figures in bold indicate the least feasible value of ENS of the three selected parameter estimation techniques.

Table 10 ENS, RMSE MAE, R2 and W of three parameter estimation techniques for Modified Kostiakov Model

SOIL TYPE	**Modified Kostiakov Model**	**LMA**					**SR**					**PCA applied prior to regression**				
	Sites	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W
CLAY SOILS	A1	0.89	2.23	2.03	0.903	0.968	0.88	2.38	1.98	0.886	0.97	0.56	4.51	3.12	0.882	0.92
	A2	0.92	1.89	1.55	0.94	0.977	0.91	2.00	1.69	0.941	0.98	0.59	4.22	3.60	0.942	0.92
	A3	0.88	3.79	3.53	0.897	0.966	0.81	4.83	3.94	0.897	0.94	0.83	4.68	3.70	0.880	0.94
	SC1	0.88	2.6	2.44	0.893	0.964	0.50	5.31	4.43	0.906	0.90	**0.47**	5.46	4.55	0.905	0.90
	SC2	0.88	3.02	2.73	0.896	0.965	0.88	3.05	2.78	0.904	0.96	0.83	3.64	2.88	0.893	0.96
	SC3	0.94	0.90	2.52	0.952	0.983	0.94	0.91	0.88	0.956	0.98	**-15.46**	15.54	11.94	0.951	0.47
	BU1	0.91	1.55	1.34	0.92	0.978	0.87	1.84	1.50	0.933	0.96	0.79	2.35	1.84	0.935	0.92
	BU2	0.89	1.75	1.59	0.909	0.97	0.83	2.22	1.84	0.917	0.94	0.84	2.20	1.82	0.918	0.94
	BU3	0.93	1.59	1.51	0.942	0.981	0.90	1.93	1.80	0.942	0.97	0.89	2.04	1.88	0.936	0.97
	BU4	0.92	1.64	1.59	0.926	0.976	0.85	2.35	1.92	0.941	0.96	0.57	3.93	3.25	0.933	0.92
	OPI	0.873					0.553					0.407				
SANDY-CLAY SOILS	A4	0.90	3.92	3.7	0.913	0.971	0.88	4.33	3.78	0.919	0.96	0.82	5.26	4.58	0.920	0.94
	A5	0.86	4.60	0.36	0.877	0.965	0.82	5.31	4.40	0.882	0.93	0.75	6.24	5.01	0.872	0.91
	A6	0.94	4.04	3.52	0.887	0.962	0.79	5.19	3.81	0.861	0.95	0.83	4.73	3.88	0.865	0.94
	A7	0.91	2.39	2.15	0.924	0.975	0.89	2.71	2.33	0.939	0.97	0.88	2.82	2.47	0.933	0.96
	SC4	0.96	5.28	4.66	0.958	0.989	0.64	15.35	11.45	0.959	0.86	0.50	18.15	13.29	0.959	0.80
	SC5	0.91	4.09	3.82	0.921	0.974	0.91	4.17	3.91	0.929	0.97	0.86	5.00	4.38	0.934	0.95
	SC6	0.88	3.35	2.99	0.896	0.965	0.62	5.99	4.96	0.911	0.92	0.87	3.57	3.21	0.906	0.96
	BU5	0.88	2.01	1.83	0.897	0.966	0.67	3.40	2.87	0.895	0.87	0.75	2.93	2.54	0.901	0.91
	BU6	0.94	1.42	1.25	0.952	0.985	0.67	3.47	2.81	0.955	0.94	0.81	2.65	2.16	0.958	0.96
	BU7	0.96	1.20	1.07	0.963	0.989	0.76	2.88	2.47	0.972	0.95	0.70	3.20	2.88	0.976	0.94
	BU8	0.93	1.77	1.57	0.941	0.979	0.91	1.94	1.68	0.950	0.97	0.91	1.93	1.52	0.942	0.98
	BU9	0.91	2.01	1.85	0.92	0.973	0.89	2.22	1.97	0.930	0.96	0.61	4.17	3.27	0.920	0.92
	BU10	0.86	2.18	2.05	0.872	0.963	0.75	2.94	2.64	0.830	0.92	**0.32**	4.84	4.08	0.823	0.77
	OPI	0.885					0.495					0.462				

Note: figures in bold indicate the least feasible value of ENS of the three selected parameter estimation techniques.

Table 11 ENS, RMSE MAE, R2 and W of three parameter estimation techniques for Philip Model

SOIL TYPE	**Philip Model**	**LMA**					**SR**					**PCA applied prior to regression**				
	Sites	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W	E_{NS}	RMSE	MAE	R^2	W
CLAY SOILS	A1	0.89	2.15	1.91	0.899	0.973	0.90	2.16	1.88	0.899	0.97	0.79	3.10	2.15	0.899	0.95
	A2	0.95	1.44	1.09	0.953	0.987	0.83	2.71	2.10	0.953	0.95	**-0.28**	7.47	6.66	0.953	0.82
	A3	0.891	3.72	3.13	0.89	0.97	0.58	7.31	5.80	0.890	0.87	0.69	6.29	5.11	0.890	0.92
	SC1	0.92	2.11	1.74	0.921	0.979	**-0.24**	8.34	6.45	0.921	0.83	**0.17**	6.82	4.00	0.921	0.88
	SC2	0.91	2.67	2.15	0.908	0.975	0.89	2.86	2.57	0.908	0.97	0.70	4.84	3.21	0.908	0.94
	SC3	0.89	1.25	0.96	0.982	0.968	0.89	1.28	0.99	0.983	0.98	0.90	1.20	0.91	0.983	0.97
	BU1	0.92	1.43	1.29	0.946	0.977	0.71	2.75	1.98	0.947	0.90	0.71	2.76	1.99	0.947	0.89
	BU2	0.92	1.51	1.32	0.927	0.979	0.91	1.60	1.35	0.927	0.97	0.54	3.69	2.95	0.927	0.85
	BU3	0.96	1.16	1.00	0.964	0.987	0.92	1.75	1.55	0.958	0.98	0.94	1.57	1.23	0.958	0.98
	BU4	0.93	1.65	1.53	0.95	0.978	**0.39**	4.68	4.07	0.950	0.89	**0.02**	5.97	5.56	0.950	0.84
	OPI	0.933					0.570					0.543				
SANDY-CLAY SOILS	A4	0.94	3.05	2.61	0.94	0.984	0.93	3.41	2.27	0.940	0.98	0.86	4.70	3.41	0.940	0.96
	A5	0.89	3.99	3.24	0.896	0.972	0.87	4.46	3.39	0.897	0.96	0.84	4.90	3.57	0.897	0.95
	A6	0.95	3.67	2.97	0.896	0.971	0.80	5.13	3.63	0.896	0.96	0.86	4.21	3.31	0.896	0.96
	A7	0.94	1.91	1.54	0.945	0.985	0.92	2.30	1.62	0.945	0.98	0.75	4.03	3.20	0.945	0.93
	SC4	0.96	5.37	4.31	0.956	0.989	0.89	8.58	6.22	0.956	0.97	**0.44**	19.28	14.17	0.956	0.79
	SC5	0.95	2.97	2.32	0.951	0.987	0.94	3.30	2.48	0.952	0.98	0.94	3.22	2.34	0.952	0.98
	SC6	0.92	2.72	2.05	0.921	0.979	0.77	4.68	3.77	0.922	0.95	0.87	3.46	2.93	0.922	0.97
	BU5	0.91	1.77	1.59	0.912	0.975	0.68	3.36	2.60	0.912	0.93	0.81	2.57	1.93	0.912	0.94
	BU6	0.96	1.15	1.01	0.974	0.99	0.97	1.00	0.75	0.975	0.99	**-0.19**	6.55	5.55	0.975	0.84
	BU7	0.98	0.76	0.65	0.983	0.996	0.70	3.20	2.12	0.983	0.95	0.80	2.62	1.74	0.983	0.96
	BU8	0.95	1.42	1.23	0.955	0.982	0.90	2.03	1.63	0.955	0.97	0.82	2.81	2.34	0.955	0.96
	BU9	0.94	1.62	1.42	0.940	0.985	0.91	2.03	1.39	0.941	0.98	**-0.66**	8.59	6.97	0.941	0.80
	BU10	0.86	2.22	2.11	0.858	0.96	**0.15**	5.42	4.40	0.858	0.73	0.76	2.89	2.49	0.858	0.93
	OPI	0.954					0.577					0.521				

Note: figures in bold indicate the least feasible value of ENS of the three selected parameter estimation techniques.

In general, from the Table 8, 9, 10 and 11 it is clearly evident that for the regression equations developed using both techniques the value of E_{NS} is greater than 0.5 (Ritter and Carpena 2013; Moriasi et al. 2007) and thus it may be concluded that the equations developed by both the techniques are of sufficient quality to predict the parameters of the selected models. However, prediction equations developed using SR have maximum sites with $E_{NS} > 0.5$, and are considered more feasible than the one developed after applying PCA. Thus, in general, it may be concluded that the prediction equations developed using simple SR and regression after PCA may be used to determine infiltration parameters directly from soil properties rather than from the observed infiltration data, thus results in saving of time and energy in performing laborious experimentation.

In order to select the overall best fit technique of parameter estimation for the selected infiltration models for the given study area, the overall performance of the three executed techniques was compared. The comparison of techniques was performed by considering the OPI computed from the statistical indices of all the selected sites irrespective of the land-cover and soil texture i.e. taking N=23 in the computational equation of OPI. The OPI of the parameter estimation techniques for the selected infiltration models for the study area is depicted in Fig. 3.

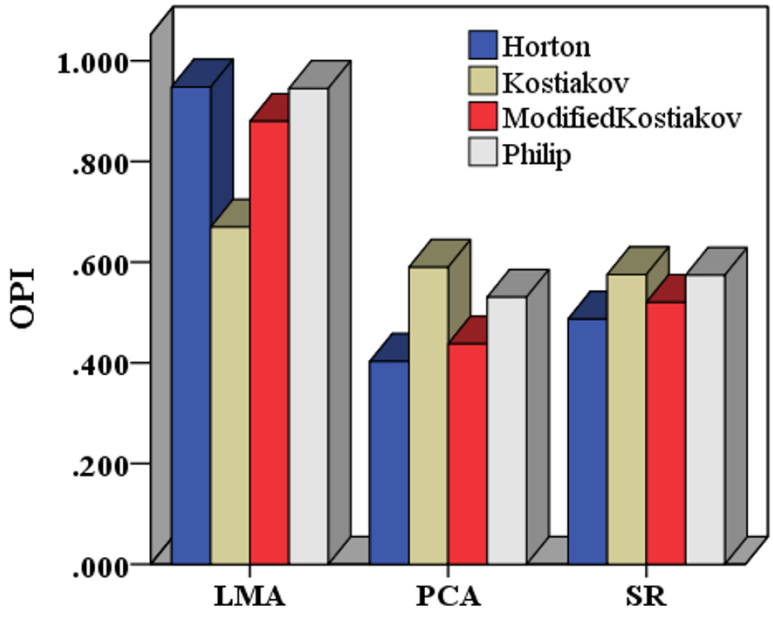


Fig. 3 OPI of Parameter estimation Techniques for the selected Infiltration Models

From Fig. 3 it is clearly depicted that LMA with the highest value of OPI is the most suitable parameter estimation technique for all the four infiltration models. Furthermore, it is clearly observed that for the selected models LMA is least feasible for the Kostiakov model. Since the

LMA for the Kostiakov model has over- and under-estimated the parameters α and β, respectively, resulting in the under-prediction of infiltration rate throughout the infiltration period and slight over-prediction at the end. Hence the OPI values for the Kostiakov model is slightly less in comparison to other models of infiltration while using LMA for parameter estimation. However in order to derive parameters using the LM algorithm, it is necessary to conduct field experimentation which is time-consuming, thus the prediction equations developed using soil properties were analysed. Moreover it is also observed that the OPI of the prediction equations developed using a maximum number of soil properties by the SR, in general, is higher than OPI of the regression equations developed after PCA with lesser number of independent variables. The prediction equation developed using SR resulted in OPI values of 0.49, 0.58, 0.52 and 0.57 for the Horton, Kostiakov, Modified Kostiakov, and Philip infiltration model, respectively. Whereas the prediction equation developed after PCA resulted in OPI values of 0.40, 0.59, 0.44 and 0.53 for the Horton, Kostiakov, Modified Kostiakov, and Philip infiltration model, respectively. It is clearly observed that for the selected models, equations developed using PTF approach either by applying SR or PCA, the Kostiakov model has the highest OPI value. The best performance of Kostiakov model may be attributed to the fact that by applying SR and PCA the variation explained by derived PTF for the model parameters α is 78% (Table 4) and 43% (Table 6b), and β is 61% (Table 4) and 45% (Table 6b) which is highest in comparison to the variation of the parameters of the other selected models. However, in general the equations developed by SR proves to be more suitable to determine the model parameter and predict the infiltration rate in the study area. Since there is no significant difference ($P>0.05$) in the OPI value of parameter prediction equations developed for the selected models using SR and regression after PCA, equations generated by both the approaches may be used successfully to determine model parameters. The values of the parameters determined in the study will also be useful for hydrologists to compute the infiltration rate precisely by substituting parameters in the selected infiltration models of H, K, MK and P, and to select the best fit infiltration model for the given area. Furthermore, accurate estimation of soil infiltration rate and thereby runoff rate will be helpful in developing proper soil management strategies and conservation measures to minimize the risk of erosion and land degradation in the study area. However, this study considered only soil properties for developing predictive equations for infiltration model parameters. Incorporation of other factors such as land use, topography, horizon type, etc. may further enhance the prediction capability of developed explicit equations.

Conclusion

Estimation of infiltration rate is very challenging because of the variability of infiltration model parameters which depend on various soil characteristics and land uses. In the current study, an effort has been made to determine the parameters of Horton, Kostiakov, Modified Kostiakov and Philip infiltration models in the urban sub-basin of lesser Himalayas from the easily measured soil properties. To collect infiltration data field experimentation using double-ring infiltrometer was conducted. Parameters of selected infiltration models were initially determined by applying non-linear Levenberg-Marquardt algorithm (LMA) on the field measured data. As in the undulating terrains, it is not easy to collect the infiltration data, therefore, an attempt was made to develop prediction equations using soil properties for the infiltration parameters. Two sets of prediction equations were developed, one by applying stepwise regression on all the measured soil properties and the other one by reducing number of parameters using PCA prior to regression. Equations developed by subjecting all the investigated soil properties to stepwise regression analysis were able to explain up to 78% of variability for some infiltration parameters and the regression equations developed after applying PCA were able to explain up to 50% of the variation. Further, equations developed by two different approaches have acceptable R^2 values and doesn't differ significantly thus implying that the regression equations may be used efficiently in the prediction of infiltration parameters. Comparison of the measured and estimated infiltration rate revealed that non-linear LMA performed better than equations developed by other two approaches with OPI values ranging from 0.67 to 0.95, 0.49 to 58, and 0.40 to 0.59 for LMA, SR and PCA method s respectively. It is also to be noted that the OPI values of the studied infiltration models with parameters estimated using the two varying information levels were not significantly different, and hence, equations developed by both approaches may be used with almost equal accuracy. Since the regression equations developed after PCA have reduced predictor variables, may be more useful to determine the infiltration parameters in case of limited data availability. In general, such predictive equations will be useful to estimate the infiltration rate in the hilly regions of Himalayas where otherwise due to undulating terrain it is difficult to measure infiltration rate precisely. Further substituting the parameters in the infiltration model identified as the most feasible in the given study area as it helps in precise calculation of infiltration rate which may be potentially helpful to the hydrologists for studying various hydrological processes, particularly the rate of runoff under different land uses. Accordingly, soil management strategies and conservation

measures may be suggested to minimize the risk of erosion and land degradation in the area of study. However, incorporation of other factors such as land use, topography, horizon type, etc. may further enhance the prediction capability of developed explicit equations.

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Figures

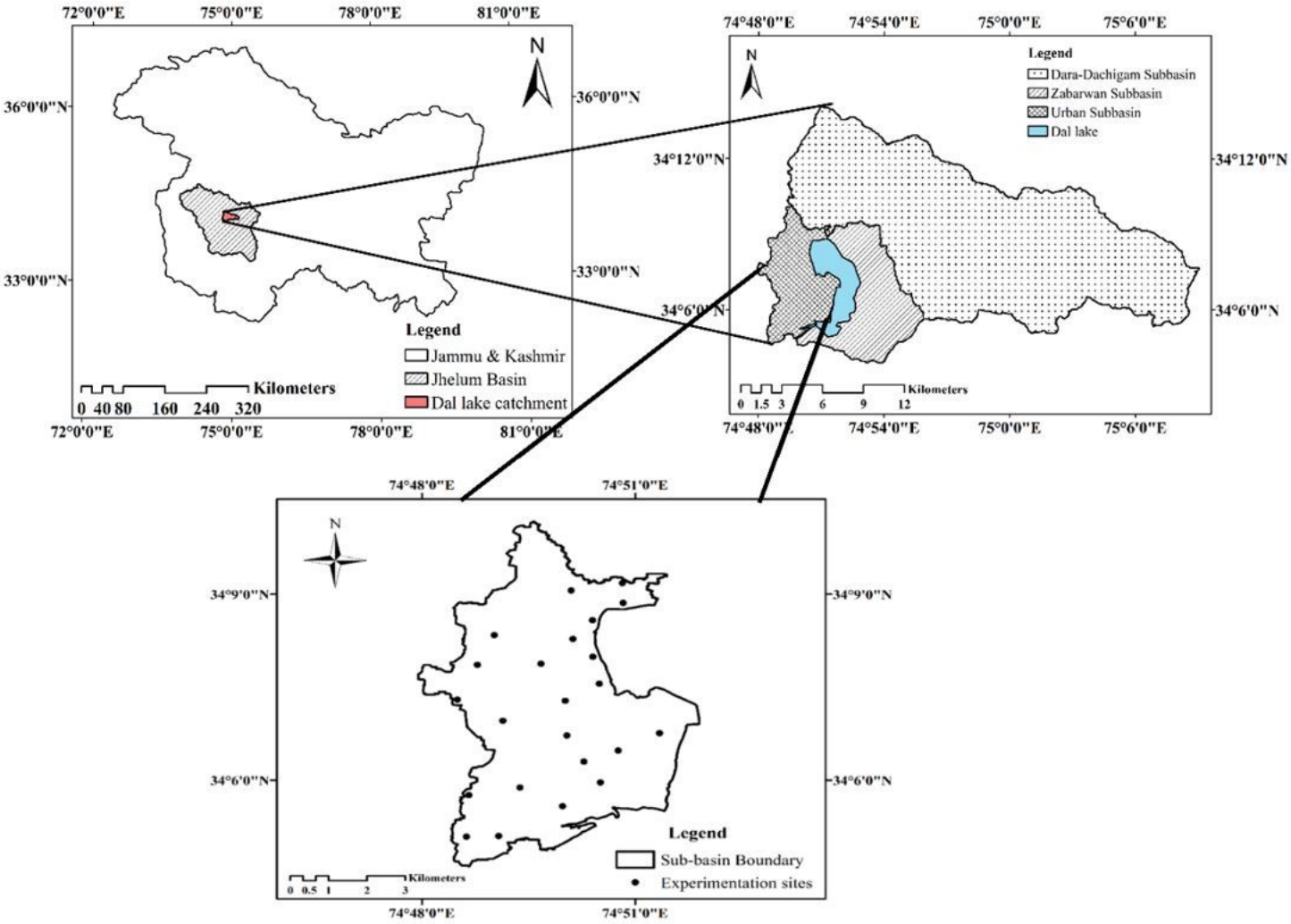

Figure 1

Study area along with selected experimentation sites. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

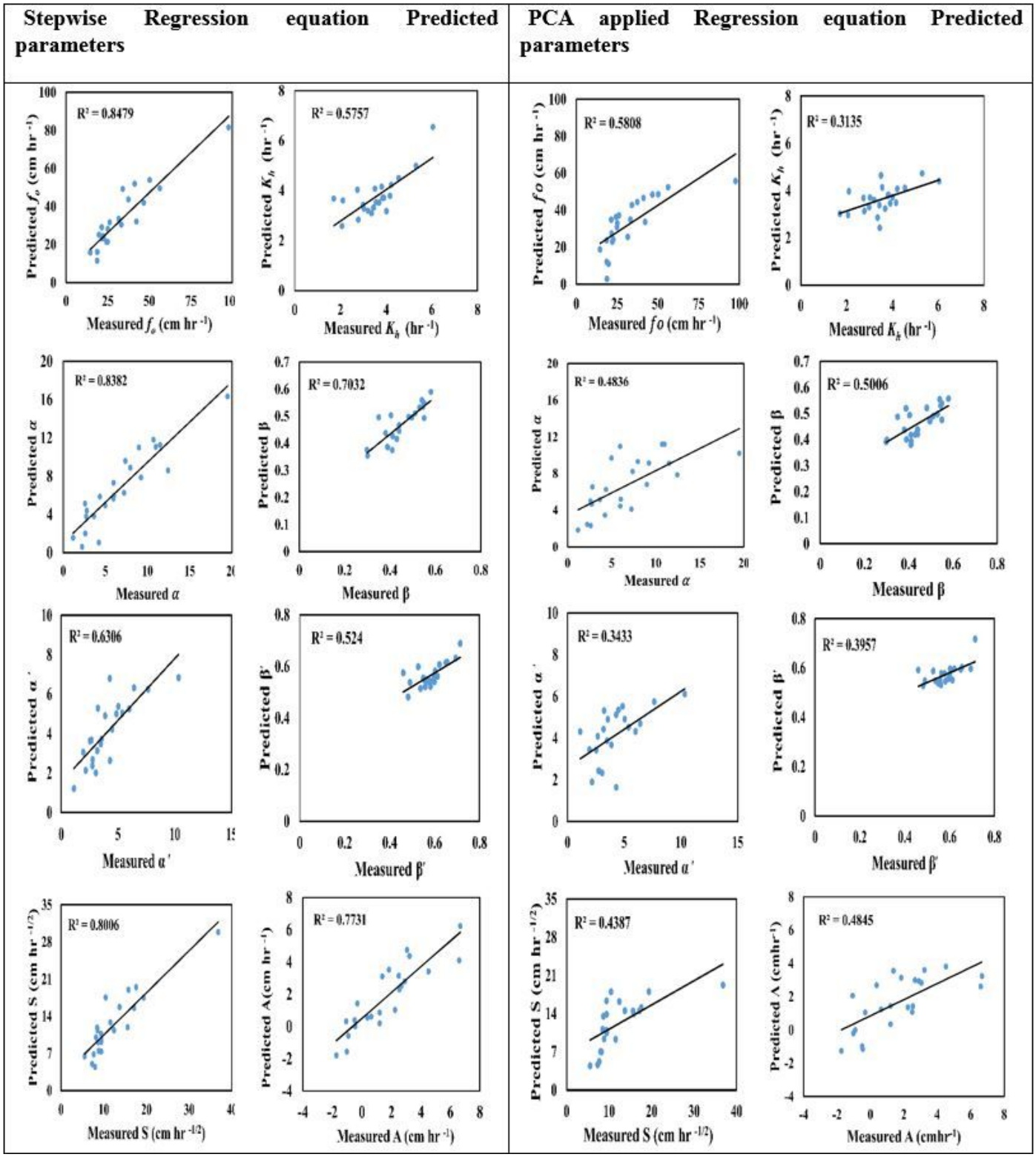

Figure 2

Measured vs. observed selected parameters of infiltration models.

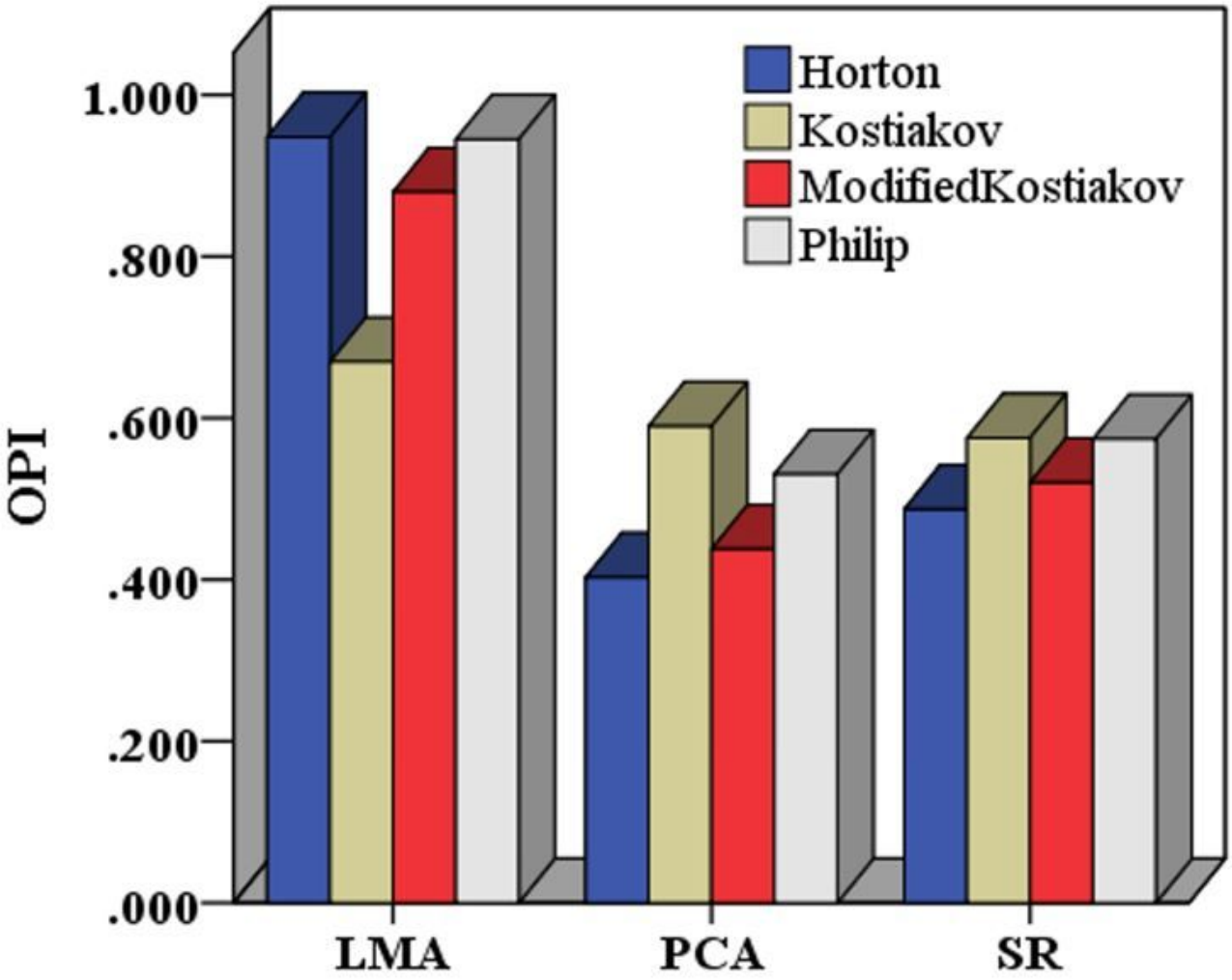

Figure 3

OPI of Parameter estimation Techniques for the selected Infiltration Models.