Performance assessment of infiltration models for varying soil textural classes

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Abstract: Field experiments were carried out to investigate the soil infiltration rates in different soil textures (clay loam, clay, and silty clay loam) with five infiltration models (Kostiakov, Modified Kostiakov, Philip, Horton, and Green-Ampt). Field experiments were conducted at the experimental stations of Sindh Agriculture University, Tandojam (Station No. 1, Faculty of Agricultural Engineering; 25°25′28′′N, 68°32′24′′E), (Station No. 2, Latif Experimental Farm; 25°26′14′′N, 68°32′30′′E) and Agriculture Research, Tandojam, (Station No. 3, Barley and Wheat Research Institute, 25° 24′ 59′′ N 68° 32′ 40′′ E), Sindh, Pakistan. These stations were selected to meet the need of three different soil textures. The composted soil samples were collected at the depth of 0-30 cm, and their textural classes were determined with the Bouyoucos hydrometer method. Field infiltration rates were measured using a double ring infiltrometer method. The results showed that the initial infiltration rates were high and gradually decreased until they reached a steady state. Using statistical parameters (NSE, RMSE, CC, and R^2), the measured infiltration rates were compared with the predicted infiltration rates of the selected infiltration models. For clay loam soil, Philip's model had the lowest RMSE and highest NSE, CC, and R^2 values, followed by Horton's model. For both clay and silty clay loam soils, Horton's model was the most accurate in predicting the infiltration rate with lowest RMSE and highest NSE, CC, and R^2 values, followed by Philip's model. The other three models (Kostiakov's, Modified Kostiakov's, and Green-Ampt's) performed poorly with higher errors and lower agreements compared to Horton's and Philip's models. In conclusion, Horton's model demonstrated the highest accuracy and agreement for clay and silty clay loam soils, while Philip's model showed the best performance for clay loam soil. These findings contribute to understanding the behavior of soil infiltration rate and provide valuable insights for land and water management practices in the studied area.
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1 Introduction

The swift expansion of the world's population has heightened the necessity for greater quantities of food, water, and land. Concurrently, the shifting climate is significantly disrupting the equilibrium between available water resources and demands, resulting in a constrained supply of water for agricultural purposes on a global scale, particularly impacting developing nations. According to data from the World Bank, irrigated agriculture contributes to 40% of global food production, and in Pakistan almost 90% of food grain production relies on it[1]. To address both current and future food requirements, it is imperative to enhance the productivity of food grains while dealing with the constraints of limited land and water resources[2]. To attain this objective, it is imperative to implement well-designed on-farm irrigation systems, where the soil's infiltration characteristics assume a critical role in guaranteeing superior water-use efficiency, the ideal application of fertilizers, and effective irrigation scheduling[3].

Recent advances in infiltration modeling have shown a significant shift toward integrating machine learning approaches with traditional empirical models to enhance predictive accuracy[4]. Contemporary research trends emphasize the importance of site-specific model validation, as demonstrated by recent studies that have highlighted the varying performance of infiltration models across different climatic zones and soil conditions[5,6]. The evolution of infiltration modeling has also seen increased attention to the physical realism of model assumptions, with researchers favoring models that better represent the complex interactions between soil structure, moisture dynamics, and hydraulic properties[7]. Furthermore, recent technological advances have enabled more precise field

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measurements and real-time monitoring of infiltration processes, contributing to improved model calibration and validation procedures[8].

Soil water, although a minor component within the Earth's total water reservoirs, holds immense significance as it governs the accessibility of water for plants across diverse soil layers[9]. It is a fundamental element that has a significant impact on soil infiltration characteristics. Rainfall and irrigation are the key inputs to the soil water[10,11]. Rainfall and irrigation water that falls on the surface is subsequently split into two parts: surface runoff, which travels to the sea via overland flow and stream channels, and infiltration, which enters the soil first. The mechanism through which water enters the soil from the surface is termed infiltration, representing a significant element within the hydrological cycle[12].

According to Angelaki[13] infiltration constitutes a multifaceted phenomenon influenced by numerous factors, including soil type, its texture, density, moisture content, impurities within the soil, the presence of vegetation, and plant root density. Soil texture is an inherent factor that influences soil infiltration; it cannot be changed[14]. Understanding the process of infiltration and its influencing factors holds significance not only for assessing surface runoff but also for gaining insights into subsurface water movement and the storage of water[15]. A reduced infiltration rate suggests a potential for increased runoff and erosion, which can have adverse effects on the water-holding capacity of soil[16]. This makes it difficult for the soil to meet the required water demand for crop production[17]. Moreover, in the pursuit of enhancing the efficiency and uniformity of surface irrigation systems when delivering water to agricultural fields, the process of infiltration stands out as exceptionally crucial[18]. Comprehending the phenomenon of infiltration holds paramount status in the framework of forecasting the requisite water volume for achieving root zone saturation, ascertaining the suitable irrigation duration, and approximating seepage losses within diverse surface irrigation systems[19]. Hence, having comprehensive insights into soil infiltration rates and their attributes is of utmost importance for improving irrigation water utilization efficiency while minimizing water wastage[20]. Likewise, infiltration data serves as a vital parameter in the context of field drainage applications[12]. As a result, irrigation engineering places significant reliance on understanding infiltration for the purpose of planning and constructing effective irrigation systems[19].

The infiltration properties of soils can be assessed through direct field measurements or by mathematically fitting field infiltration data to infiltration models[21]. In the field the infiltration process has been measured using several types of instruments such as single-ring, double-ring, tension, and mini disk infiltrometers. But the experimental estimation of infiltration poses challenges as it is costly, labor-intensive, and time-consuming[4]. Consequently, to determine soil infiltration, numerous infiltration models have been developed, and these models have undergone thorough and comprehensive reviews, presentations, and summaries[10]. These models are grouped into three categories: empirical (Kostiakov, Modified Kostiakov), semi-empirical (Horton), and physical (Philip, Green-Ampt) models[5].

Numerous infiltration models exist, but their applicability to real-world data remains uncertain[6]. The applicability of models varies depending on soil types due to the dependence of infiltration rate on soil texture[7]. Choosing the right model to precisely estimate the infiltration rate for a specific field condition can be a challenging task due to the existence of numerous available models, each with distinct origins, underlying assumptions, and parameters[8]. To establish model parameters and compare efficiencies of infiltration models for different soil conditions, several studies have been conducted[20]. Several researchers have performed a comparative analysis of the performance of models for different regions and soil types[6,15,22,23]. Building upon the previously mentioned information, this study aims to assess the efficacy of diverse infiltration models customized for distinct soil textures. The primary purpose of this study is to evaluate the performance of five widely used infiltration models—Kostiakov, Modified Kostiakov, Philip, Horton, and Green-Ampt—for accurately predicting soil infiltration rates across different soil textures (clay loam, clay, and silty clay loam) under field conditions in Tandojam, Sindh, Pakistan. The study aims to identify the most suitable infiltration model for each soil type by comparing measured infiltration data with model predictions using statistical indices (NSE, RMSE, CC, and R^2). This analysis provides critical insights into the selection of appropriate models for effective land and water management in varying soil conditions.

2 Materials and methods

2.1 Study area

The lab experiments were conducted in the department of Land and Water Management and the field experiments were conducted at experimental stations in the vicinity of Sindh Agriculture University, Tandojam. Three stations (Figure 1) were selected for field experiment, i.e. Station No. 1 (Faculty of Agricultural Engineering; 25°25′28″N, 68°32′24″E), Station No. 2 (Latif Experimental Farm; 25°26′14″N, 68°32′30″E), and Station No. 3 (Barley and Wheat Research Institute, Agriculture Research Institute, Tandojam; 25°24′59″N, 68°32′40″E). These stations were selected on the basis of three various soil textures and were within easy reach.

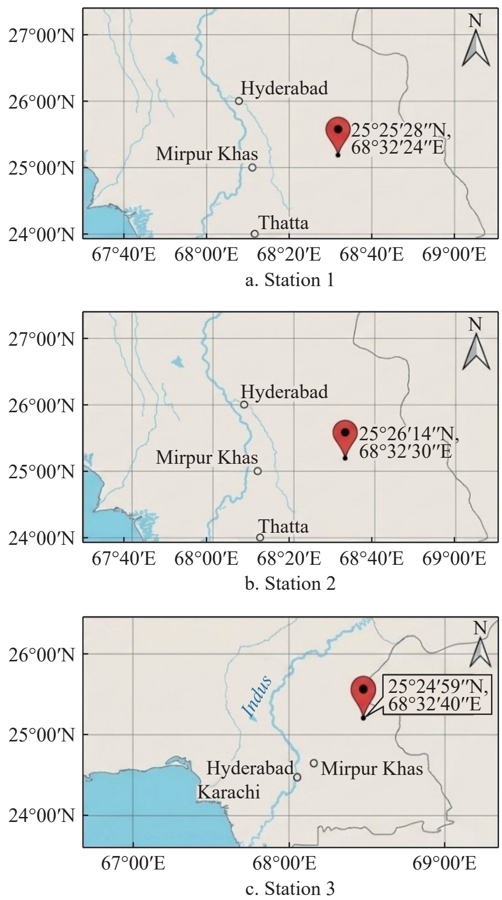


Figure 1 Location map of study area

2.2 Soil analysis

The composted soil samples were collected from experimental stations with an auger at 0-30 cm depths for the determination of soil texture (Table 1). The samples were oven dried, grinded, and sieved through a 2 mm mesh to separate the soil fractions. The textural class of the soil was determined in the laboratory by Bouyoucos hydrometer method[24] using USDA textural triangle.

Table 1 Effect of soil physical properties on soil permeability character

Indicator	Unit	Sand	Silt	Clay	Effect on Permeability
Bulk density (ρb)	g·cm^{-3}	1.50-1.70	1.30-1.50	1.10-1.30	Higher density reduces pore space and water movement
Particle size distribution	%	>70	40-50	>40	Coarse particles→high K; fine→low K
Particle mass (0-2 mm)	%	90-95	85-90	75-85	Higher fine particles reduce permeability
Porosity (n)	%	35-40	40-50	50-60	Higher porosity generally improves infiltration
Moisture content (W)	% (by wt.)	5-10	15-25	30-40	High water content fills pores, reducing air-filled space
Organic matter content	%	0.5-1.0	1.5-3.0	2.0-4.0	Improves structure and infiltration
Hydraulic conductivity (K)	cm·h^{-1}	5.00-20.00	1.00-5.00	0.01-0.50	Direct measure of permeability

2.3 Determination of infiltration rate in the field

The double-ring infiltrometer method was used to determine soil infiltration. Two concentric rings, an inner ring of approximately 30 cm diameter and an outer ring of about 60 cm diameter, were driven 10-15 cm into the soil at a level, representative site after removing surface debris. Both rings were sealed at the edges to prevent leakage, and the outer ring was filled first, followed by the inner ring, to minimize lateral water movement. A constant ponded head of 2-5 cm was maintained in both rings using a Mariotte bottle or by manually adding water as needed. The volume of water added to maintain the head was recorded at short intervals, every 30 s during the first 5 min, every 1-2 min up to 20 min, every 5 min up to 60 min, and then every 10-15 min until the infiltration rate approached steady state. The infiltration rate was calculated as the volume of water added divided by the area of the inner ring and the corresponding time interval, while cumulative infiltration was obtained by summing the total volume infiltrated per unit area. Care was taken to minimize soil disturbance during installation, prevent evaporation with protective covers, and ensure accurate measurements until steady infiltration was achieved.

2.4 Infiltration models

Five distinct infiltration models were selected to estimate infiltration rates, with parameters determined from field data using graphical methods[25]. The models and their key characteristics are shown in the following:

2.4.1 Empirical models

1) Kostiakov's model: Kostiakov[26] introduced a simple empirical equation through curve fitting data that correlates infiltration with time using a power function as Equation (1).

$$f(t) = at^{-b} \tag{1}$$

where, parameters a and b are determined by plotting ln[$f(t)$] vs ln(t).

2) Modified Kostiakov's model: Smith[27] made modifications to Kostiakov's model by introducing the term (f_c) to account for long-term behavior as Equation (2).

$$f(t) = a't^{-b'} + f_c \tag{2}$$

where, f_c represented the steady-state infiltration rate.

2.4.2 Semi-empirical model

1) Horton's model: The Horton[28] presented a model based on the assumption that the infiltration starts at higher rates, then decreases exponentially with time and eventually reaches a steady state when the soil becomes saturated as Equation (3).

$$f(t) = (f_0 - f_c) \times e^{-\beta t} + f_c \tag{3}$$

This study assumed exponential decay from the initial rate f_0 to the steady rate f_c.

2.4.3 Physical models

1) Philip's model: Philip[29] introduced an empirical infiltration model derived by truncating the solution series from a pounded surface as Equation (4).

$$f(t) = 0.5 \times S \times t^{-0.5} + A \tag{4}$$

The analysis was based on infiltration theory with sorptivity S and transmission parameter A.

2) Green-Ampt model: Green and Ampt[30] presented a model based on the assumption that soil may be regarded as a bundle of tiny capillary tubes irregular in area, direction and shape, as Equation (5).

$$f(t) = m + \frac{n}{F} \tag{5}$$

The research related the infiltration rate to cumulative infiltration F. m represents Saturated Hydraulic Conductivity (K). This is the rate at which water can move through the soil when it is fully saturated. n represents the product of three physical parameters.

$$n = K \times \psi \times \Delta\theta \tag{6}$$

where, K represents saturated hydraulic conductivity, ψ represents wetting front soil suction head (capillary potential), $\Delta\theta$ represents moisture deficit (or initial moisture deficit).

Parameter estimation for each model followed established graphical procedures, with detailed methodologies available in the literature[9].

2.5 Comparison of field measured and predicted infiltration rate

A comparison between the measured infiltration rate in the field and the predicted values was carried out using the following statistical parameters (Table 2) to assess the performance of the infiltration models.

Table 2 Statistical parameters for assessment of infiltration models

No.	Statistical Parameter	Equation	Parameters
1	Nash-Sutcliffe model efficiency coefficient	$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(a_i - b_i)^2}{\sum_{i=1}^{n}(a_i - \bar{a})^2}$	Where: a=observed field values; b=model predicted values; n=total number of observations

(To be continued on the next page)

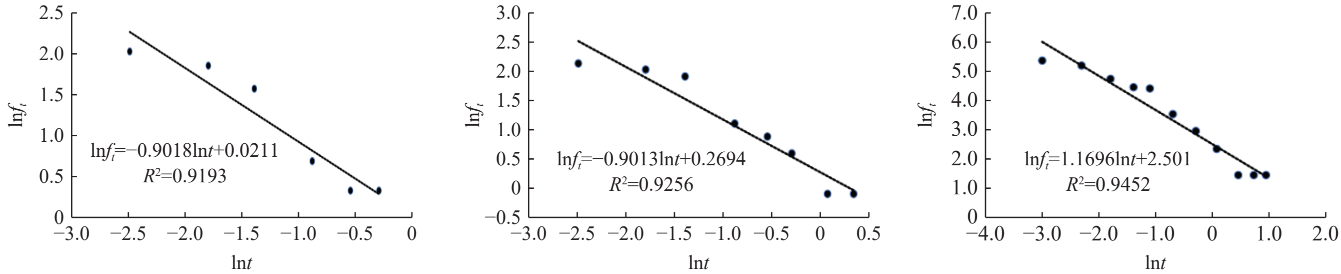
Table 2 (*Continued*)

No.	Statistical Parameter	Equation	Parameters
2	Root means square error	$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i-b_i)^2}$	
3	Coefficient of correlation	$r=\dfrac{n\cdot\left(\sum_{i=1}^{n}a_i\cdot b_i\right)-\left(\sum_{i=1}^{n}a_i\right)\cdot\left(\sum_{i=1}^{n}b_i\right)}{\sqrt{n\cdot\left(\sum_{i=1}^{n}a_i^2\right)-\left(\sum_{i=1}^{n}a_i\right)^2}\sqrt{n\cdot\left(\sum_{i=1}^{n}b_i^2\right)-\left(\sum_{i=1}^{n}b_i\right)^2}}$	
4	Coefficient of determination	$R^2=r^2$	

3 Results and discussion

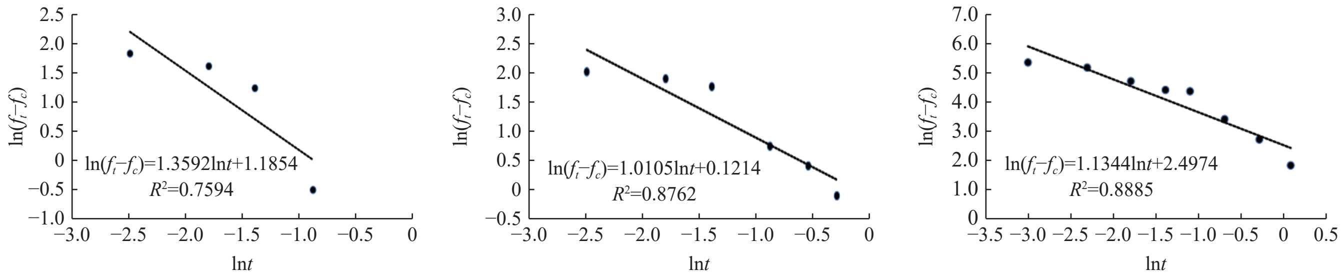
3.1 Models estimated parameters

The estimated values were found to be consistent with those reported in the literature, as summarized in Figures 2-6 and Table 3. These estimated values of infiltration model parameters are valuable for developing an infiltration equation specific to the study area.



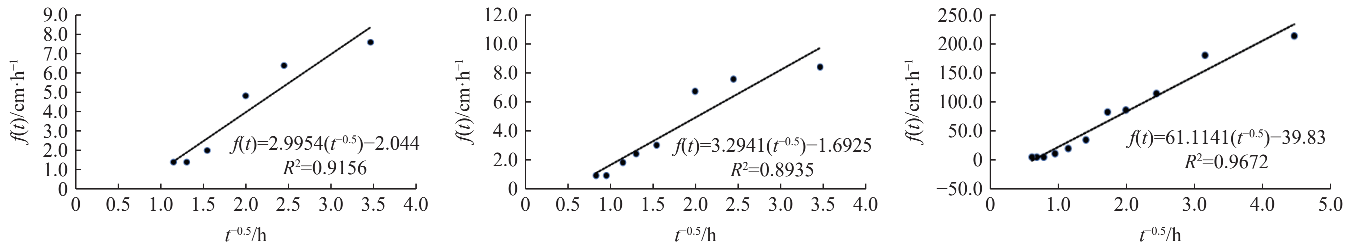
a. Clay loam (Station 1) b. Clay (Station 2) c. Silty clay loam (Station 3)

Figure 2 Plot for estimation of Kostiakov's model parameters under different soil textures



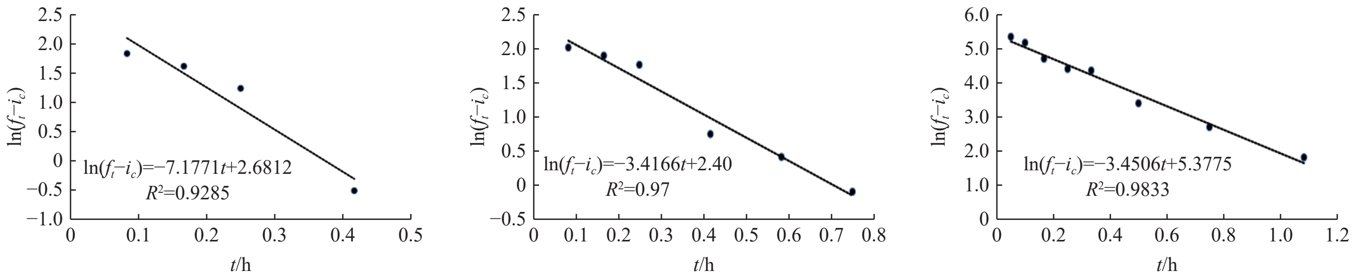
a. Clay loam (Station 1) b. Clay (Station 2) c. Silty clay loam (Station 3)

Figure 3 Plot for estimation of Modified Kostiakov's model parameters under different soil textures



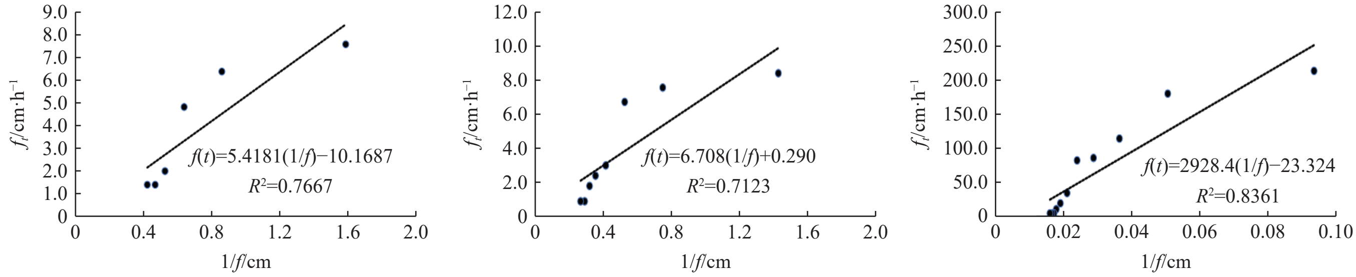
a. Clay loam (Station 1) b. Clay (Station 2) c. Silty clay loam (Station 3)

Figure 4 Plot for estimation of Philip's model parameters under different soil textures



a. Clay loam (Station 1) b. Clay (Station 2) c. Silty clay loam (Station 3)

Figure 5 Plot for estimation of Horton's model parameters under different soil textures



a. Clay loam (Station 1) b. Clay (Station 2) c. Silty clay loam (Station 3)

Figure 6 Plot for estimation of Green-Ampt's model parameters under different soil textures

Table 3 Estimated values of the model parameters for the three stations

Models	Parameters	Stations		
		1	2	3
Kostiakov's	a	1.0230	1.3091	12.1920
	b	0.9018	0.9013	1.1696
Modified Kostiakov's	a'	0.3057	0.8857	12.1480
	b'	1.3529	1.0105	1.1340
Philip's	A	−2.0442	−1.6925	−39.8300
	S	5.9908	6.5882	122.2280
Horton's	β	7.1771	3.4166	3.4506
Green-Ampt's	m	−0.1687	0.2907	−23.3240
	n	5.4181	6.7080	2928.4000

3.2 Infiltration rate in the field

The data of infiltration rate collected from each station was then used to plot the infiltration rate curves, which show the relationship between the infiltration rate and time. The results showed that the initial infiltration rates were high in the beginning, which were 7.56, 8.40, and 213.40 cm/h for stations 1, 2, and 3, respectively. However, these rates decreased over time until they reached a steady state, which were 1.38, 0.90, and 4.20 cm/h for stations 1, 2, and 3, respectively. Silty clay loam soil exhibits higher initial infiltration rates because of its relatively loose structure compared to other soil textures and a higher concentration of silt particles. The infiltration rates varied significantly across the three locations.

3.3 Simulated infiltration rate with different models

The models showed their ability to accurately simulate the infiltration process in different soil textures as illustrated in Figures 7-9, respectively. As illustrated in Figure 7, Philip's model closely predicted the measured infiltration rate for the clay loam soil, with only minor deviations observed. The infiltration rate is initially overpredicted by Philip's model, then underpredicted in the intermediate stage, and overpredicted again in the final stage. The other models also have a similar trend of overestimating and underestimating the infiltration rate for the clay loam soil, but with more deviations than Philip's model.

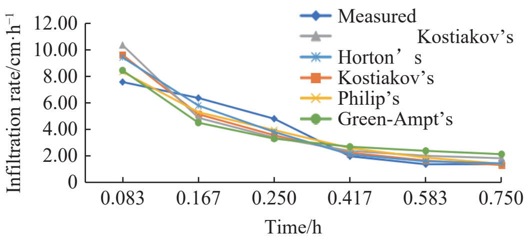


Figure 7 Measured and predicted values for clay loam (Station 1)

As illustrated in Figure 8, Horton's model closely predicted the measured infiltration rate for clay soil, except for some minor deviations at the initial and final stages. Horton's model slightly over-predicted at the beginning and under-predicted at the end. On the other hand, Kostiakov's, Modified Kostiakov's, and Philip's models over-predicted throughout the experiment until the final stage. Green-Ampt's model over-predicted at the first reading, then under-predicted at the next readings, and over-predicted again towards the end. As illustrated in Figure 9, Horton's model closely predicted the measured infiltration rate for silty clay loam soil, except for a minor underestimation at the beginning and a minor overestimation at the end, while the other models had more deviations than Horton's model in predicting the infiltration rate. The other models, namely Kostiakov's, Modified Kostiakov's, and Green-Ampt's, tended to overpredict the infiltration rate for most of the duration, except for the final stage. Philip's model showed a reverse pattern, with an initial overprediction and a final underprediction.

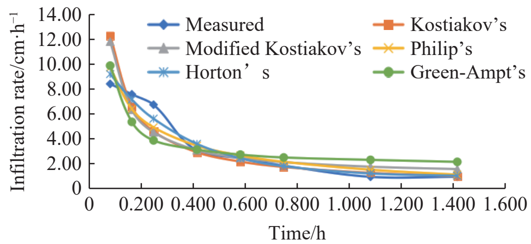


Figure 8 Measured and predicted values for clay (Station 2)

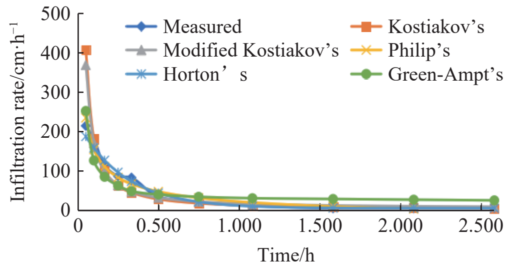


Figure 9 Measured and predicted values for silty clay loam (Station 3)

The results indicate that the values simulated by the models align well with the actual field measurements and the studied models are also consistent with the previous research in this field, which adds to their validity. Moreover, the models have been validated and verified by Mahapatra[2] and Basset[31], who have commended their reliability and accuracy. The models can be used in different classes of soil texture and provide different levels of accuracy, as Sihag[5] has indicated. The models are therefore useful tools for predicting infiltration in various conditions.

3.4 Performance of models

The performance indices for the five infiltration models at three distinct stations are outlined in Table 4.

Table 4 Performance indices between measured and predicted infiltration rate under different soil textures

Models	Kostiakov's	Modified Kostiakov's	Philip's	Horton's	Green-Ampt's
Clay loam (Station 1)					
NSE	0.800	0.654	0.916	0.869	0.767
RMSE	1.106	1.454	0.718	0.894	1.194
CC	0.923	0.875	0.957	0.954	0.876
R^2	0.852	0.766	0.916	0.909	0.767
Clay (Station 2)					
NSE	0.688	0.713	0.893	0.963	0.712
RMSE	1.618	1.552	0.945	0.556	1.553
CC	0.897	0.882	0.945	0.981	0.844
R^2	0.805	0.777	0.893	0.963	0.712
Silty clay loam (Station 3)					
NSE	0.294	0.529	0.967	0.970	0.836
RMSE	59.623	48.705	12.859	12.257	28.733
CC	0.908	0.914	0.983	0.990	0.914
R^2	0.825	0.835	0.967	0.980	0.836

3.4.1 Clay loam soil (Station 1)

Philip's model exhibited the highest accuracy (NSE=0.916, RMSE=0.718 cm/h) for clay loam soil, which can be attributed to the model's ability to capture the dual-phase infiltration behavior characteristic of medium-textured soils. The relatively balanced pore size distribution in clay loam allows for both rapid initial infiltration through macropores and sustained infiltration through micropores, which aligns well with Philip's theoretical framework that considers both gravity and capillary forces. The moderate bulk density and intermediate hydraulic conductivity of clay loam soils provide conditions where Philip's sorptivity parameter effectively represents the soil's water retention characteristics. Surprisingly, this finding contrasted with previous research[32,33]. These studies had highlighted Horton's model as superior to Philip's model for clay loam soils. However, in the present study, Philip's model outperformed Horton's model, indicating its greater effectiveness.

3.4.2 Clay soil (Station 2)

Horton's model demonstrated superior performance (NSE=0.963, RMSE=0.556 cm/h) for clay soil, primarily due to its exponential decay function that effectively captures the rapid transition from initial high infiltration to steady-state conditions typical of fine-textured soils. Clay soils, with their predominant micropore structure and low hydraulic conductivity, exhibit infiltration behavior that closely matches Horton's assumption of exponential decrease. The high clay content results in swelling upon wetting, which creates a more pronounced transition between initial and final infiltration rates, making Horton's exponential decay parameter (β) particularly effective in representing this behavior. This finding found consonance with earlier studies conducted[14,34], where Horton's model exhibited impressive agreement with measured data. Adding to the strength of Horton's model, some scholars investigated the infiltration behavior of clay soil under various conditions[35-38].

3.4.3 Silty clay loam soil (Station 3)

Similar to clay soil, Horton's model emerged as the most accurate (NSE=0.970, RMSE=12.257 cm/h) for silty clay loam. The high silt content in this soil type creates a unique pore structure characterized by intermediate-sized pores that maintain relatively high initial infiltration rates but quickly approach steady-state conditions. The exponential decay function in Horton's model effectively captures this transition, while the model's flexibility in accommodating different initial and final infiltration rates makes it well-suited for the complex infiltration dynamics of silty clay loam soils. This conclusion corresponds with the findings of the literatures[39,40], whose authors also noted Horton's model's superiority over Philip's model in silty clay loam soil.

3.5 Model limitations and soil property interactions

The comparative analysis showed that the poor performance of Kostiakov's, Modified Kostiakov's, and Green–Ampt's models across all soil types could be traced to their structural assumptions and mismatch with field heterogeneity: Kostiakov's empirical power-law was simplistic and lacked a physical representation of pore-scale sorption and redistribution processes, which limited its ability to reproduce the slow, often exponential-like decay of infiltration in fine-textured soils[41]. Green–Ampt, although physically based, assumed a uniform initial water content and a sharp, piston-like wetting front, so it systematically overpredicted early-time fluxes and failed to capture the gradual moisture-profile development and layered or heterogeneous media common in clay-rich field soils[42,43]. The Modified Kostiakov model improved fits by adding a steady-state term but still depended on the underlying power-law form and therefore could not fully reproduce macropore-dominated or strongly retarded infiltration behavior observed in many measured datasets, which explained why comparative studies frequently found its skill limited or soil-dependent[44,45]. From a methodological viewpoint, the literature indicated that best results were obtained when empirical flexibility was combined with physically meaningful constraints, and that hybrid or generalized forms consistently improved fits across textures[43,45]. In summary, the innovative points to emerge for future work are to: 1) retain physically interpretable parameters, 2) allow explicit representation of heterogeneity/ponding time, and 3) adopt hybrid fitting frameworks that combine a parsimonious empirical term for early-time behavior with a physics-based asymptotic term for long-time conductivity, an approach that the reviewed studies showed produced more robust, transferable infiltration predictions across soil types[44,45].

4 Conclusions

From the results of the model predictions and correlation with field data, it is concluded that the performance of infiltration models is strongly influenced by soil physical properties, particularly texture, pore structure, and hydraulic characteristics. Horton's model consistently predicted accurate infiltration rates for both clay and silty clay loam soil, primarily due to its exponential decay function that effectively captures the rapid transition from initial high infiltration to steady-state conditions characteristic of fine-textured soils. The predictions of Philip's model exhibited the highest accuracy for clay loam soil, attributed to the model's ability to represent the dual-phase infiltration behavior through its sorptivity parameter, which effectively accounts for the balanced pore size distribution in medium-textured soils.

The remaining three models, namely Kostiakov's, Modified Kostiakov's, and Green-Ampt's models, demonstrated inferior performance with larger errors as compared to Horton's and Philip's models. This can be attributed to their oversimplified assumptions that fail to capture the complex pore-scale processes and heterogeneous nature of field soils. The study highlights the importance of considering soil physical properties when selecting infiltration models, as the interaction between model assumptions and soil characteristics significantly influences predictive accuracy. Future research should focus on developing more comprehensive models that explicitly incorporate soil structure parameters and consider the effects of soil layering and temporal moisture variations.

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[References]

[1] Yang Y C E, Ringler C, Brown C, Mondal Md A H. Modeling the agricultural water–energy–Food nexus in the indus river basin, Pakistan. Journal of Water Resources Planning and Management, 2016; 142(12): 04016062.
[2] Mahapatra S, Jha M K, Biswal S, Senapati D. Assessing variability of infiltration characteristics and reliability of infiltration models in a tropical sub-humid region of India. Scientific Reports, 2020; 10(1): 1515.
[3] Pereira L S, Oweis T, Zairi A. Irrigation management under water scarcity. Agricultural Water Management, 2002; 57(3): 175–206.
[4] Muhammed Pandhiani S. Exploring the application of machine learning techniques for prediction of infiltration rate. Arab J Geosci, 2022; 15(11): 1068.
[5] Sihag P, Tiwari N K, Ranjan S. Estimation and inter-comparison of infiltration models. Water Sci, 2017; 31(1): 34–43.
[6] Mishra S K, Tyagi J V, Singh V P. Comparison of infiltration models. Hydrol Process, 2003; 17(13): 2629–2652.
[7] Haghighi Fashi F, Sharifi F, Kamali K. Modelling infiltration and geostatistical analysis of spatial variability of sorptivity and transmissivity in a flood spreading area. Span J Agric Res, 2014; 12(1): 277–288.
[8] Failache MF, Zuquette LV. Soil water infiltration under different land use conditions: in situ tests and modeling. RBRH, 2021; 26(2): e26.
[9] Musa J J, Adeoye P A. Adaptability of infiltration equations to the soils of the Permanent Site Farm of the Federal University of Technology, Minna, in the Guinea savannah zone of Nigeria. AU J. T, 2010; 14(2): 147–155.
[10] Daly E, Porporato A. A review of soil moisture dynamics: from rainfall infiltration to ecosystem response. Environ Eng Sci, 2005; 22(1): 9–24.
[11] Shaikh S A, Li Y, Ma Z, Ali Chandio F, Hussain Tunio M, Ahmad F, et al. Effects of soil mechanical properties on the height and tractive performance of rubber grouser at different moisture contents. Int J Agric Biol Eng, 2022; 15(6): 31–37.
[12] Haghighi F, Kheirkhah M, Saghafi B. Evaluation of soil hydraulic parameters in soils and land use change. In: Dar I A, Dar I A. editors. Earth and Environmental Sciences. InTech. 2011. Available: http://www.intechopen.com/books/earth-and-environmental-sciences/evaluation-of-soil-hydraulic-parameters-in-soils-and-land-use-change. Accessed on [2024-11-27].
[13] Angelaki A, Singh Nain S, Singh V, Sihag P. Estimation of models for cumulative infiltration of soil using machine learning methods. ISH J Hydraul Eng, 2021; 27(2): 162–169.
[14] Muneer A S, Sayl K N, Kamal A H. A comparative study to assess the suitable models for predicting the infiltration rate in an arid region. Iraqi J Civ Eng, 2020; 14(1): 29–38.
[15] Ogbe V B, Jayeoba O J, Ode S O. Comparison of four soil infiltration models on a sandy soil in Lafia, Southern Guinea Savanna Zone of Nigeria. Prod Agric Technol, 2011; 7(2): 116–126.
[16] Ogban PI. Effect of land use on infiltration characteristics of soils in Northern Akwa Ibom State, South-eastern Nigeria. Agro-Sci, 2018; 16(3): 29.
[17] Thomas A D, Ofosu A E, Emmanuel A, De-Graft A J, Ayine A G, Asare A, et al. Comparison and estimation of four infiltration models. Open J Soil Sci, 2020; 10(2): 45–57.
[18] Rashidi M, Seyfi K. Field comparison of different infiltration models to determine the soil infiltration for border irrigation method. 2007. Available: https://www.cabidigitallibrary.org/doi/full/10.5555/20083150824. Accessed on [2024-11-27].
[19] Bajirao T S, Vishnu P. Comparative performance of different infiltration models for prediction of infiltration rate under different land-use conditions. Environ Earth Sci, 2023; 82(4): 112.
[20] Xing X G, Li Y B, Ma X Y. Effects on infiltration and evaporation when adding rapeseed-oil residue or wheat straw to a loam soil. Water, 2017; 9(9): 700.
[21] Oku E, Aiyelari A. Predictability of Philip and Kostiakov infiltration models under inceptisols in the humid forest zone, Nigeria. Kasetsart Journal, 2011; 45(4): 594–602.
[22] Igbadun H, Othman M K, Ajayi A. Performance of selected water infiltration models in sandy clay loam soil in Samaru Zaria. Glob J Res Eng J Gen Eng, 2016; 16(4): 8–14.
[23] Mistry P, Suryanarayana T M V. Comparative evaluation of various infiltration models: A case study of WREMI samiala field, Vadodara. SSRN Electron J, 2022. Available: https://www.ssrn.com/abstract=4176309. Accessed on [2024-11-27].
[24] Bouyoucos G J. The hydrometer as a new method for the mechanical analysis of soils. Soil Sci, 1927; 23(5): 343–354.
[25] ASTM. Test method for infiltration rate of soils in field using double-ring infiltrometer. 2018. Available: http://www.astm.org/cgi-bin/resolver.cgi?D3385-18. Accessed on [2024-11-27].
[26] Kostiakov A N. On the dynamics of the coefficient of water-percolation in soils and on the necessity of studying it from a dynamic point of view for purposes of amelioration. Trans 6th Cong Int Soil Sci Russ Part A, 1932; 17–21.
[27] Smith R E. The infiltration envelope: Results from a theoretical infiltrometer. J Hydrol, 1972; 17(1-2): 1–22.
[28] Horton R E. An approach toward a physical interpretation of infiltration - capacity. Soil Sci Soc Am J, 1941; 5(C): 399–417.
[29] Philip J R. The theory of infiltration: 1. The infiltration equation and its solution. Soil Sci, 1957; 83(5): 345–358.
[30] Heber Green W, Ampt G A. Studies on soil phyics. J Agric Sci, 1911; 4(1): 1–24.
[31] Basset C, Abou Najm M, Ghezzehei T, Hao X, Daccache A. How does soil structure affect water infiltration? A meta-data systematic review. Soil Tillage Res, 2023; 226: 105577.
[32] Fadadu M H, Shrivastava P K, Dwivedi D K. Application of Horton's infiltration model for the soil of Dediapada (Gujarat), India. J App.Nat Sci, 2018; 10(4): 1254–1258.
[33] Bayabil H K, Dile Y T, Tebebu T Y, Engda T A, Steenhuis T S. Evaluating infiltration models and pedotransfer functions: Implications for hydrologic modeling. Geoderma, 2019; 338: 159–169.
[34] Vaezi A R, Behtari M, Foroumadi M. Evaluation of water infiltration models in soil textures under different initial water contents. Iran J Ecohydrol, 2019; 6(3): 707–717.
[35] Mousavi Dehmurdi A, Ghorbani-dashtaki S, Mashayekhi P. Performance of some infiltration models based on obtained data from double-ring and HYDRUS-1D software. App.Soil Res, 2019; 7(2): 182–195.
[36] Farid H U, Mahmood-Khan Z, Ahmad I, Shakoor A, Anjum M N, Iqbal M M, et al. Estimation of infiltration models parameters and their comparison to simulate the onsite soil infiltration characteristics. Int J Agric & Biol Eng, 2019; 12(3): 84–91.
[37] Shaikh S A, Li Y, Zheng M, Chandio F A, Ahmad F, Tunio M H, et al. Effect of grouser height on the tractive performance of single grouser shoe under different soil moisture contents in clay loam terrain. Sustainability, 2021; 13(3): 1156.
[38] Shaikh S A, Yaoming L, Chandio F A, Tunio M H, Ahmad F, Mari I A, et al. Effect of wheat residue incorporation with tillage management on physico-chemical properties of soil and sustainability of maize production. Fresenius Environ Bull, 2020; 29(7): 4921–4929.
[39] Ghorbani Dashtaki S, Homaee M, Mahdian M H, Kouchakzadeh M. Site-dependence performance of infiltration models. Water Resour Manag, 2009; 23(13): 2777–2790.
[40] Razzaghi S, Khodaverdiloo H, Dashtaki S G. Effects of long-term wastewater irrigation on soil physical properties and performance of selected infiltration models in a semi-arid region. Hydrol Sci J, 2016; 61(10): 1778–1790.
[41] Mirzaee S, Zolfaghari A A, Gorji M, Dyck M, Ghorbani Dashtaki S. Evaluation of infiltration models with different numbers of fitting parameters in different soil texture classes. Archives of Agronomy and Soil Science, 2014; 60(5): 681–693.
[42] Sihag P, Singh B. Field evaluation of infiltration models. Technogenic and Ecological Safety, 2018(4): 3–12.
[43] Vand A S, Sihag P, Singh B, Zand M. Comparative evaluation of infiltration models. KSCE Journal of Civil Engineering, 2018; 22(10): 4173–4184.
[44] Zolfaghari A A, Mirzaee S, Gorji M. Comparison of different models for estimating cumulative infiltration. International Journal of Soil Science, 2012; 7(3): 108–115.
[45] Dahak A, Boutaghane H, Merabtene T. Parameter estimation and assessment of infiltration models for Madjez Ressoul Catchment, Algeria. Water, 2022; 14(8): 1185.