Modeling of potassium leaching from contrasting sandy soils (Case study: Western Australia sandy soils)

Babak Motesharezadeh[1*], Richard Bell[2,3], Hamed Ebrahimian[4]

[1]Soil Science Department Eng., University College of Agriculture and Natural Resource, University of Tehran, Karaj, Iran
[2]Centre for Sustainable Farming System, Food Futures Institute, Murdoch University, Western Australia, Australia
[3]SoilsWest, Murdoch University, Perth, WA, Australia
[4]Department of Irrigation and Reclamation Eng., University College of Agriculture and Natural Resource, University of Tehran, Karaj, Iran
[*]Corresponding author. E-mail: moteshare@ut.ac.ir

ABSTRACT

Maintaining an unlimited supply of nutrients to roots in sands is a challenge in agricultural lands. Potassium leaching (KL) in small-scale columns was continued for five pore volumes with four types of sand (5-6% clay including limed and non-limed Merredin sands, Ballidu sand, Whitby sand) from Western Australia and treated with three levels of K (0, 20 and 60 kg K ha^{-1}). The HYDRUS-1D model was applied for simulation of drainage water volume and K leaching for each soil. The model simulated drainage volume and KL for all treatments. The values of root mean square error in simulating K concentration of leachate ranged from 0.0011 to 0.0619 mg/cm^3 depending on soil type and the level of K. At the equivalent of 60 kg K ha^{-1}, K leaching in Merredin unlimed and limed soils occurred after pore volumes of 2.5 and 4.75, respectively. Application of 60 kg K ha^{-1} in Ballidu soil caused a leaching of 57 mg L^{-1} while the model estimates for KL in this soil was 31.5 mg L^{-1}. Results related to the observed and simulated K concentration of leachate in Ballidu soil, showed that with the application of 60 kg K ha^{-1} the mean values of these parameters were 27.8 and 34.3 mg L^{-1}, respectively, with indicating that increased pH delayed the KL process. While HYDRUS-1D modeling can be a practical tool in monitoring the leaching of K from sands further improvements are needed to capture the effects of K fertilizer on rates of leaching.

Keywords: soil features, fertilizing practice, nutrient leaching, light soils.

INTRODUCTION

Potassium (K) leaching is detrimental to the maintenance of sustainable arable land K fertility, especially in light soil textures (Werle et al., 2008), and low-K fixation soils (Dianjun et al., 2022). Due to the high percentage of potassium (60%) and reasonable economic price, potassium chloride supplies about 90% of potassium fertilizer used in the world (www.statista.com), and like urea, has a high solubility. Increasing the concentration of potassium from agricultural practices and the discharge of untreated wastewater from industries can contribute to water pollution. This can result in the contamination of water sources, posing a threat to aquatic life and human health (Sharpley and Halvorson, 1994; Skowron et al., 2018). Based on what World Health Organization (2011) and Griffioen (2001) reported, potassium concentrations in groundwater near agricultural areas are often more than the permissible level for drinking water (12 mg L^{-1}).

Since potassium plays an important role in increasing crop production, it is important to investigate the concentration of potassium in the soil and the main pathways for loss from the soil profile. Kolahchi and Jalali (2007), reported that potassium fertilizers application in calcareous sandy soils due to low clay content and limited soil buffering capacity of these soils, caused a high amount of potassium entered the soil solution phase and drainage which increased its loss. Field-based studies of potassium leaching are limited by soil non-uniformity. So, to answer this need, simulation models have been developed (Zhang et al., 2020). The HYDRUS model, known as an advanced simulator model,

Received 13 December 2024; accepted 16 April 2025.

simulates the one-, two-, and three-dimensional movement of water, salts, and heat in the soil (Šimůnek et al., 2012). There are limited studies evaluating the HYDRUS model performance in potassium transport simulation in the soil. Shekhar et al. (2021) successfully used the one-dimensional HYDRUS model to predict potassium movement in rice cultivated lands. Shekhar et al. (2024) applied the HYDRUS-1D model to simulate potassium (K) transport in rice fields under alternating wetting and drying (AWD) irrigation. Results showed that maintaining a 4-5 cm ponding water depth with a soil matric potential head of 400 cm optimized K availability and reduced leaching losses. HYDRUS-1D proved effective for managing K fertilization in AWD systems for sustainable rice production.

The texture of the soil has a major impact on K leaching (Jalali and Jalali, 2022). Potassium leaching has received less attention than phosphorus and nitrate leaching in sandy soils with a variety of soil characteristics. To date, the ability of the HYDRUS model in simulating potassium transfer in sandy soils has been rarely evaluated. Since 70% of the soils of Western Australia (the largest state of Australia and center of grain and oilseed production) are in the soil textural class of sandy (Tennant et al., 1992), it is necessary to be aware of the process of solute transfer as well as the entry of potassium into the drain and its loss, especially since the potassium storage capacity of these soils is limited. Indeed, potassium leaching prediction can play an important role in enhancing fertiliser use efficiency, and then minimise K leaching. Thus, the present study aimed to investigate potassium leaching experiments in small-scale columns (column K leaching experiments are time-consuming and labor-intensive) and assess the potential of one-dimensional HYDRUS model in predicting the process of potassium transfer in the soils.

MATERIAL AND METHODS

Experiments

Several representative sands from southwest Western Australia were collected (see Table 2, 31°48'32" S, 118°22'64" E, altitude 320 m) and standard methods were used to analyze their important physical and chemical properties (Motesharezadeh et al., 2021). Extractable concentrations of macro and micronutrients, soil texture, EC and pH were determined, in addition to the measurement of nitrate and potassium leaching from small-scale columns (Table 1). Based on previous leaching studies in small columns (Kolachi and Jalali, 2007; Wong and Wittwer, 2009), the small plastic columns with 10.6 cm in length and 3 cm in diameter were used through the present study. Each column was filled with contained 90 g of dry soil. In this study, for all studied soils, the meaning of 1 pore volume (PV) was 24 ml of leaching solution. 1 PV was applied to saturate the soil column and after that the leachates were collected every 0.25 PV (6 mL) until 5 PV was reached. Our primitive leaching study with up to 20 PV indicated the slight K leaching from the studied soil after 5 PV, similar to findings previously reported (Wong et al., 1990; Kolahchi and Jalali, 2007).

Treatments and measurements for each soil were mentioned in the following. K applied to soil were at the rates of equal to zero (0K), 20 (20K) and 60 kg K/ha (60K) using KCl applied on soil surface area basis to the leaching columns and there were three replications for each treatment. Each column had a surface area of 7 cm^2, so 0, 2.8, 8.4 mg KCl/column were added to obtain the treatments of 20 and 60 kg K/ha, respectively. Nitrogen fertilizer was applied at equivalent to 50 kg N/ha as urea. The leaching processes were carried out at room temperature (22-24°C). After each 0.25 PV, leachate from each soil was analyzed for K, NO_3 concentrations, pH and electrical conductivity (EC). K content of leachates was measured using a flame photometer (Model 410- Sherwood), and NO_3 content was measured using ion selective electrode (Model: HORIBA), EC and pH were also determined by use of EC meter (Model WP-981) and pH meter (Model PC 700 EUTECH MEAS), respectively.

Table 1. Values of soil hydraulic parameters for all study soils

Soil type	θr ($cm^3.cm^{-3}$)	θs ($cm^3.cm^{-3}$)	α (cm^{-1})	n (–)	Ks (cm min^{-1})
Merredin limed	0.0486	0.34	0.035	2.03	0.2857
Merredin unlimed	0.0486	0.34	0.035	2.03	0.2857
Whitby	0.0492	0.34	0.033	3.29	0.2857
Ballidu	0.0486	0.34	0.035	2.03	0.2857

Table 2. Some chemical features of studied soils of Merredin sands (limed, unlimed), Whitby and Ballidu sands (unlimed)

Soil type/Soil properties	Merredin (limed)	Merredin (unlimed)	Whitby	Ballidu
pH ($CaCl_2$)	6.20	4.5	4.6	5.8
Electrical conductivity (dS/m)	0.09	0.11	0.02	0.05
Organic carbon (gkg^{-1})	9.2	8.2	12.0	4.3
NO_3 ($mgkg^{-1}$)	32	22	1	6
NH_4 (mg/kg)	1	4	2	1
P Colwell (mg/kg)	64	86	19	21
K Colwell (mg/kg)	85	70	<15	34
Exc. Ca (cmol/kg)	4.31	1.55	0.75	1.5
Exc. Mg (cmol/kg)	0.45	0.37	0.16	0.19
Exc. Al (cmol/kg)	0.12	0.49	0.57	0.02
Exc. K (cmol/kg)	0.16	0.15	0.03	0.12
Exc. Na (cmol/kg)	0.07	0.11	0.05	0.03
Effective CEC (cmol/kg)	5.11	2.67	1.56	1.86
Sand%	93	92	94	94
Clay%	6	5	5	5
Longitude and latitude	31°48'32.53"S 118°22'64"E	31°28'59.7"S 118°13'12.2"E	32°29'14"S 116°13'49.2"E	30°59'44"S 116°77'23"E

HYDRUS-1D

One-dimensional HYDRUS model was used to model potassium leaching using the obtained data from the present experiment. The HYDRUS-1D model (Šimůnek et al., 1998, 2012) uses one-dimensional form of the Richards' equation for simulating water movement in the soil:

$$\frac{\partial\theta}{\partial t} = \frac{\partial}{\partial x}\left[K\left(\frac{\partial h}{\partial x} + \cos\alpha\right)\right] - S \quad (1)$$

where θ is the volumetric water content (cm^3/cm^3), h is the pressure head (cm), S is a sink term (day^{-1}), x is the spatial coordinate (cm), t is time (day), K is the unsaturated hydraulic conductivity (cm/day), α is the angle between the flow direction and the vertical axis ($\alpha = 0^0$ for vertical flow, 90^0 for horizontal flow, and $0^0 < \alpha < 90^0$ for inclined flow).

The HYDRUS-1D model implements the soil-hydraulic functions proposed by van Genuchten (1980) and Mualem (1976) to describe the soil water retention curve, $\Theta(h)$, and the unsaturated hydraulic conductivity function, $K(h)$, respectively:

$$\theta(h)\begin{cases}\Theta_r + \dfrac{\theta s - \theta r}{[1+ |\alpha h|^n]^m} & h < 0\\ \theta s & h \geq 0\end{cases} \quad (2)$$

$$K(h) = KsS_e^l[1 - S_e^{\frac{1}{m}})m]^2 \quad (3)$$

$$m = 1 - \frac{1}{n},\ n > 1 \quad (4)$$

$$Se = \frac{\theta - \theta r}{\theta s - \theta r} \quad (5)$$

where Θ_r and Θ_s denote the residual and saturated water content, respectively (cm^3/cm^3); α is the inverse of the air-entry value (cm^{-1}); K_s is the saturated hydraulic conductivity (cm/day), n is the pore-size distribution index (dimensionless), Se is the effective water content (dimensionless); and l is the pore-connectivity parameter (dimensionless), with an estimated value of 0.5, resulting from averaging conditions in a range of soils (Mualem, 1976).

HYDRUS-1D numerically solves the convection - diffusion equation with zero - and first-order reaction and sink term. The Galerkin finite element method is used in this model to solve the governing equation subjected to appropriate initial and boundary conditions. In this study, potassium (K^+) transfer was simulated by solving the following equation:

$$\frac{\partial \theta c}{\partial t} + \frac{\partial ps}{\partial t} = \frac{\partial}{\partial x}\left(\theta Dw \frac{\partial c}{\partial x}\right) - \frac{\partial qc}{\partial x} \tag{6}$$

where c and s are the potassium concentration in the liquid and solid phases [ML^{-3}], respectively; ρ is the soil bulk density [ML^{-3}], q is the volumetric flux [LT^{-1}] and D^w is the dispersion coefficient tensor [L^2T^{-1}] which can be defined as follows:

$$\theta D^{\,w} = DL|q| + \theta Dw\, \tau^{w} \tag{7}$$

where D_w is the molecular diffusion coefficient in free water [L^2T^{-1}]; τ_w is the tortuosity factor (dimensionless) and D_L is the longitudinal dispersivity [L]. Proper profile discretization is key to achieving acceptable mass balance error (Valiantzas et al., 2011). In this study, the number of nodes was considered as 100 (the discretization was 0.1 cm).

HYDRUS assumes nonequilibrium interaction between the solution (*c*) and adsorbed (*s*) concentrations in the soil system. The adsorption isotherm relating to *s* and *c* is described by the following nonlinear equation of the form:

$$s = \frac{K_d\, c^{\beta}}{1+\eta\, c^{\beta}} \tag{8}$$

where K_d [L^3M^{-1}], β [-] and η [L^3M^{-1}] are empirical coefficients. Kd is known as an adsorption coefficient.

Measured values of soil potassium concentration and water content before the experiment were used as initial conditions within the flow domain. The soil profile was saturated before the experiment. Therefore, the initial soil moisture was equal to the saturated water content for each soil type (Table 1). The upper and lower water flow boundary conditions were set to variable pressure head/flux and free drainage, respectively. In this study, there was no plant (i.e., transpiration) on the soil columns. Evaporation from the soil surface was neglected due to the short period of the experiments (about 15-25 min) and indoor conditions. The upper and lower solute transport boundary conditions were also set to concentration flux and zero concentration gradient, respectively. The vertical soil profile was taken into account in the model to mimic the soil column experiments. In addition, 100 nodes were considered for the spatial discretization (0.1 cm). The model was calibrated for the control treatment (K_0) and then validated for other treatments (K_1 and K_2) for each soil. Some solute transport parameters were estimated using an inverse solution approach implementing the Levenberg-Marquardt optimization module built-in HYDRUS-1D (Simůnek et al., 1998). The inverse method is based on the minimization of the difference between the observed and simulated values. The objective function was defined as the sum of squared residuals (*SSQ*):

$$SSQ = \sum_{j-1}^{m} Vj \sum_{j-1}^{n} Wij[qj\ (\mathrm{x,z,ti}) - qj\ (x,z,ti,b)]^2 \tag{9}$$

where *n* is the number of measurements for the j^{th} measurement set (e.g., solute concentrations, ...); $q_i{*}(x,z,t_i)$ is the measurement at time t_i, location *x*, and depth *z*; $q_i(x,z,t_i,b)$ is the corresponding model prediction obtained with the vector of optimized parameters $b=(\theta_s,\ K_s\ D_L,\ ...)$, and v_j and w_{ij} are weights associated with a particular measurement set or point, respectively.

In this paper, inverse estimation was applied to four potassium transport parameters, including D_L, K_d, β and η. The values of the *α*, *n* and θ_r parameters were estimated using the Neural Network approach - ROSETTA (Schaap et al. 2001) provided by HYDRUS-1D. The measured values of K_s and *θs* were used in the model (Table 1). The inverse optimization method simultaneously uses all measured data, i.e., potassium concentrations of leachate for five pore volumes. HYDRUS-1D was run for the 20K and 60K treatments using the parameters calibrated for the control (0K) treatment.

Ɵr and Ɵs are the residual and saturated water content, respectively; α is the inverse of the air-entry value; Ks is the saturated hydraulic conductivity, n is the pore-size distribution index.

Evaluation

Two evaluation indices including coefficient of determination (R^2) and root mean square error (RMSE) were used to evaluate the model performance in simulating K leachate:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(S_i-\bar{S})(O_i-\bar{O})\right]^2}{\sum_{i=1}^{n}(S_i-\bar{S})^2\ \sum_{i=1}^{n}(O_i-\bar{O})^2} \tag{10}$$

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2\right)} \tag{11}$$

where O_i, S_i, and n represent observed values, simulated values and number of samples, respectively, $\bar{O}$ and and $\bar{S}$ are the average observed and simulated values, respectively.

RESULTS AND DISCUSSION

The results given in Table 2 provide the important physical and chemical properties of the studied sandy soils while Figure 1 shows their location. The results of these traits were run in a one-dimensional model of HYDRUS and used to analyze the model results.

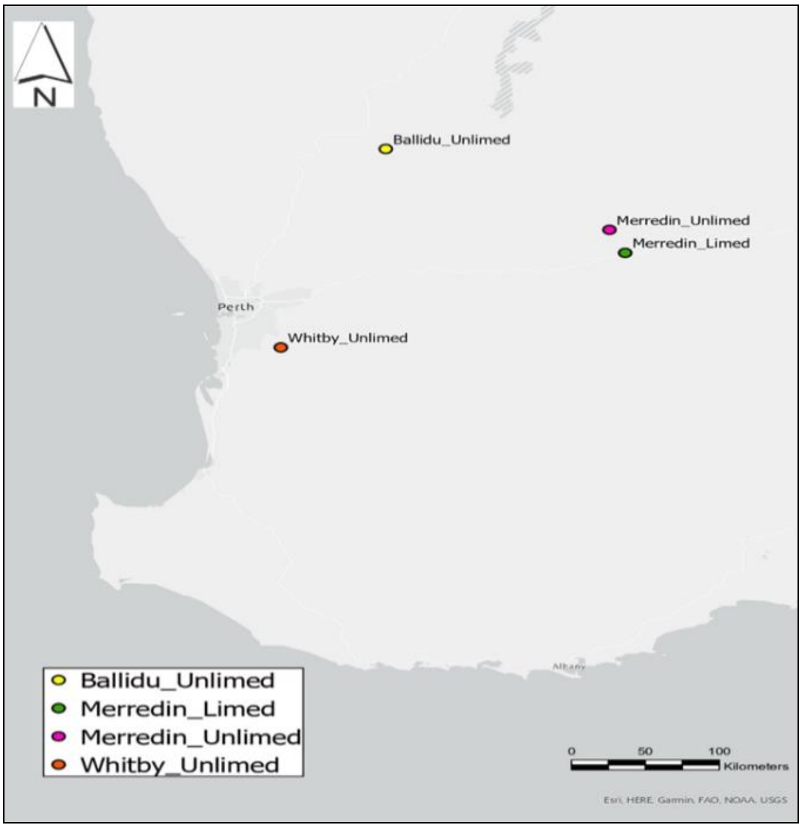


Figure 1. Locations of sampled soils in Western Australia

Model calibration

The model was able to closely simulate drainage water of five pore volumes (120 ml) for all cases indicating that soil hydraulic parameters were well determined. Data given in Table 3 indicates the optimized values of the potassium transport parameters for all soils, explaining the minimum error between the observed and simulated values for the control soils. There were acceptable values for R^2 and SSQ indices in all soils (Ebrahimian et al., 2013; Ranjbar et al., 2019). As a result of their study on clay loam and sandy loam soils, Nie et al. (2021) reported the reliable soil hydraulic and solute transport parameters determined from the inverse solution with the HYDRUS model under different potassium nitrate (KNO_3) concentrations.

Table 3. Optimized potassium transport parameters for all soils

Soil type	D_L (cm)	Kd (mg^{-1} cm^3)	η (mg^{-1} cm^3)	β (–)	R^2	SSQ
Merredin limed	10	0.7931	6.784	0.645	0.683	1.083
Merredin unlimed	8.56	0.8095	1.688	1.264	0.973	0.027
Whitby	6.44	0.0922	21.23	1.093	0.960	0.041
Ballidu	10	0.4747	1.849	0.952	0.933	0.069

D_L is the longitudinal dispersivity; *Kd* is the adsorption coefficient, η and β are empirical coefficients of the adsorption isotherm equation, R^2 is coefficient of determination and *SSQ* is the sum of squared residuals.

Model validation

Table 4 presents the error of the model for all studied soil types and treatments. The values of RMSE ranged from 0.0011 to 0.0619 mg/cm^3 depending on soil type and the level of potassium application. HYDRUS-1d successfully simulated potassium concentration of leachate for all soil types under the control treatment. However, the accuracy of the model was reduced by potassium application and by increasing the level of potassium added. The greatest and lowest values of RMSE were obtained for the Merredin unlimed and Ballidu soils under the 20K and 60K treatments, respectively. The performance of the model was best for the Whitby soil under the control treatments as compared to other soils.

Table 5 presents the simulated and observed cumulative K leached for all treatments and soils. The simulated values of cumulative K leached match well to the observed values for control treatments. However, the model largely overestimated cumulative K leached for both 20K and 60K treatments. Both simulation and observation showed that the Merridin unlimed and Whitby soils had the most and least values of cumulative K leached. K leaching increased by increasing the level of potassium application for all studied soils.

Table 4. Error of the model in simulating potassium concentration of leachate for K treatments

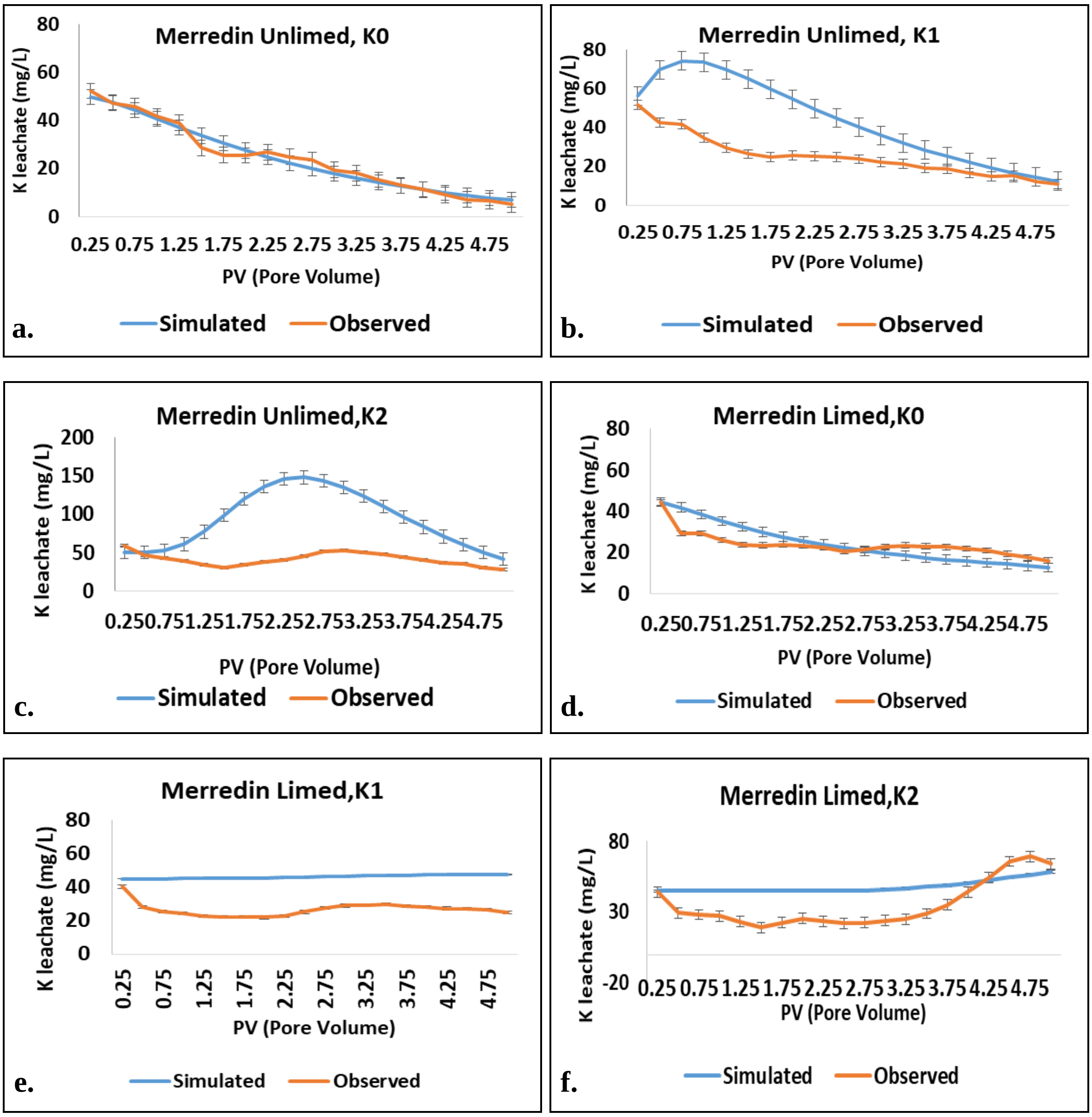
Soil type	Treatment	RMSE (mg/cm^3)
Merredin limed	0K	0.0059
	20K	0.0120
	60K	0.0176
Merredin unlimed	0K	0.0023
	20K	0.0226
	60K	0.0619
Whitby	0K	0.0011
	20K	0.0157
	60K	0.0202
Ballidu	0K	0.0018
	20K	0.0045
	60K	0.0165

Table 5. Comparison of simulated and observed cumulative K leached (mg)

Soil type	K0		K1		K2	
	Simulated	Observed	Simulated	Observed	Simulated	Observed
Merredin limed	2.90	2.84	5.54	3.19	5.75	4.20
Merredin unlimed	2.90	2.91	5.17	3.00	11.10	4.97
Whitby	0.49	0.51	2.41	1.13	2.64	1.56
Ballidu	1.43	1.44	2.20	1.96	4.11	3.33

K Leaching results

Changes in simulated and observed trends for K leachate of four sandy soils (limed and non-limed Merredin sands, Ballidu sand, Whitby sand) treated with nil K (K0), 20 kg K/ha (K1) and 60 kg K/ha (K2) is presented in Figure 2. Based on these results, simulated and observed results for Merredin were closely to each other in K0 treatment, which is the same trend for all four studied sandy soils (limed and non-limed Merredin sands, Ballidu sand, Whitby sand). In dead, HYDRUS could simulate the trends in nil treatment. For K1 treatment in Merredin unlimed, milestone was observed at first PV, however in K2 it was in 2.5 PV and 147.5 mg/kg K concentration in leachate with significant delay due to impact of more K on soil features. Amazing results were observed in Merredin limed treatment K2, at 4.75 and 5 PV with 69.37 and 64 mg/kg K concentration for observed and simulated respectively (Figure 2) due to impact of lime on soil physical and chemical properties especially pH and CEC. The same trend was observed for K2 treatment from Ballidu and Whitby at 2.75 and 1.75 PV with 57.9 and 45.5 K mg/kg concentration. Finally, the last graph (Yellow dotted line) showed 20% of data were over or underestimated with correlation between observed data model used data (Figure 2).



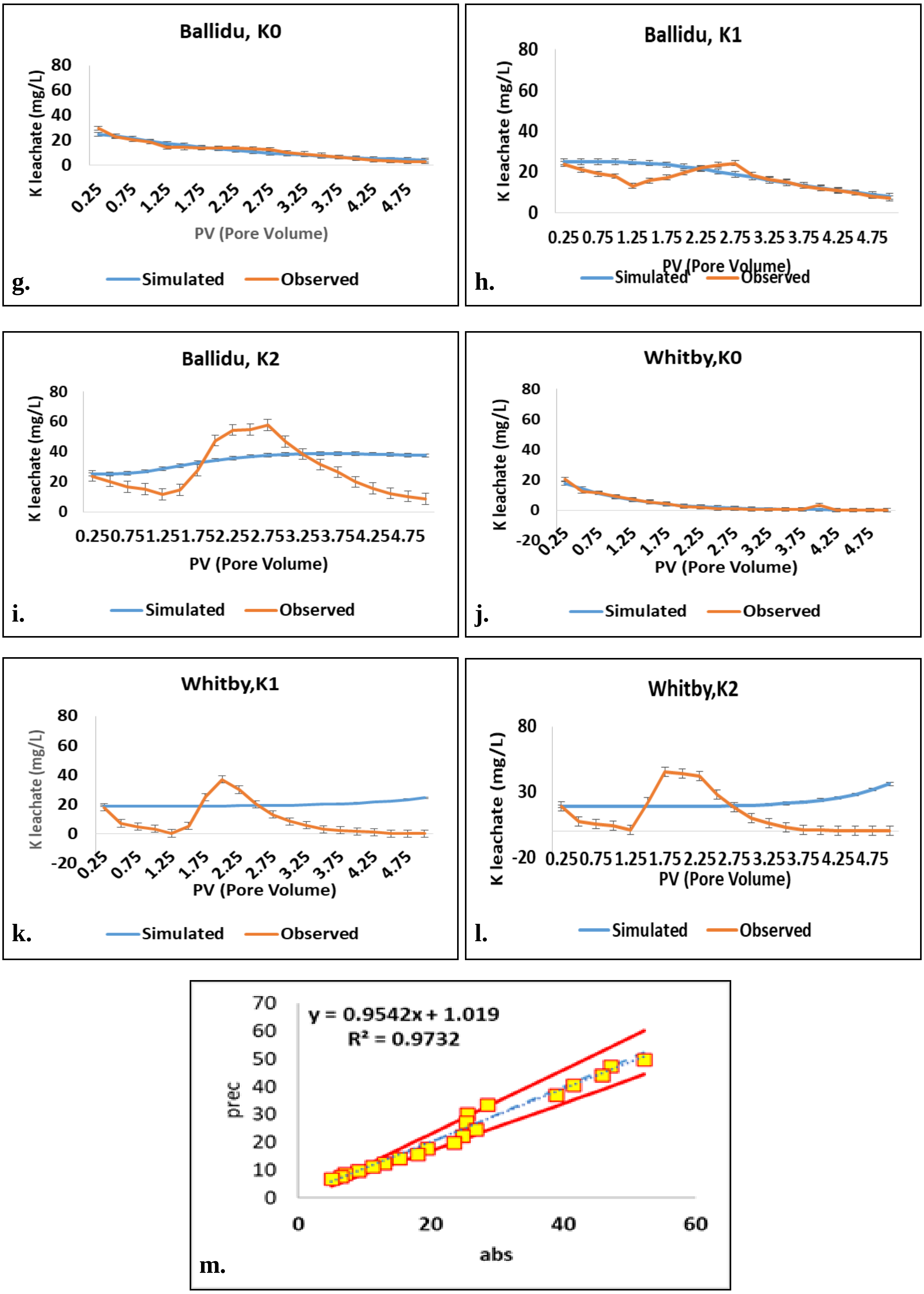


Figure 2. Changes in simulated and observed trends for K leachate of four sandy soils (limed and non-limed Merredin sands, Ballidu sand, Whitby sand) treated with nil K (K0), 20 kg K/ha (K1) and 60 kg K/ha (K2). The effect of K treatments [K0, 20 kg K/ha (K1) and 60 kg K/ha (K2)] on the changes of simulated and observed trends for K leachate in studied soils (limed and non-limed Merredin sands, Ballidu sand, Whitby sand). Values are means of three replicates.
1a. Merredin unlimed K0; 1b. Merredin unlimed K1; 1c. Merredin unlimed K2; 1d. Merredin limed K0;
1e. Merredin limed K1; 1f. Merredin limed K2; 1g. Ballidu sand K0; 1h. Ballidu sand K1;
1i. Ballidu sand K2; 1j. Whitby sand K0; 1k. Whitby sand K1; 1l. Whitby sand K2;
1m. K leaching equation and relationship between K-absorption and prediction

In the four control sands, where soil solution and exchangeable K were uniformly distributed in the column, the studied model fit well with the actual data. In all sands, K concentration was a range (15-85 mg/kg soil, Table 2) and in leachate was almost nil in the initial leaching events, and increased depends on soil features like lime, CEC, Ec and pH, between PV 2 up to PV 4 and finally the trend declined progressively with leaching events to below 5 mg/L after 5 PV. The milestone observation for Merredin unlimed was 52.45 mg/L for K2 treatment in PV=2.75, for Merredin limed K2 was 69.37 mg/L in PV=4.75 (maximum delay phase due to impact of lime on soil characteristics), for Ballidu in K2 was 57.9 mg/L in PV=2.75 and finally for Whitby K2 treatment was 44.15 mg/L in PV=1.75 (Figure 2). By contrast, the potassium concentration in the leachate was overestimated by the studied model at the K1 and K2 levels for the soils. It seems that placing the soluble K at the surface of the column produces a different pattern of K leaching to the control soil where the K is uniformly mixed in the column. HYDRUS is not correctly calibrated to analysis the topdressing of KCl.

A number of physical and chemical properties appeared to explain the variation in K leached from control sands. Sandy soil of Merredin limed had a pH of 6.2 which was close to neutral, while the pH of the other three sandy soils was acidic. Also, R^2 of the soil (Merredin limed) was lower than the other three soils (Table 3 and 6). Furthermore, the results showed that the leaching amount in sandy soil of Ballidu was much less than Merredin. Perhaps one of the reasons for the high accuracy of the studied model was the relatively low leaching in this soil, which can be induced by the physical and chemical properties of this soil such as soil texture components, pH 5.8 and also low CEC (Table 1). According to the reported results from Table 6, correlation between K 7 NO_3, K & Ec for Merredin unlimed was 0.73 and 0.79, respectively, and it was correlation 0.53 for K & Ec in Merredin limed. For Whitby between K & pH, K & Ec there were positive correlations 0.77 and 0.54, respectively, which was with low CEC for this sandy soil. Paltineanu et al. (2021) conducted an experiment to evaluate the environmental risk of application of NPK fertilizers in light and medium textured soils. The present study was carried out with the aim of investigation of the possibility of NPK removal from the soil and then providing recommendations limiting the losses of these nutrients. The results of three studied soils treated with two levels of NPK fertilizer indicated that among these nutrients the most losses from the root zone followed the order potassium > nitrogen > phosphorus.

Table 6. Pearson Correlations between measured soil characteristics

a: Merredin unlimed

		K	NO_3	pH	EC
K	Pearson Correlation	1	.733**	.118	.792**
	Sig. (2-tailed)		.000	.620	.000
NO_3	Pearson Correlation	.733**	1	-.167	.890**
	Sig. (2-tailed)	.000		.482	.000
pH	Pearson Correlation	.118	-.167	1	-.375
	Sig. (2-tailed)	.620	.482		.103
EC	Pearson Correlation	.792**	.890**	-.375	1
	Sig. (2-tailed)	.000	.000	.103	

**. Correlation is statistically significant at 0.01 level (2-tailed).
*. Correlation is statistically significant at 0.05 level (2-tailed).

b: Merredin limed

		K	NO_3	pH	EC
K	Pearson Correlation	1	.259	-.871**	.535*
	Sig. (2-tailed)		.270	.000	.015
NO_3	Pearson Correlation	.259	1	-.580**	.930**
	Sig. (2-tailed)	.270		.007	.000
pH	Pearson Correlation	-.871**	-.580**	1	-.798**
	Sig. (2-tailed)	.000	.007		.000
EC	Pearson Correlation	20	20	20	20
	Sig. (2-tailed)	.535*	.930**	-.798**	1

**. Correlation is statistically significant at 0.01 level (2-tailed).
*. Correlation is statistically significant at 0.05 level (2-tailed).

c: Ballidu

		K	NO_3	pH	EC
K	Pearson Correlation	1	.242	.023	.376
	Sig. (2-tailed)		.304	.922	.103
NO_3	Pearson Correlation	.242	1	-.826**	.879**
	Sig. (2-tailed)	.304		.000	.000
pH	Pearson Correlation	.023	-.826**	1	-.758**
	Sig. (2-tailed)	.922	.000		.000
EC	Pearson Correlation	.376	.879**	-.758**	1
	Sig. (2-tailed)	.103	.000	.000	

**. Correlation is statistically significant at 0.01 level (2-tailed).
*. Correlation is statistically significant at 0.05 level (2-tailed).

d: Whitby

		K	NO_3	pH	EC
K	Pearson Correlation	1	.377	.770**	.546*
	Sig. (2-tailed)		.101	.000	.013
NO_3	Pearson Correlation	.377	1	.004	.805**
	Sig. (2-tailed)	.101		.985	.000
pH	Pearson Correlation	.770**	.004	1	.453*
	Sig. (2-tailed)	.000	.985		.045
EC	Pearson Correlation	.546*	.805**	.453*	1
	Sig. (2-tailed)	.013	.000	.045	

**. Correlation is statistically significant at 0.01 level (2-tailed).
*. Correlation is statistically significant at 0.05 level (2-tailed).

Based on the results which is presented in Figure 2 "last graph (Yellow)", almost 20% of observation data which were used in modeling showed overestimate and underestimate trend. In fact, these results show almost a high variety range of used data for this research as already there were a couple of reports regarding to low accuracy of HYDRUS-1D for prediction light soil behavior. In accordance with the results of the present study, the efficiency of the HYDRUS-1D model in terms of simulating potassium transfer in the sandy soils was somewhat unsatisfactory under the high potassium application level. However, there are a few studies reporting that the HYDRUS model could successfully simulate potassium transfer in the soil. Shekhar et al. (2021)

evaluated the one-dimensional HYDRUS model to investigate the movement and transfer of potassium in rice fields. The two-dimensional HYDRUS model was also evaluated with an acceptable potential to estimate potassium transfer in sugarcane cultivation (Grecco et al., 2019). Through another study conducted by Yang et al. (2016), field plot sandy loam (64% sand and 6% clay) with *ke* parameter reflecting the effects of surface conditions and water-flow dynamics on transfer of soil solute was used to measuring reached potassium compared to simulated. The results showed the same results as current research in terms of steady state for K concentration after 15 minutes. The two-dimensional HYDRUS model was also evaluated with an acceptable potential to estimate potassium transfer in sugarcane cultivation (Grecco et al., 2019). Also, the study utilized both ground-station and satellite-based meteorological data. The model was found to be most suitable for the 0-30 cm soil layer. The results of a study carried-out by Formaglio et al. (2023) in Sao Paulo state, Brazil, reported that HYDRUS-1D successfully simulated leaching fluxes of potassium in, on Ferralsols fertilized with potassium, phosphorus, and lime. Greco et al. (2019) also reported that to simulate soil water content in a tropical soil, the two-dimensional HYDRUS model showed a favorable capacity. While it had not shown any successful performance in terms of predict potassium movement in drip irrigated tropical soil cultivated with sugarcane. Nie et al. (2021) conducted a simulation study using the HYDRUS-2D model under fertilizer solution infiltration for clay loam and sandy loam soils. They stated that the horizontal distribution range of potassium increased by increasing water depth in irrigated furrows.

Potassium interaction with soil properties (Key factors affecting K leaching)

Soil texture impact on K leaching

The texture of the soil has a major impact on K leaching (Jalali and Jalali, 2022). Potassium leaching from agricultural land occurs in a wide range of soil texture groups. Potassium leaching has received less attention compared to phosphorus and nitrate leaching in a wide range of soil textures. As a main concept, the application of K^+ fertilizers to sandy and light texture soils with low clay substance and little buffer capacity, in which K^+ does not link with the soil features for more fixing, led to an increase to potassium in solution and then it can be leached easily (Kolahchi and Jalali, 2007)

K leaching with and without K addition

The results of the studies investigated the relationship between soil and plant potassium with calcification operations in acidic soils reported that lime application increased the average concentration of exchangeable potassium and increased its uptake by plants (wheat and corn) by 37 to 155% compared to the control (Han et al., 2019). The researchers attributed their results to an increase in exchangeable calcium, a decrease in exchangeable aluminum, and an improvement in plant potassium uptake affecting the exchange phase of calcium and magnesium. Generally, they concluded that the use of lime improved the potassium uptake by the plant and also increased soil potassium availability. Investigating the potential leaching of potassium in 14 arable soils in China, Dianjun et al. (2020) found that the highest levels of potassium leaching were related to the soils with less K-bearing minerals and lower pH. Doulgeris et al. (2023) reported that adding biochar to soil substantially increases the availability of potassium in a common agricultural field in Northern Greece. It is important to study the interaction of potassium with the physicochemical properties of soil and other ions, including nitrate. Vilela et al. (2018) in their research on potassium transport parameters leaching, presented K breakthrough curve in different PV in soil deformed small column including 180 g soil and as a result of KCl solutions assessments, reported a higher value for retardation factor in comparison with that was observed for the effluent reasoned by higher soil-solute interaction. They concluded that less potassium adsorption by soil particles was done at the presence of other competitor cations in the effluent, reporting the fact that there was a greater groundwater pollutant potential for potassium when applied via effluent compared to the application of solutions of potassium chloride with the same ion concentrations. This may be very crucial when soil texture is lighter, especially in sandy soils.

The results of several studies have shown that the optimal use of fertilizers and soil conditioners such as liming of acidic soils, improve the uptake of cations and anions and increase the CEC of soils (Haynes, 2019; Motesharezadeh et al., 2021). Also, in the absence of roots and the occurrence of phenomena such as floods and heavy rains or heavy irrigation, there will be the possibility of nutrients leaching to out of reach of the plant and soil/groundwater contamination with potassium and nitrate (Singh and Crawell, 2021). Nonetheless, knowing the amount of potassium and nitrate leaching, which causes environmental pollution, is economically to the detriment of the farmer.

Soils are enriched with potassium (K) in areas with intensive agriculture and/or Sandy texture, increasing the risk of K being transferred to below the rhizosphere of soil profile through leaching. It is noteworthy that limitation in knowledge of soil and solute parameters is considered as an inability of HYDRUS-1D to accurate estimation of potassium concentrations, not as a limitation of the model in question. In fact, the accuracy of the model in sandy soils is highly controversial. In one hand prediction of K leaching was accurate in some studied sandy soils with high Pearson correlation, on the other hand this behavior was very weak. The HYDRUS model needs to be more assessed for simulating potassium transport in the soil under different soil and field conditions, especially in light soil textural limitation.

CONCLUSIONS

This study investigated potassium leaching in four types of sandy soils from Western Australia under varying potassium applications using small-scale column experiments and HYDRUS-1D modeling. The results showed that soil properties such as pH, clay content, and cation exchange capacity significantly influenced potassium leaching rates. Lime application delayed potassium leaching, demonstrating the importance of soil amendments in managing nutrient losses. The HYDRUS-1D model effectively simulated potassium leaching in control treatments but showed limitations at higher potassium levels, where it tended to overestimate leaching. These findings highlight the need for further calibration of the HYDRUS-1D model, particularly for top-dressing potassium applications. This study provides valuable insights into nutrient management for sandy soils, emphasizing the need for tailored fertilization and soil conditioning practices to minimize potassium loss and mitigate environmental impacts.

ACKNOWLEDGEMENTS

This study was supported by the Grains Research and Development Corporation and Murdoch University, Australia (Project 9175701) and a fellowship from University of Tehran.

REFERENCES

Dianjun, L.U., Yanhong, D., Xiaoqin, C., Huoyan, W., Jianmin, Z., 2022. *Comparison of potential potassium leaching associated with organic and inorganic potassium sources in different arable soils in China*. Pedosphere, 32: 330-338. https://doi.org/10.1016/S1002-0160(21)60077-2

Doulgeris, C., Kypritidou, Z., Kinigopoulou, V., Hatzigiannakis, E., 2023. *Simulation of potassium availability in the application of biochar in agricultural soil*. Agronomy, 13: 784. DOI: 10.3390/agronomy13030784

Ebrahimian, H., Liaghat, A., Parsinejad, M., Playán, E., Abbasi, F., Navabian, M., 2013. *Simulation of 1D surface and 2D subsurface water flow and nitrate transport in alternate and conventional furrow fertigation.* Irrigation Science, 31: 310-316.

Formaglio, G., Krusche, A.V., Mareschal, L., Bouillet, J.P., De Moraes Gonçalves, J.L., Nouvellon, Y., Laclau, J.P., 2023. *Planting nitrogen-fixing trees in tropical Eucalyptus plantations does not increase nutrient losses through drainage*. Forest Ecology and Management, 537, 120940. https://doi.org/10.1016/j.foreco.2023.120940

Grecco, K.L., de Miranda, J.H., Silveira, L.K., van Genuchten, M.T., 2019. *HYDRUS-2D simulations of water and potassium movement in drip irrigated tropical soil container cultivated with sugarcane*. Agricultural Water Management, 221: 334-347. https://doi.org/10.1016/j.agwat.2019.05.010

Griffioen, J., 2001. *Potassium adsorption ratios as an indicator for the fate of agricultural potassium in groundwater*. Journal of Hydrology, 254: 244-254.

Han, T., Cai, A., Liu, K., Huang, J., Wang, B., Li, D., Qaswar, M., Feng, G., Zhang, H., 2019. *The links between potassium availability and soil exchangeable calcium, magnesium, and aluminum are mediated by lime in acidic soil*. J. Soils Sediments, 19: 1382-1392. https://doi.org/10.1007/s11368-018-2145-6

Haynes, R.J., 2019. *What effect does liming have on silicon availability in agricultural soils?* Geoderma, 337: 375-383. doi.org/10.1016/j.geoderma.2018.09.026

Jalali, M., and Jalali, M., 2022. *Investigation of Potassium Leaching Risk with Relation to Different Extractants in Calcareous Soils*. J. Soil Sci. Plant. Nutr., 22: 1290-1304. https://doi.org/10.1007/s42729-021-00731-6

Kolahchi, Z., and Jalali, M., 2007. *Effect of water quality on the leaching of potassium from sandy soil.* Journal of Arid Environment, 68: 624-639. DOI: 10.1016/j.jaridenv.2006.06.010

Motesharezadeh, B., Ma, Q., Bell, R., 2021. *Lime application reduces potassium and nitrate leaching on sandy soils.* Journal of Cultivated Plants, 73(3-4): 83-93. DOI: https://doi.org/10.5073/JfK.2021.03-04.03

Mualem, Y., 1976. *A new model for predicting the hydraulic conductivity of unsaturated porous media*. Water Resources Research, 12: 513-522.

Nie, W.B., Nie, K.K., Li, Y.B., Ma, X.Y., 2021. *HYDRUS-2D Simulations of nitrate nitrogen and potassium transport characteristics under fertilizer solution infiltration of furrow irrigation*. Water Supply, 21: 2665-2680. https://doi.org/10.2166/ws.2020.266

Paltineanu, C., Domnariu, H., Marica, D., Lăcătușu, A.R., Popa, G.A., Grafu, I., Neagoe, A.D., 2021. *Fertilizers` leaching from the root system zone - a potential environmental risk for groundwater pollution in coarse and medium-textured soils*. Carpathian Journal of Earth and Environmental Sciences, 16: 139-150. Doi:10.26471/cjees/2021/016/162

Ranjbar, A., Rahimikhoob, A., Ebrahimian, H., Varavipour, M., 2019. *Simulation of nitrogen uptake and distribution under furrows and ridges during the maize growth period using HYDRUS-2D*. Irrigation Science, 37: 495-509. DOI: 10.1007/s00271-019-00627-5

Schaap, M.G., Leij, F.J., van Genuchten, M.T., 2001. *Rosetta: a computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions.* Journal of Hydrology, 251: 163-176.

Sharpley, A.N., and Halvorson, A.D., 1994. *The management of soil phosphorus availability and its impact on surface water quality*. Soil Processes and Water Quality, 7: 90.

Šimůnek, J., Sejna, M., van Genuchten, M.T., 1998. *The HYDRUS-1D software package for simulating the one–dimensional movement of water, heat, and multiple solutes in variably saturated media*. Version 2.0. IGWMC-TPS-700, Golden Colorado School of Mines, International Ground Water Modeling Center.

Šimůnek, J., Van Genuchten, M.T., Šejna, M., 2012. *HYDRUS: Model use, calibration, and validation.* Transactions of the ASABE, 55: 1263-1274.

Šimůnek, J., Jacques, D., Hopmans, J.W., Inoue, M., Flury, M., van Genuchten, M.T., 2002. *Solute transport during variably - saturated flow - Inverse methods.* In: Dane, J.H., and Topp, G.C. (eds.), Methods of Soil Analysis: Part 1, Chapter 6.6., Physical Methods, 3rd ed., Madison, Wisc., SSSA: 1435-1449.

Singh, B., and Crawell, E., 2021. *Fertilizers and nitrate pollution of surface and ground water: an increasingly pervasive global problem*. SN Applied Sciences, 3: 518. https://doi.org/10.1007/s42452-021-04521-8

Skowron, P., Skowrońska, M., Bronowicka-Mielniczuk, U., Filipek, T., Igras, J., Kowalczyk-Juśko, A., Krzepiłko, A., 2018. *Anthropogenic sources of potassium in surface water: The case study of the Bystrzyca river catchment*. Poland. Agriculture, Ecosystems and Environment, 265: 454-460. DOI:10.1016/J.AGEE.2018.07.006

Shekhar, S., Mailapalli, D.R., Sankar Das, B., Mishra, A., Raghuwanshi, N.S., 2021. *Hydrus-1D for Simulating Potassium Transport in Flooded Paddy Soils*. Communications in Soil Science and Plant Analysis, 52(22): 2803-2820. DOI: 10.1080/00103624.2021.1966437

Shekhar, S., Pohshna, C., Khose, S.B., Mailapalli, D.R., Raghuwanshi, N.S., 2024. *Hydrus-1D Model for Simulating Potassium Transport in Rice Crop Irrigated with Alternate Wetting and Drying Practice.* Communications in Soil Science and Plant Analysis, 55(18): 2781-2798.

Tennant, T., Scholz, D.G., Dioxon, J., Purdie, B., 1992. *Physical and chemical characteristics of duplex soils and their distribution in the south-west of Western Australia.* Australian Journal of Experimental Agriculture, 32(7): 827-843. DOI: 10.1071/ EA9920827

Valiantzas, J.D., Pollalis, E.D., Soulis, K.X., Londra, P.A., 2011. *Rapid Graphical Detection of Weakness Problems in Numerical Simulation Infiltration Models Using a Linearized Form Equation*. Journal of Irrigation and Drainage Engineering, 137: 524-529. DOI:10.1061/(ASCE)IR.1943-4774.0000318

Van Genuchten, M.T., 1980. *A closed form equation for predicting the hydraulic conductivity of unsaturated soils.* Soil Science Society of America Journal, 44: 892-898.

Vilela, N.M.S., Thebaldi, M.S., Leal, B.P., Silva, A.V., Martins, I.P., 2018. *Transport parameters of Potassium from different sources in soil columns*. Engenharia Agrícola, Jaboticabal, 38: 135-141. DOI:10.1590/1809-4430

Werle, R., Arroyo, R., Rosolem, C.A., 2008. *Potassium leaching as affected by soil texture and potassium availability,* Revista Brasileira de Ciência do Solo, 32(6): 2297-2305. DOI: 10.1590/S0100-06832008000600009

Wong, M.T.F., Hughes, R., Rowell, D.L., 1990. *Retarded leaching of nitrate in acid soils from the tropics: measurement of the effective anion exchange capacity.* Journal of Soil Science, 41(4): 655-663. DOI: 10.1111/j.1365- 2389.1990.tb00234.x

Wong, M.T.F., and Wittwer, K., 2009. *Positive charge discovered across Western Australian wheatbelt soils challenges key soil and nitrogen management assumptions.* Australian Journal of Soil Research, 47(1): 127-135. DOI: 10.1071/SR08098

World Health Organization, 2011. *Guidelines for drinking-water quality.* 4th ed. World Health Organization, https://apps.who.int/iris/handle/10665/44584.

Zhang, H., Yang, R., Guo, S., Li, Q., 2020. *Modeling fertilization impacts on nitrate leaching and groundwater contamination with HYDRUS-1D and MT3DMS*. Paddy Water Environ., 18: 481-498. https://doi.org/10.1007/s10333-020-00796-6

Yang, T., Wang, Q., Wu, L., Zhang, P., Zhao, G., Liu, Y., 2016. *A mathematical model for the transfer of soil solutes to runoff under water scouring,* Science of the Total Environment, 569-570: 332-341. doi.org/10.1016/j.scitotenv.2016.06.094