DISTRIBUTIONS AND MODELS OF TOPSOIL TOTAL POTASSIUM FOR 20-YEARS CULTIVATED FARMLANDS IN CHINA

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Abstract. Soil potassium is a vital macronutrient and element for both crops and biogeochemical cycles. However, studies on variety of soil potassium and environmental factors in long term cultivated farmlands are still lack. In this study, both soil properties of topsoil (0-20 cm) and environmental factors of ten soil health monitoring station in China were investigated from 1990 to 2018. Seven learning methods were used to build soil total potassium (TK) prediction model. Results showed that the mean value of soil TK content in 0-20 cm was 15.64±0.09 g·kg^{-1} with the range of 3.17-31.04 g·kg^{-1}. TK significantly increased with both the increasing of soil pH and elevation, while significantly decreased with the increasing of total organic carbon, organic matters, air temperature, amount of precipitation, humidity, and atmospheric pressure. The order of R^2 of soil TK prediction models from low to high was Linear Regression < Support Vector Regression < Decision Tree < Light Gradient Boosting Machine < Random Forest < eXtreme Gradient Boosting < Feedforward neural networks with the highest R^2 at 0.91 and the lowest values of RMSE and EF. Soil pH, air temperature, and precipitation could be important environmental factors affecting significantly soil total potassium. Machine learning methods generally showed better performances than that linear regression one. Based on long-term and in-situ monitor of soil properties and environmental factors, a sustainability management strategy for farmlands could come true.
Keywords: *agriculture soil, total potassium, learning methods, model performances, crops*

Introduction

Potassium (K), as an essential macronutrient in soil, is vital for efficient fertilizer management and environmental sustainability (Masood and Bano, 2016; Gao et al., 2019; Yahaya et al., 2023). Furthermore, potassium significantly contributes to the biogeochemical cycles of carbon and nitrogen. For example, K-selected microbial community has correlation with soil organic matters (OM) decompositions (Li et al., 2021), and as an indicator, potassium was strongly related to the release of nitrogen (Yang et al., 2022). Soil potassium is not only the second most abundant element in plants (Sardans and Peñuelas, 2015), but also the third essential macronutrient for crops and food (Rawat et al., 2016). In addition, soil potassium negatively related to land use intensity (Feng et al., 2022; Yahaya et al., 2023). Understanding the distribution patterns and the various factors influencing the levels of potassium in the soil is essential for making informed decisions related to agricultural practices and preserving the environment by efficient using of potassium resources (He et al., 2015). However, soil potassium is the most commonly neglected macronutrient element (Han et al., 2023), as

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previous studies suggested that soil potassium contents was relatively low in farmland (Hu et al., 2023). Ignoring soil potassium can adversely affect crop yields, as its deficiency impedes vital agricultural processes (Han et al., 2023). Hence, it is necessary to investigate soil potassium in a long term cultivated farmlands for a sustainability management strategy.

Previous studies have focused on soil potassium variation in regional scale (Hu et al., 2023) and national scale (He et al., 2015) in China, which mainly explored the temporal and spatial variation of soil potassium. However, the variation of environmental factors and their underlying mechanisms on soil potassium are still inadequate. Thus, it is necessary to assessment soil potassium contents and driving factors in a national scale, especially when the variation of environmental factors is quite large across a country scale. Through comprehending potassium distribution within topsoil profiles and identifying the key factors influencing its availability, we can optimize fertilization strategies, leading to enhancing crop productivity while minimizing potential environmental impacts.

In fact, many environmental factors could significantly affect soil potassium. For a better assessment and management of soil potassium, previous studies suggested that soil properties (e.g. pH) involving soil physicochemical biology and climate factors (e.g. temperature and precipitation) should to be taken into account (Han et al., 2023). For example, soil pH has a bidirectional relationship with biogeochemical processes, including the leaching and fixation of potassium (Masood and Bano, 2016; Neina, 2019). It is claimed that lime application significantly reduced topsoil exchangeable potassium content in a meta-analysis (Han et al., 2023). However, some studies argued that increasing soil pH could improve non-exchangeable potassium contents of soil aggregates, and a high soil exchangeable potassium was found in plots with a high soil pH (Liu et al., 2020; Nobis et al., 2022). The paradox results could be attributed to interactions among environmental factors, including plants species, management strategies, soil properties, and climate zones.

For climate factors, the significance of climatic conditions in influencing soil potassium variations has been highlighted in recent research (Li et al., 2021). For example, both temperature and precipitation are important factors affecting soil properties (Feng et al., 2022). Similar observation has been reported that the maximum solubilization of potassium release occurred at 25℃ (Rawat et al., 2016) and 15.6-26.7℃ (60-80°F) is an optimum soil temperature for potassium uptake (Mouhamad et al., 2016). Despite the acknowledged importance of climatic conditions in potassium variations, a notable gap exists in the literature regarding the exploration of interactions and the relative importance of specific climatic factors, such as temperature, precipitation, relative humidity, and atmospheric pressure.

Furthermore, in order to assess soil quality and optimize fertilizer strategies, it is also imperative to estimate soil potassium content after decades of cultivation. Previous studies on evaluating soil productivity has shown that modeling serves as an effective approach, and various modelling methods have been employed to predict soil potassium (Han et al., 2023). Many of these studies apply chemometrics, often alongside soil sampling (Song et al., 2020). For example, the random forest modelling approach was utilized to predict available soil potassium of East China (Jin et al., 2020; Song et al., 2020; Barra et al., 2021). The gradient boosted regression, a popular boosting method (Natarajan et al., 2022), was employed to predict soil available potassium concentrations, using 29 different pretreatment methods (Jin et al., 2020). Moreover, this method also

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included the use of remote sensing data for estimating soil pH values. Additionally, the prediction of soil available potassium has been conducted in the Yellow River Delta (Xu et al., 2020), which employed interpolation techniques and some traditional machine learning algorithms, such as random forest, decision tree (Tao et al., 2024) and XGBoost (Cao et al., 2023). However, the utilization of deep learning methods, like feedforward neural networks, remains limited in the development of models for soil properties, despite their demonstrated success in other fields such as carbon cycles (Li et al., 2020).

Overall, this study seeks to address this gap by conducting a comprehensive evaluation of these specific environmental factors and their impact on variations in soil potassium within farmlands across China. We conducted an investigation into the soil total potassium content through using a soil dataset over a period of 20 years (starting from 1998) and systematically sampled each year. The primary objectives were twofold: (1) to assess the relationship between soil total potassium and environmental factors in farmlands following a long-term cultivation, and (2) to examine the response of model performance when using different model learning methods for a better prediction soil total potassium. This research aims to contribute to a deeper understanding of soil nutrient dynamics, especially with regard to the influence of cultivation duration and national scale.

Material and methods

Study area and sampling

Our data are from ten soil health monitoring stations, which have been established across various farmlands in China (*Fig. 1*). These stations span the five regions which represents the climatic zones in China (He et al., 2015). The mean annual air temperature at these stations varies significantly, ranging from 1.5℃ to 19.9℃, while the mean annual precipitation fluctuates between 425 mm and 1785 mm. The predominant crops cultivated in the stations are wheat and rice, which are grown in distinct soil types. Specifically, the wheat cultivation areas primarily consist of fluvo-aquic soils, salinized fluvo-aquic soils, and dark loessial soils. In contrast, the rice cultivation areas are characterized by paddy soils, latent paddy soils, and red soils, as detailed in our prior study (Chen et al., 2022).

From 1998 to 2018, according to the guidelines outlined in Chinese Standard (Environment, 2011), 0-20 cm soil samplings were collected with six or more plots for replications in each soil health monitor stations. Specifically, soil total potassium levels were measured using Atomic Absorption and Flame Photometry, organic matter content was determined through oil bath heating with potassium dichromate (Tabatabai, 1996), and soil pH was assessed via Potentiometric Measurement. Moreover, the Total Organic Carbon (TOC) data were directly obtained from the Food and Agriculture Organization (FAO) database, as per the methodology advocated by Fischer (2008), which ensured the accuracy and comparability of TOC data across the different soil types and stations.

Besides these soil properties, climate factors (such as air temperature, precipitation, humidity, and atmospheric pressure) and a geographical factor, elevation, are also used in our study. These climate factors sourced from the National Meteorological Science Data Center (http://www.cma.gov.cn/2011qxfw/2011qsjgx/) have been systematically recorded, which are crucial for the comprehensive assessment of soil health. The details of our data are shown in *Table 1*. And the geographical factor, elevation, was collected from the soil health monitoring locations.

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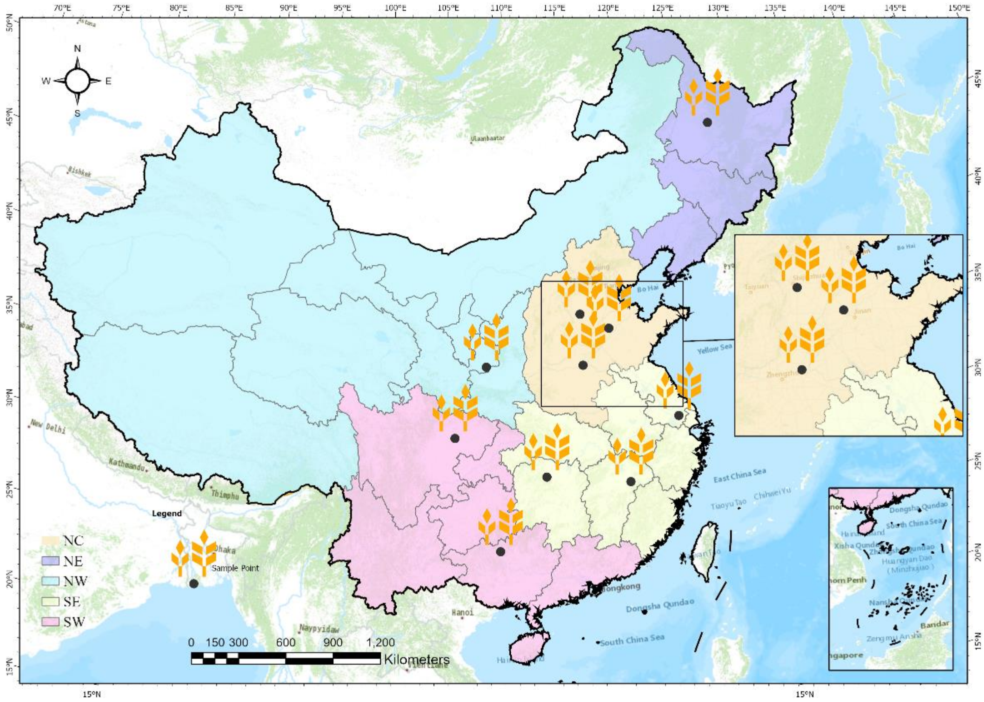

__Figure 1.__ A sketch map of sample locations of the soil health monitor stations for farmland in this study

__Table 1.__ Statistical parameters of soil and climate factors

Factors	Unit	n	Min	Max	Median	Mean	S.D.	S.E.	VC(%)
TK	$g \cdot kg^{-1}$	1988	3.17	31.04	16.51	15.64	4.04	0.09	25.83
pH	-	1988	5.40	8.30	6.40	6.70	1.07	0.02	15.98
TOC	$g \cdot kg^{-1}$	1988	4.10	19.50	11.20	9.57	3.76	0.08	39.32
OM	$g \cdot kg^{-1}$	1988	11.30	42.23	28.40	23.96	8.35	0.19	34.85
E	m	1988	1.30	1220.00	46.00	70.38	176.55	3.96	250.87
T	°C	1988	3.96	20.66	16.73	15.90	2.58	0.06	16.22
AP	hPa	1988	880.92	1016.79	1010.27	1008.20	19.97	0.45	1.98
AOP	mm	1988	1010.80	5165.90	3164.50	2959.56	1054.51	23.65	35.63
H	%	1988	57.12	82.10	72.47	72.12	6.52	0.15	9.04

Note: n, the sample size for the testing and training datasets, including 1058 of the wheat sampling and 930 of the paddy sampling; Min, the minimum value; Max, the maximum value; S.E., the standard error; VC, the variation of coefficient; TK, total potassium contents of soil; pH, soil pH value; E, elevation; TOC, total organic carbon; OM, organic matters; T, air temperature; AP, atmospheric pressure; AOP, amount of precipitation; H, humidity

Model learning method

To better estimate soil total potassium, the following seven learning methods were used to develop soil total potassium prediction models:

(1) Linear Regression(Linear) (Su et al., 2012): It represents a fundamental method in statistical analysis, particularly for modeling relationships between variables. This approach is predicated on the assumption of a linear relationship between the independent and dependent variables. It is a common method used to estimate relationships between environmental factors such as air temperature and soil potassium (Arheimer and Lidén,

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2000). Its simplicity and effectiveness make it a popular choice for estimating relationships in various scientific fields.

(2) Support Vector Regression (SVR) (Platt, 1998): It is an advanced regression technique derived from the principles of support vector machines. It aims to find a hyperplane that best captures the relationship between input variables and output variable. SVR is effective when dealing with non-linear relationships in high-dimensional spaces. One of the main advantages of SVR is its ability to handle complex datasets with various kernel functions.

(3) Decision Tree (DT) (Quinlan, 2014): It is a tree-like model where each internal node represents a decision based on a specific input variable, and each leaf node represents the outcome. They recursively split the input data based on their variable. It is interpretable, handles non-linearity, and can be a part of ensemble learning methods.

(4) Light Gradient Boosting Machine (LGB): Light Gradient Boosting Machine (LightGBM) is an efficient gradient boosting framework, particularly adept at handling large-scale datasets. As part of the gradient boosting methodology, LightGBM is renowned for its computational efficiency and capacity to manage extensive datasets. It utilizes a histogram-based algorithm for decision tree splitting, which is more efficient than traditional decision tree algorithms.

(5) Random Forest (RF) (Xu et al., 2020): It is an ensemble learning method that constructs multiple decision trees during training, and then outputs the average prediction for regression problems. It introduces randomness in the tree-building process and provides insights into the importance of input variables. RF is effective in reducing overfitting and improving predictive accuracy.

(6) eXtreme Gradient Boosting (XGB) (Chen et al., 2015): It is an optimized gradient boosting method that builds a series of weak learners (usually decision trees) and combines them to create a strong predictive model. XGBoost is widely used for its high predictive performance and speed as parallel processing is included.

(7) Feedforward neural networks (FFN) (Bebis and Georgiopoulos, 1994): It is a fundamental architecture in the neural network design, characterized by an unidirectional flow of information that precludes any feedback connections. This architecture typically comprises multiple layers, including an input layer, two hidden layers, and an output layer. In an FFN, neurons from one layer are connected exclusively to neurons in the subsequent layer, thus forming a non-cyclic network structure. Each neuron in this network is equipped with an activation function, which determines its output by calculating the weighted sum of its inputs. Notably, the Gaussian Error Linear Unit (GELU) is often employed as the activation function in FFNs. Such a choice contributes to the network's ability to model complex, non-linear relationships in data.

Experimental settings

The experimental dataset primarily focuses on topsoil (0-20 cm) total potassium data. The experimental methodology encompasses three key stages: data splitting, model training, and model testing. In the data splitting stage, the dataset is randomly divided into two subsets: 80% for training and 20% for testing. During the model training phase, a specific model learning method is employed to train the model using the training dataset (Li et al., 2020). To guarantee robust statistical results, this splitting process is repeated 10 times, and the average performance metrics are subsequently reported. Such a rigorous approach is designed to yield credible and reliable results, facilitating meaningful comparisons across different training datasets and learning methods.

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Performance evaluation metrics

As our previous studies, five indexes were used to assess the performance of the six learning methods: the coefficient of determination(R^2), root mean squared error (RMSE), mean absolute error (MAE), mean deviation (RMD), and model effective (EF) (Smith et al., 1997; Li et al., 2020). The criteria were determined as follows:

$$RMSE = \frac{100}{\bar{O}}\sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad \text{(Eq.1)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \quad \text{(Eq.2)}$$

$$\mathrm{RMD} = \frac{100}{\bar{O}}\sum_{i=1}^{n}\frac{P_i - O_i}{n} \quad \text{(Eq.3)}$$

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(\bar{O} - O_i)^2} \quad \text{(Eq.4)}$$

where, P and O represent the predictive and observed values of TK, respectively, and n is the sampling size. $\bar{O}$ is the mean value of observed data, and i is the sample index (Chen et al., 2022).

Implementation details

The whole experiment was implemented using Python language. The performance evaluation metrics, R^2, RMSE, RMD, MAE and EF were coded by Python (ver.3.7). The used model learning methods are directly used the ones provided by Scikit-learn (a Python-based machine learning library (Pedregosa et al., 2011). A partial least square path modeling (PLS-PM) was used to estimate the unidirectional casual effects of environmental factors on soil total potassium contents (Afthanorhan et al., 2020). The ten soil health monitoring stations were divided into five regions according to He et al. (2015) to compare the difference of soil total potassium contents. Tables and Figs were created by Python and ArcGIS (ver., Berkely, California, USA). A regression analysis was made to detect the relationship between soil total potassium and environmental factors. A detailed regression analysis, employing inverse, quadratic, and exponential regression methods, was conducted to assess the relationship between soil total potassium and various environmental factors. These advanced statistical techniques were chosen to comprehensively evaluate how different environmental conditions influence soil total potassium levels in soil. The outcomes of this multifaceted analysis are illustrated in *Fig. 2*. Only $p<0.05$ was considered as a statistically significant.

Result

Statistics of soil properties and environmental factors

The statistics of both the soil properties and the environmental factors of our data are shown in *Table 1*. For the soil properties, the mean value of soil total potassium content was 15.64±0.09 g·kg^{-1} with the range of 3.17-31.04 g·kg^{-1}, and the median value was 16.51, which is similar with the mean value with the difference value of 0.87. *Fig. 3* showed that significantly different of soil total potassium was found among five regions

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in China. Soil total potassium in the northeast region was the largest, followed by the northwest, north central, southeast, and southwest region.

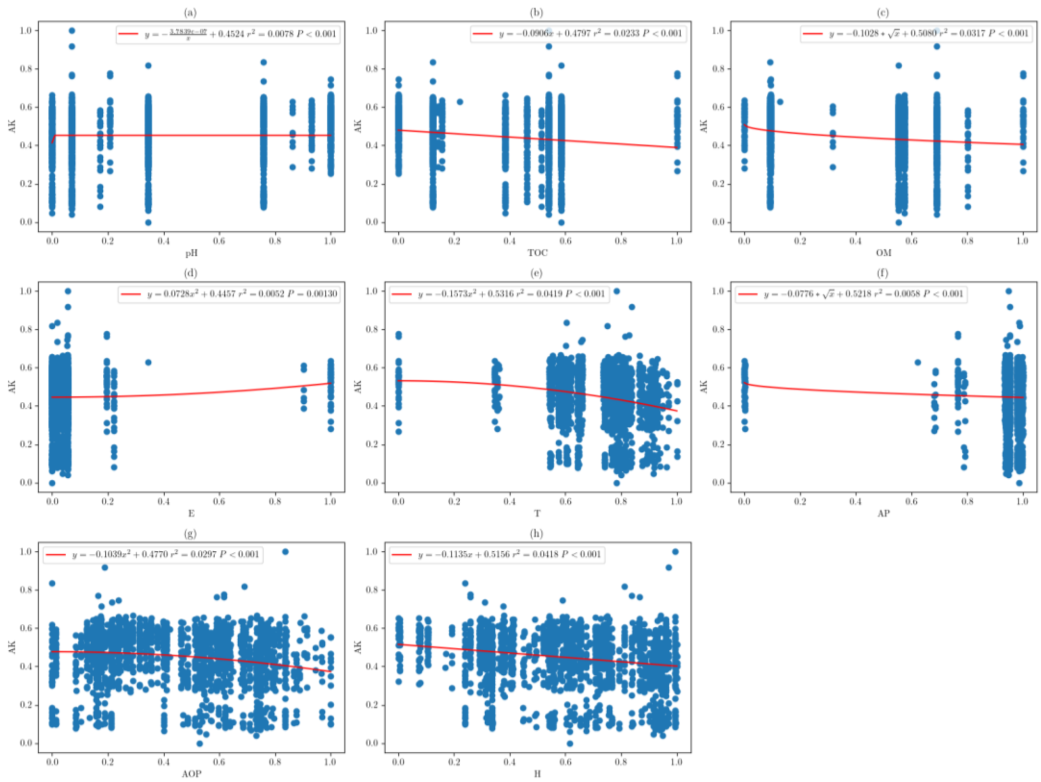

Figure 2. *Regression analysis between soil total potassium (TK) and environmental factors. Note: TK, total potassium contents of soil; pH, soil pH value; E, elevation; TOC, total organic carbon; OM, organic matters; T, air temperature; AP, atmospheric pressure; AOP, amount of precipitation; H, humidity*

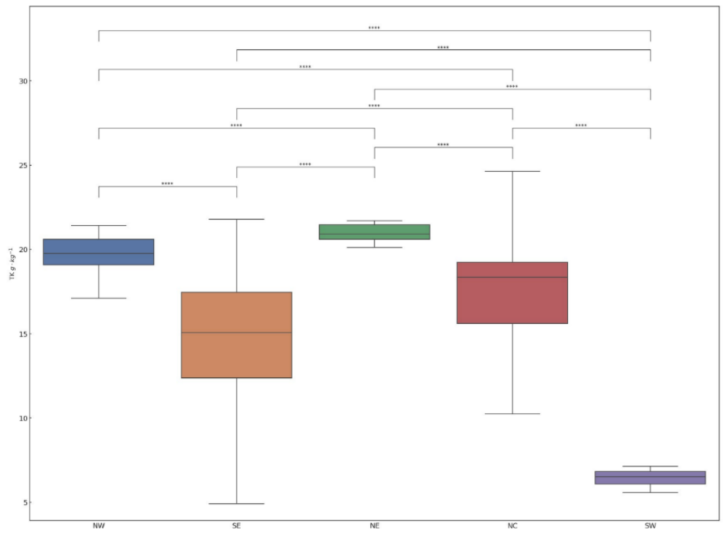

Figure 3. *Distribution of soil total potassium across five regions in China. Note: The sampling size were 44, 1142, 31, 746, and 25 for NW (northwest), SE (southwest), NE (northeast), NC (north central), and SW (southwest) regions of China*

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Similar with soil total potassium, the difference between the mean and median values of soil pH was small (0.3, *Table 1*). For soil pH, the minimum and maximum value were 5.40 and 8.30 with the mean value was 6.70±0.02. The mean value of soil TOC was 9.57±0.08 g·kg^{-1} with the range of 4.10-19.50 g·kg^{-1}, and the mean value of soil organic matters (OM) was 23.96±0.19 g·kg^{-1} with the range of 11.30-42.23 g·kg^{-1}. Overall, the order from high to low of the variation of coefficient (VC) was TOC (39.32%)> OM (34.85%)> TK (25.83%)> pH (15.98%).

For the environmental factors (*Table 1*), the difference between the mean value (70.38) and median value (46.00) of the elevation was quite large, reaching at 24.38 m, as shown in *Table 1*. The minimum value of the elevation was only 1.30 m, compared to the maximum value was 1220.00 m, leading to the largest value of VC (250.87%). However, the atmospheric pressure (AP) has the smallest value of VC (1.98%), whose mean value was 1008.20±0.45 hPa. The variance of humidity (H) was not large, whose VC value is at 9.04%. Similarly, the difference between the median (72.47) and mean (72.12) value of H was only 0.36. The mean of air temperature (T) was 15.90±0.06 °C with the range of 3.96-20.66 °C. The VC value of the amount of precipitation (AOP) was relatively high (35.63%) with the mean value at 2959.56±23.65 mm.

Relationships between environmental factors and soil TK

As illustrated in *Fig. 2*, our study found significant effects of eight environmental factors on soil total potassium contents. A notable increase in soil total potassium was observed with rising soil pH (p<0.001) and elevation (E, p<0.001). In contrast, soil total potassium significantly decreased in response to other six soil and climate factors: total organic carbon (TOC, p<0.001), organic matters (OM, p<0.001), air temperature (T, p<0.001), amount of precipitation (AOP, p<0.001), humidity (H, p<0.001), and atmospheric pressure (AP, p<0.01). This was similar with a result of a partial least square path modeling that soil total potassium had a significant positive relationship with soil pH and had a significant negative relationship with TOC (*Fig. 4*).

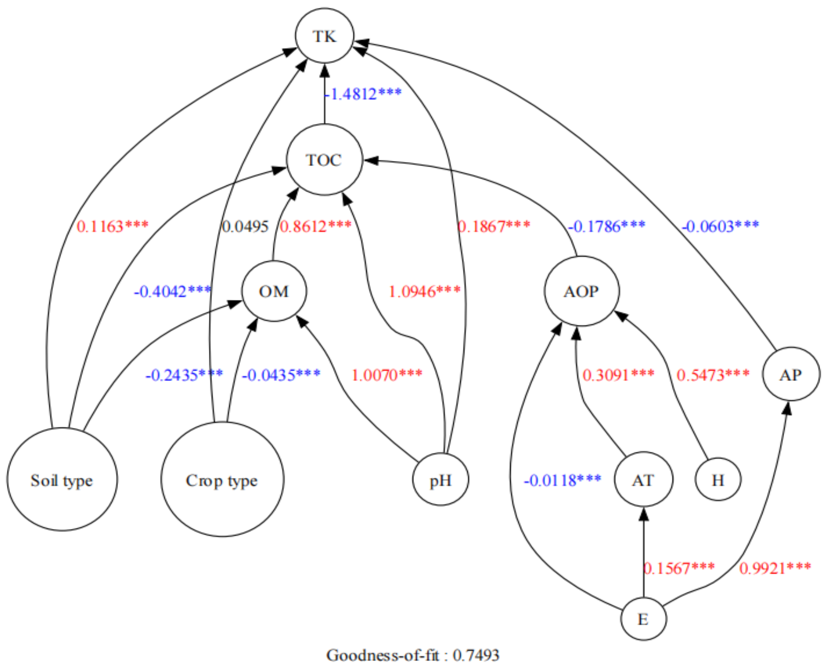

Figure 4. *Partial least square path modeling (PLS-PM) results*

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Interestingly, the degree of soil total potassium reduction varied for these factors. For instance, compared to AP and TOC, more pronounced declines in soil total potassium were associated with T, AOP, and H. Additionally, when evaluating the coefficients of determination (R^2), we observed the following order from the lowest to the highest: T (0.393) > pH (0.273) > AOP (0.214) > H (0.156) > OM (0.142) > E (0.021) ≈ TOC (0.021) > AP (0.003). This indicates that there are differential predictive powers for these factors on soil total potassium levels.

When the vertical and horizontal coordinate values in *Fig. 2* were standardized to a 0-1 scale, we observed no significant alteration in the regression relationships between soil total potassium and the environmental factors, as illustrated in *Fig. A1*. This standardization process did affect the coefficients of determination (R^2) associated with different environmental factors. However, it should be noted that the standardization process applied in our analysis influenced the coefficients of determination (R^2) for various environmental factors, highlighting the intricacies involved in interpreting these statistical relationships. Notably, the R^2 for soil pH and air temperature (T) showed an increase when standardized values were used, suggesting a stronger predictive relationship. Conversely, for total organic carbon (TOC), organic matters (OM), atmospheric pressure (AP), and amount of precipitation (AOP), the R^2 values decreased, indicating a weaker predictive relationship under these standardized conditions. Interestingly, no significant change in R^2 was detected for elevation (E), implying that its predictive strength remained consistent regardless of standardization.

Performance of soil TK models among different learning methods

In our comparative analysis of machine learning methods, it was evident that Random Forest (RF, $R^2 = 0.91$) exhibited superior performance in terms of R^2 values compared to the linear regression model (Linear, LN, $R^2 = 0.75$), as detailed in *Table 2*. The order of these methods ranking based on R^2 values from lowest to highest was as follows: LN < Support Vector Regression (SVR) < Decision Tree (DT) < Light Gradient Boosting Machine (LGB) < RF < Extreme Gradient Boosting (XGB) < Feedforward Neural Network (FFN). Notably, the R^2 values for FFN, XGB, RF, and LGB were quite similar, hovering around the high mark of 0.91.

Table 2. *Performance statistics of different learning methods for soil total potassium (TK)*

Learning Methods	*n*	R^2	RMSE%	MAE	RMD%	EF
LN	199	0.7475	2.0089	1.4698	-0.0590	0.7475
SVR	199	0.8529	1.5256	1.0362	0.1822	0.8529
DT	199	0.9007	1.2424	0.8010	-0.0411	0.9007
LGB	199	0.9054	1.2156	0.8133	0.2707	0.9054
RF	199	0.9058	1.2142	0.8037	-0.0948	0.9058
XGB	199	0.9098	1.1882	0.7866	0.0131	0.9098
FFN	199	0.9103	1.1849	0.7809	0.0196	0.9103

Note: n, the sample size for the testing dataset, including 106 of the wheat sampling and 93 of the paddy sampling; LN, Multiple Linear model; RF (Random Forest); SVR (Support Vector Regression); DT (Decision Tree); XGB (eXtreme Gradient Boosting); LGB (Light Gradient Boosting Machine); FFN,. RMSE, root mean squared error of testing datasets; MAE, Mean Absolute Error; RMD, relative mean error of testing datasets; EF, model effective

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Additionally, this trend of performance was consistent across other metrics. The order for both the Root Mean Square Error (RMSE) and Efficiency Coefficient (EF) mirrored that of the R^2 values. For the top four methods based on R^2 (LGB, RF, XGB, FFN), the Mean Absolute Error (MAE) and Relative Mean Deviation (RMD, absolute value) also followed the same order. Furthermore, among these top performers, the range of variation between the highest and lowest values for R^2, RMSE, MAE, RMD (absolute value), and EF was relatively narrow, with the differences being 0.0050-0.0049 for R^2, 0.0033-0.0307 for RMSE, 0.0057-0.0324 for MAE, 0.0065-0.2511 for RMD, and 0.0005-0.0049 for EF.

Discussion

Environmental factor impact

For the soil properties, soil pH had a more significant effect on soil total potassium than soil organic matters (OM) and TOC, which was in agreement with previous studies in regional scale that soil pH had a significant and positive correlation with potassium. Our finding confirmed that soil pH could play an important positive part to potassium accumulation in farmland, which was consistent with previous studies that both a high soil exchangeable and non-exchangeable potassium content could be found with a high soil pH value (Liu et al., 2020; Nobis et al., 2022). In fact, soil pH plays an important part in biogeochemical processes (Han et al., 2023).To be more specific, soil pH can obviously affect the potassium in soil and potassium availability, as increasing pH value (i.e. by liming) could reduce potassium leaching especially at low soil pH conditions and improve soil potassium availability (Li et al., 2019; Liu et al., 2020). Possibility because of increasing of potassium absorption sites resulted from soil clay minerals and metal oxides on the condition of circumneutral soil pH (Coyle et al., 2023). Hence, soil pH adjusted could be an effective way to improve soil potassium contents and availability in farmland and meet crop potassium uptake for increasing crop yields. In addition, soil pH could be an assistant index for assessment of soil potassium contents in farmland fertility management. In addition, for geographical factors, the importance of elevation (E) was not very high, compared to previous studies that elevation was the top third important factor affecting soil potassium contents (Hu et al., 2023). The paradox might be attributed to different study scale. Thus, it is recommended to assess soil potassium contents in different scales for a better understanding.

For climate factors, the effect of air temperature (T) and amount of precipitation (AOP) showed more significantly effects on soil total potassium than humidity (H) and atmospheric pressure (AP). This indicated that bot high temperature and larger AOP could significantly accelerate soil potassium decomposition. Our finding was in agreement with previous studies in farmland that both air temperature and precipitation were the two most important climate factors for soil potassium (Hu et al., 2023). Similar findings in forest soil that there was a negative impact of air temperature and precipitation on potassium were found (Wu et al., 2021; Feng et al., 2022). As well known that air temperature had significant effect on soil temperature (Lembrechts et al., 2022) that can increase physiological activity, leading to the increase of potassium uptake by crops (Mouhamad et al., 2016). This could be one reason that soil potassium contents decreased sharply with the increasing of air temperature. Additionally, a previous study showed that both temperature and precipitation were the main drivers of potassium decomposition (Yang et al., 2022), which promoted the weathering of minerals that is an important source of potassium release (Rawat et al., 2016). Hence, with the increasing temperature

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and precipitation caused by climate change, it is recommended to monitoring soil total potassium of farmlands in the future.

Learning method impact

For regression analysis method, both observed and standardized values can be used to identify relationship between soil total potassium and environmental factors. However, our results showed that the difference in R^2 of soil pH between the two methods (building regression equation with observed and standardized values) was a factor of 1.6, indicating that it could be overestimated using standardized values compared to that of observed values. Thus, it is recommended to prioritize the absolute values to build the regression equation to avoid potential uncertainly.

This study showed that machine learning methods (i.e. FFN) showed much better performance compared to normal statistical learning method (LN, *Table 2*), showing learning methods could be a good way to enhance accurate of estimated soil prosperities that could be influenced by complex factors. This was consistent with previous studies that machine learning methods had showed higher R^2 and model effective (EF), but lower RMSE, MAE, and RMD (Li et al., 2020; Munawar et al., 2020; Chen et al., 2022). Accordingly, there were very little differences on performance indexes for the machine learning methods whose R^2 was above 0.91 in the study, suggesting that the error among the top four R^2 of the learning methods could be very small and any of the four methods could be used for K model development. Furthermore, this indicated that there could be a threshold value that there was not a significant different of the model performance when R^2 reached a very high value.

Compared to previous studies with the R^2 of soil potassium models ranged from 0.02 to 0.90 (*Table A2*), our learning methods used in this study showed relatively high R^2 ranged from 0.75 to 0.91 (*Table A1*). The variant performance indicated the necessity of model performance comparison for selecting a better prediction model. Additionally, although the sampling size in this study was much higher than that of Munawar et., al. (2020), the R^2 of potassium models were similar (*Table A1*). This indicated that it is need more sampling size to development of soil potassium predication model in a national scale with a long-term farming practice, compared to a regional scale with a short-time farming practice. Hence, it is recommended that soil potassium as well as other fertility should be monitored constantly *in-situ* and in real time situation for a sustainable management in the future.

Conclusion

The mean value of soil total potassium (TK) content in 0-20 cm was 15.64±0.09 g·kg^{-1} with the range of 3.17-31.04 g·kg^{-1}. Compared to soil total potassium significantly increased with soil pH and elevation (E), soil total potassium significantly decreased with other six soil and climate factors, including TOC, organic matters (OM), air temperature (T), amount of precipitation (AOP), humidity (H), and atmospheric pressure (AP). Soil pH, air temperature, and precipitation could be important environmental factors affecting significantly soil total potassium. For learning methods, machine learning methods generally showed better performances than that linear regression one. The order of R^2 from low to high was LN< SVR< DT< LGB< RF< XGB< FFN with the highest R^2 at 0.91 and the lowest values of RMSE and EF. The FFN model achieved the highest R^2 value at 0.91 and recorded the lowest values in RMSE and EF, indicating superior

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predictive accuracy. Based on a long-term and in-situ monitor of soil properties and environmental factors, a precise prediction of soil total potassium could come true with comparison of machine learning methods for a sustainable management of soil fertility for crops.

Declaration of Competing Interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX

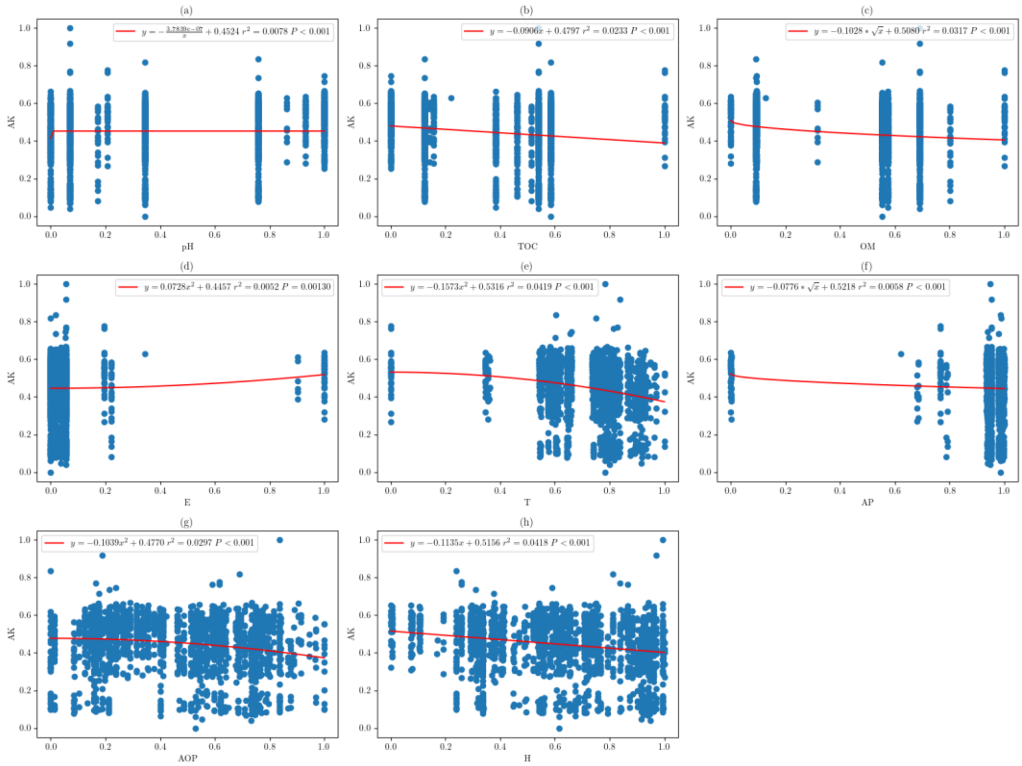

Figure A1. *Regression analysis between soil total potassium (TK) and environmental factors (standardization edition). Note: TK, total potassium contents of soil (g kg-1); pH, soil pH value; E, elevation; TOC, total organic carbon; OM, organic matters; T, air temperature; AP, atmospheric pressure; AOP, amount of precipitation; H, humidity. Vertical and horizontal coordinate values were converted using standardization*

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Table A1. *Statistical parameters of both soil content and climate factors for soil total potassium (TK) models*

Parameters	Unit	*n*	Min	Max	Median	Mean	S.D.	S.E.	*VC*
T(30)	℃	1988	9.98	29.86	21.93	21.63	3.70	0.08	0.17
T(90)	℃	1988	13.21	28.86	19.45	20.04	3.62	0.08	0.18
T(180)	℃	1988	7.61	27.00	11.68	15.86	6.94	0.16	0.44
T(360)	℃	1988	3.96	20.66	16.73	15.90	2.58	0.06	0.16
Tmax(30)	℃	1988	20.30	40.00	34.20	33.65	4.04	0.09	0.12
Tmax(90)	℃	1988	29.30	40.90	36.70	36.16	2.40	0.05	0.07
Tmax(180)	℃	1988	30.00	40.90	37.70	36.77	2.50	0.06	0.07
Tmax(360)	℃	1988	32.30	41.20	38.30	38.36	1.59	0.04	0.04
Tmin(30)	℃	1988	-1.60	23.10	10.50	11.45	4.39	0.10	0.38
Tmin(90)	℃	1988	-8.20	17.30	1.70	3.89	6.04	0.14	1.55
Tmin(180)	℃	1988	-19.80	14.20	-4.20	-3.13	9.85	0.22	-3.15
Tmin(360)	℃	1988	-32.70	3.00	-6.20	-7.92	5.93	0.13	-0.75
AP(30)	hPa	1988	874.37	1020.77	1006.36	1003.84	20.91	0.47	0.02
AP(90)	hPa	1988	877.48	1016.06	1008.29	1004.68	20.10	0.45	0.02
AP(180)	hPa	1988	878.38	1021.27	1010.08	1007.62	20.71	0.46	0.02
AP(360)	hPa	1988	880.92	1016.79	1010.27	1008.20	19.97	0.45	0.02
APmax(30)	hPa	1988	880.70	1033.40	1016.60	1013.38	21.03	0.47	0.02
APmax(90)	hPa	1988	890.50	1035.80	1026.00	1021.96	20.92	0.47	0.02
APmax(180)	hPa	1988	890.50	1044.40	1032.60	1028.51	21.75	0.49	0.02
APmax(360)	hPa	1988	898.60	1045.10	1037.40	1032.76	20.96	0.47	0.02
APmin(30)	hPa	1988	866.80	1013.80	995.40	993.80	20.77	0.47	0.02
APmin(90)	hPa	1988	864.90	1000.20	992.70	989.08	19.35	0.43	0.02
APmin(180)	hPa	1988	860.00	999.40	991.50	987.87	19.84	0.44	0.02
Apmin(360)	hPa	1988	860.00	997.00	989.60	986.36	19.58	0.44	0.02
AOP(30)	mm	1988	4.70	951.00	238.00	251.96	165.37	3.71	0.66
AOP(90)	mm	1988	86.20	1929.30	696.80	736.22	389.36	8.73	0.53
AOP(180)	mm	1988	206.10	3026.10	1293.60	1428.51	760.40	17.05	0.53
AOP(360)	mm	1988	1010.80	5165.90	3164.50	2959.56	1054.51	23.65	0.36
H(30)	%	1988	51.07	94.73	69.03	69.72	10.32	0.23	0.15
H(90)	%	1988	47.81	88.31	70.26	69.60	9.57	0.21	0.14
H(180)	%	1988	47.21	86.23	70.66	69.36	9.43	0.21	0.14
H(360)	%	1988	57.12	82.10	72.47	72.11	6.52	0.15	0.09
Hmin(30)	%	1988	7.00	51.00	18.00	21.51	9.69	0.22	0.45
Hmin(90)	%	1988	3.00	36.00	15.00	17.24	7.20	0.16	0.42
Hmin(180)	%	1988	0.00	32.00	14.00	14.51	6.00	0.13	0.41
Hmin(360)	%	1988	0.00	22.00	13.00	12.70	4.43	0.10	0.35

Note: n, the sample size for compare predictive and observed values. Min, the minimum value; Max, the maximum value; S.E., the standard error; VC, the variation of coefficient; TK, total potassium contents of soil; pH, soil pH value; E, elevation; TOC, total organic carbon; OM, organic matters; T, air temperature; AP, atmospheric pressure; AOP, amount of precipitation; H, humidity

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Table A2. *Statistical parameters of learning method performance for soil potassium of previous studies*

Parameter	Learning Methods	Soil layer cm	*n*	R^2	RMSE%	Scale	Cultivated time	Systems of study area	*Ref.*
K_{ex}	RF	0-30	200	0.02	57.2	regional		farming (winter wheat, barley, alfalfa, and canola)	(Khosravani et al., 2023)
	k-NN			0.03	53.2				
	CB			0.39	43.6				
	RF	30-60	50	0.02	41.5				
	k-NN			0.06	46.1				
	CB			0.24	41.3				
K	CB	0-10	342	0.66	2.18	regional		farming (dryland cropping)	(Sharififar, 2022)
	RF			0.65	2.20				
	SVM			0.67	2.14				
	EBK			0.72	2.02				
	SGS			0.74	1.96				
K	PCR	0-20	40	0.88	0.25	regional	short time	farming	(Munawar et al., 2020)
	PLSR			0.90	0.19				
AK		0-15	155	0.649	0.404	regional		coastal wetland	(Xu et al., 2020)

Note: Kex, exchangeable potassium; AK, available potassium; K, potassium; n, sampling size; R2, coefficient of determination; RMSE, root mean squared error; RF, Random Forest; K-NN, K Neighborhood; CB, Cubist; SVM, Support Vector Machine; EBK, Empirical Bayesian Kriging; SGS, Sequential Gaussian Simulation; PCR, Principal Component Regression; PLSR, Partial Least Square Regression; Ref., references

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