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Topographical Influences on Soil Phosphorus Content in a Lowland: Insights from Random Forest Analysis

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ABSTRACT: Soil nutrient analysis is crucial for understanding the dynamics of agricultural fertility and productivity. Phosphorus (P) stands out among soil nutrients for its fundamental role in vital biological processes such as photosynthesis, respiration, and cell division. The study of variations in phosphorus content along toposequences, according to the specific topography of the lowlands, is proving to be a relevant approach to elucidate the complex interactions between abiotic factors and biogeochemical dynamics that govern soil fertility. This study aims to characterize spatial variations in soil assimilable phosphorus (P_2O_5) content as a function of edaphic parameters, using a multidimensional approach along the longitudinal and transverse axes of the lowland. This study was carried out in the locality of N'Zoupouri, in the department of Botro, about 40 km from Bouaké, in the Gbêkê region of central Côte d'Ivoire. The physicochemical analyses of the soil samples were carried out by French and international standard methods. The BORUTA algorithm used in this study can select the truly significant characteristics while ranking their importance. The result shows that potassium (K) content is a determining factor directly influencing this essential nutrient's spatial variations and temporal changes. The close relationship between potassium and phosphorus in the soil highlights the importance of optimized agronomic management, in which potassium not only plays a supporting role but also acts as a key element in the release and stabilization of phosphorus that is available to plants.

KEYWORDS: soil nutrients, phosphorus, lowland, statistical learning, Côte d'ivoire.

1 INTRODUCTION

Soil nutrient analysis is crucial for understanding the dynamics of agricultural fertility and productivity [1]. By providing an accurate estimate of the stock of potentially available nutrients, this analysis allows not only to adapt fertilization practices to the specific needs of crops but also to optimize yields while minimizing negative environmental impacts ([2], [3]). Such an approach is essential for the development of sustainable soil management strategies, which are essential for resilient and efficient agriculture [4].

Phosphorus (P) stands out among soil nutrients for its fundamental role in vital biological processes such as photosynthesis, respiration, and cell division [5]. In tropical soils, however, the availability of this nutrient is often severely limited by a variety of abiotic factors. Among these, the intense fixation of phosphorus by clay minerals, the consequent losses due to leaching under the effect of high rainfall, and the low organic matter content pose major challenges to its effective management [6]. These challenges are particularly acute in tropical lowlands, where hydrological and sedimentological characteristics create distinct environmental gradients that influence the spatial distribution and availability of nutrients [7].

In this context, the study of variations in phosphorus content along toposequences, according to the specific topography of the lowlands, is proving to be a relevant approach to elucidate the complex interactions between abiotic factors and biogeochemical dynamics that govern soil fertility. The use of the Random Forest method, a robust statistical learning technique based on the aggregation of multiple decision trees, offers significant analytical power for exploring these interactions due to its ability to handle non-linearities and complex interactions between variables [8].

This study aims to characterize spatial variations in soil assimilable phosphorus (P_2O_5) content as a function of edaphic parameters, using a multidimensional approach along the longitudinal and transverse axes of the N'Zoupouri lowland. This methodology aims to identify spatial patterns and potential correlations between these variables, thus providing essential information for optimized soil management in tropical wetlands. Through this analysis, the study aims to contribute to the development of more sustainable and resilient agricultural strategies. The depth of the multi-dimensional soil analysis thus appears crucial for an advanced understanding of the mechanisms underlying soil fertility and soil health, especially in environments as complex as the lowlands of N'Zoupouri. The expected results should broaden the prospects for integrated and sustainable management of edaphic resources in these fragile ecosystems.

2 MATERIALS AND METHODS

This study was carried out in the locality of N'Zoupouri, in the department of Botro, about 40 km from Bouaké, in the Gbêkê region of central Côte d'Ivoire (Figure 1). The geographical coordinates of the study site are 07°50'31" north latitude and 05°18'24" west longitude. The region has an average annual temperature of 26.1°C and an average annual rainfall of 899.6 mm [9]. The soils of Botro are characterized by their depth and low gravel content (<30%), with a ferruginous texture typical of tropical soils.

2.1 DATA COLLECTION

A 100 m long north-facing baseline (L1N150/100 m) was laid longitudinally to the watercourse, above the hydromorphic zone. Every 20 meters, secondary tracks were laid transversely to allow systematic sampling. A total of 93 soil samples were collected at regular 20-meter intervals along these secondary paths.

2.2 ELEMENTAL ANALYSIS

The physicochemical analyses of the soil samples were carried out by French and international standard methods, particularly about sample storage conditions (ISO 18512). The pH was measured by mixing 20 g of soil with distilled water in a ratio of 1: 2.5 (ISO 10390). Granulometric analysis by sedimentation using the pipette method on an automatic granulometer. Total carbon (C) and total nitrogen (N) were determined by combustion (ISO 10694), while available phosphorus (P) was measured by the Olsen method (NF ISO 11263). Exchangeable cations (calcium (Ca), potassium (K), magnesium (Mg), and sodium (Na)) were extracted by the cobaltihexamine method (NF X 31-130) and quantified by inductively coupled plasma optical emission spectrometry (ICP-OES) (ISO 22036). Iron (Fe) was extracted with aqua regia according to ISO standard NF 11466 and its concentration was also measured by ICP-OES (NF EN 13651).

2.3 APPLICATION OF THE BORUTA ALGORITHM

The study of the physicochemical characteristics of the soils, including variables such as pH, texture (clay, silt, sand), organic carbon, nitrogen, assimilable phosphorus, exchangeable cations (Ca, Mg, Na) and iron, reveals a large variability influencing the dynamics of soil properties along the Bandama River at N'Zoupouri. This variability requires a robust method to identify the relevant properties among those studied. The BORUTA algorithm [10] used in this study can select the truly significant characteristics while ranking their importance.

The BORUTA algorithm is based on the use of Random Forests, a powerful statistical learning model for classification and regression based on a set of independent decision trees. This 'wrapper' type algorithm adds 'shadow features' whose values are randomly permuted to eliminate any correlation with the decision variable, to assess the relevance of the features. The importance of each feature is calculated by measuring the loss of classification accuracy caused by these random permutations, expressed as a Z-score obtained by dividing the average loss by its standard deviation. The maximum Z-score (MZS) among the shaded features is used as a reference to classify the features into three categories: confirmed, pending, and rejected [10].

The relevant features identified by the BORUTA algorithm were then used to develop a prediction model using regression models such as simple linear regression (SLR) and multiple linear regression (MLR). Model performance was assessed using metrics such as coefficient of determination (R^2), mean bias error (MBE), coefficient of variation of the root mean square error (CV RMSE), and mean absolute percentage error (MAPE) to ensure robust predictions and exclusion of non-significant variables.

2.4 STATISTICAL ANALYSIS

The experimental data were subjected to unifactorial analysis of variance (ANOVA) after validation of the previous application conditions. The Shapiro-Wilk test was used to check the normality of the residuals, while the Levene test was used to check the homogeneity of the variances. When a significant difference was found between the means, the Fischer LSD post-hoc test was used at a 5% significance level to perform pairwise comparisons, allowing the identification of homogeneous groups. All statistical analyses were performed using R software, version 4.3.3.

3 RESULTS

Tableau 1. Characteristics of factors influencing the dynamics of lowland soil properties along the Bandama River at N'Zoupouri

Var	Topog	Long	Min.	Max.	Moy.	CV*
pH_{H2O}	BF	Amont	5,5	6,9	5,99	5,92
		Avale	5,6	7	6,36	5,94
		Médiane	5,6	6,4	6,09	4,38
	Hydro	Amont	6	6,8	6,43	4,25
		Avale	5,9	7,2	6,54	7,38
		Médiane	5,7	7,1	6,6	7,37
pH_{KCl}	BF	Amont	4,5	5,9	4,89	7,17
		Avale	4,3	6,2	5,39	9,68
		Médiane	4,3	5,2	4,82	6,86
	Hydro	Amont	5,2	6,2	5,68	7,5
		Avale	4,8	6,6	5,7	10,58
		Médiane	4,5	6,7	5,7	11,9
Clay	BF	Amont	22,37	66,71	48,84	26,25
		Avale	17,53	59,26	39,12	29,43
		Médiane	27,08	52,1	40,97	17,57
	Hydro	Amont	14,04	57,45	23,19	72,8
		Avale	13,35	37,91	19,87	35,97
		Médiane	10,66	34,39	19,01	34,37
Silt	BF	Amont	26,57	46,85	36,1	14,28
		Avale	29,39	50,34	38,96	18,01
		Médiane	27,19	39,27	34,37	12,21
	Hydro	Amont	31,66	39,18	36,32	8,21
		Avale	25,81	40,62	32,97	14,97
		Médiane	24,16	41,12	33,85	14,88
Sand	BF	Amont	3,6	36,07	15,06	72,98
		Avale	9,55	40,32	21,92	44,91
		Médiane	15,17	37,73	24,67	29,18
	Hydro	Amont	6,96	54,3	40,49	41,84
		Avale	36,29	59,32	47,16	16,33
		Médiane	40,85	55,07	47,14	11,85
K	BF	Amont	0,14	1,13	0,7	45,92
		Avale	0,16	2,72	0,65	92,75
		Médiane	0,16	0,98	0,52	46,91
	Hydro	Amont	0,29	0,93	0,45	53,2
		Avale	0,18	10,79	1,6	194,12
		Médiane	0,24	9,15	1,15	220,18
Fe	BF	Amont	167,48	533,17	346,1	29,67
		Avale	38,12	24564,94	1805,3	336,26
		Médiane	150,64	407,4	349,37	24,04
	Hydro	Amont	28,58	415,26	133,88	114,35
		Avale	33,06	24150,1	2385,95	302,57
		Médiane	19,6	370,44	208,79	52,06
N	BF	Amont	0,04	0,14	0,08	36,64
		Avale	0,03	0,71	0,19	94,81
		Médiane	0,01	0,25	0,13	65,92
	Hydro	Amont	0,05	0,14	0,08	41,34
		Avale	0,06	0,31	0,16	58,36
		Médiane	0,02	0,13	0,06	47,2
C	BF	Amont	0,9	4,84	2,19	52,27
		Avale	0,7	4,22	2,14	42,52
		Médiane	0,64	2,34	1,35	38,37

	Hydro	Amont	0,7	2,24	1,42	37,24
		Avale	0,71	3,88	2,17	54,78
		Médiane	0,48	2,2	1,28	40,55
P_2O_5	BF	Amont	1	16	4,73	77,61
		Avale	1	18	6,19	86,37
		Médiane	1	11	4,89	86,45
	Hydro	Amont	1	6	2,67	65,67
		Avale	1	19	5	113,14
		Médiane	1	5	1,92	56,54
Ca	BF	Amont	4,18	11,1	6,96	27,04
		Avale	4,32	15,33	7,77	41,83
		Médiane	3,1	10,16	6,1	40,79
	Hydro	Amont	2,76	9,3	5,44	49,16
		Avale	0	15,93	6,86	69,1
		Médiane	2,58	8,5	5,74	29,98
Mg	BF	Amont	0,46	5,46	3,03	44,4
		Avale	1,74	10,43	4,74	55,77
		Médiane	2,03	6,64	3,7	39,39
	Hydro	Amont	1,25	4,72	2,33	52,97
		Avale	1,06	10,78	4,69	62,74
		Médiane	0,96	3,04	2,19	25,99
Na	BF	Amont	0,09	0,14	0,12	12,53
		Avale	0,08	0,22	0,14	31,59
		Médiane	0,1	0,15	0,13	13,44
	Hydro	Amont	0,06	0,15	0,08	46,09
		Avale	0,06	0,31	0,14	51,02
		Médiane	0,06	0,1	0,07	18,53

3.1 Correlation Between Soil Characteristics

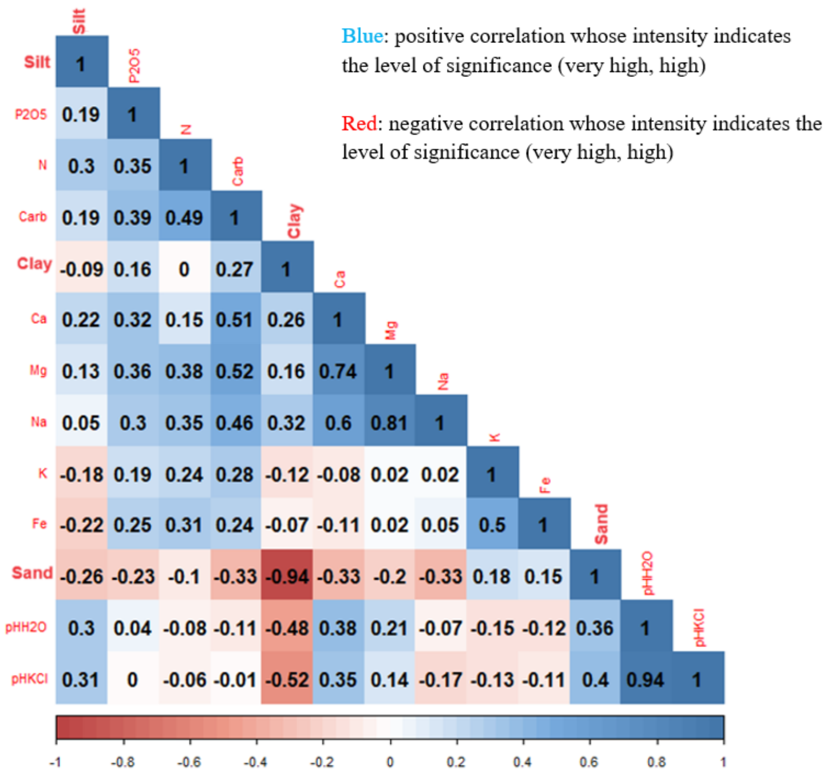

Fig. 1. Correlogram of soil characteristics studied along the toposequences, with Pearson significance level

3.2 Longitudinal Variation Of Soil P2O5 At Upstream Exposure

In Table 2, the BORUTA algorithm answered the importance of the features in the dataset. Of the 11 features, seven were rejected and one was confirmed. Three features were marked as uncertain. The uncertain features have values so close to their best shadow features that BORUTA is unable to make decisions with the desired confidence in the default number of random forest runs.

The resulting graph, generated using the BORUTA package in the R environment, shows the importance (y-axis) of the analyzed features (placed on the x-axis) by ranking and color-coding them after feature classification (Figure 2).

Tableau 2. Selection of soil characteristics influencing upstream assimilable phosphorus content

Varind	MoyImp	medianImp	MinImp	MaxImp	NormHits	Decision
K	4,51	4,52	2,43	6,45	0,84	Confirmed
Mg	3,06	3,09	-0,2	5,67	0,56	Pending
Na	1,91	2	-2,07	3,89	0,42	Pending
Clay	2,03	2,03	-0,22	4,61	0,43	Pending
pH_{H2O}	-1,17	-1,54	-1,96	0,6	0	Rejected
pH_{KCl}	-0,53	-0,46	-1,86	1,12	0	Rejected
Silt	-2,51	-2,92	-3,48	-0,71	0	Rejected
Sand	0,37	0,55	-2,57	2,12	0,1	Rejected
N	-0,4	-0,8	-2,71	1,39	0	Rejected
Carb	0,56	0,56	-1,01	2,13	0,03	Rejected
Ca	1,05	1,21	-1,1	2,21	0,01	Rejected

The columns respectively represent the independent variables, the mean of their importance (moyImp), the median of their importance (medianImp), the minimum importance (minImp), the maximum importance (maxImp), the number of standardised successes (normHits), and the decision for each variable (Confirmed, Pending or Rejected).

From the box plots in Figure 2, the blue rectangles correspond to the shadow features. We have three blue boxes for the minimum, mean, and maximum values of the shadow features. The green rectangle corresponds to the feature that was confirmed as valid, while the red rectangles correspond to the features that were confirmed as irrelevant. The yellow rectangles correspond to the uncertain features, i.e. the algorithm could not conclude their importance. Based on the selection results, it can be concluded that the important (confirmed) feature influencing phosphorus dynamics in upstream exposure in the N'zoupri lowland is potassium (K) content. However, it is uncertain (but cannot be ruled out) whether characteristics such as exchangeable base content (Mg and Na) and clay content of the lowland have an effect on phosphorus dynamics in this lowland exposure.

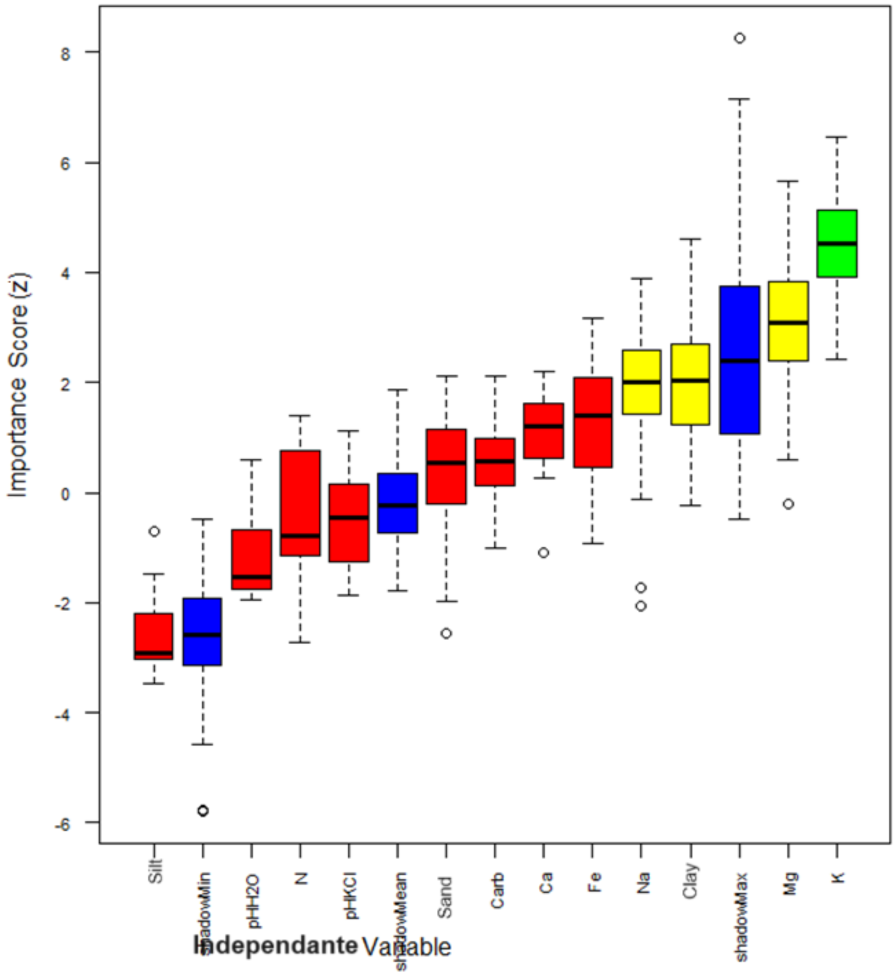

Fig. 2. ***Variable reduction process based on Random Forest, assessing the importance of the independent variables measured in this study on the N'zoupri lowland***

Shadow variables are shown in blue, variables confirmed as not important are shown in red, provisional variables are shown in yellow, and variables confirmed as important (relevant) are shown in green. N = nitrogen; Carb = organic carbon; Ca = exchangeable calcium, Na = exchangeable sodium, Mg = exchangeable magnesium, Fe = free iron. The characteristics of the box plot are as follows: the circles represent outliers, the dotted 'whiskers' correspond to 1.5 times the interquartile range, the rectangle indicates the first and third quartiles and the horizontal bar represents the median.

The feature sets presented in Table 3 will help to determine whether it is necessary, when building a predictive model, to select the feature K identified as "confirmed" relevant by the BORUTA algorithm, or whether it is possible to limit the number of features to the group for which the value of the NormHits index will be greater than or equal to 0.80, and how such a limitation will affect the accuracy of the prediction of energy consumption. The selected features were used to build a model for predicting phosphorus dynamics in upstream exposure, based on test sets for Mean Absolute Percentage Error (MAPE (%)), Mean Bias Error (MBE (%)), Coefficient of Variation of Root Mean Square Error (CV RMSE (%)) and CV RMSE (%). CV RMSE (%)) and, where applicable, the Coefficient of Determination R^2.

Tableau 3. Ensembles de caractéristiques pour les modèles prédictifs analysés

Characteristics	Characteristic Packages	
	Set 1	Set 2
K	1	1
Mg		1
Na		1
Clay		1

The results of the calculation of the quality and accuracy of the models built according to the selected feature set are presented in Table 4. A lower MAPE value indicates better prediction accuracy. Set 1 stands out with a MAPE of 1.32%, indicating very high prediction accuracy, and an MBE of -0.07%, showing minimal bias in the predictions. Although the CV RMSE is high (75.70%), suggesting greater relative variability in the predictions, the accuracy and low bias make this set particularly suitable in contexts where accurate and unbiased predictions are crucial. Thus, Dataset 1 (marked as 'confirmed' by the BORUTA algorithm) improves the fit of the model to real data and is recommended for applications requiring high accuracy and minimization of bias errors, despite potentially greater variability in predictions.

Tableau 4. Evaluation of the prediction model of phosphorus dynamics in upstream exposure in the lowland based on the tested feature sets obtained by the BORUTA algorithm

Characteristics	Characteristic Packages	
	Set 1	Set 2
MAPE (%)	1,32	4,88
MBE (%)	-0,07	0,09
CV RMSE (%)	75,70	23,65
R^2 (-)	∞	0,98

Set 2, which also includes data marked as "uncertain" by BORUTA, gives poorer predictive results (only a high CV RMSE index of 75.70% is more favorable than in Set 1). This indicates that increasing the number of characteristics negatively affected the predictive quality of the model.

There is no direct numerical comparison, as infinity is not a real number but a concept representing unbounded growth. In this context, we can say that 0.983 is negligible compared with infinity. The prediction results presented, based on the features selected by the algorithm, give significantly better results than the model built using manual feature selection based on domain knowledge.

3.3 Regression Models Related To Upstream Exposure Of Assimilable Phosphorus

To adjust the evolution of assimilable phosphorus levels in upstream exposure as a function of potassium levels associated with important characteristics (Figure 3), simple linear regression (SLR) and second-order polynomial regression (PR^2) models are compared. The general equations compared are of the form:

1. Simple linear regression (SLR): $YP_2O_5 \sim b + a*X$
2. Polynomial regression of order 2 (RP ^2): $YP_2O_5 \sim c + a*X^2 + b*X$

The letters a, b, c, and d denote the constants of this non-linear regression. Y represents P2O5 and X is the soil characteristics associated with P2O5 content.

Based on the test result, the P_2O_5 content of the soil at the upstream exposure is fitted to an RLS equation whose model and variable (K) explain the variations in P_2O_5 under this exposure very significantly ($F (1, 19) = 6.197$, $p = 0.022$). The model parameters of the RP ^2 model were significantly lower ($F (2, 18) = 3.293$, $p = 0.056$).

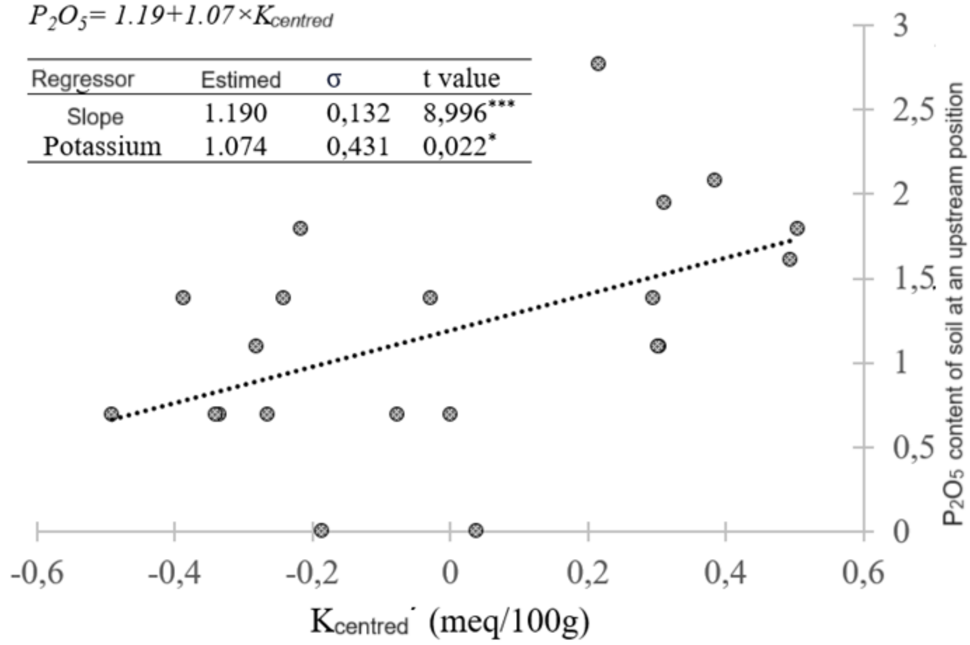

Fig. 3. ***Adjustment model for the influence of potassium on changes in assimilable phosphorus in upstream exposure in the N'zoupri lowland***

The linear regression equation based on the estimated coefficients provided is as follows: *P_2O_5 = b + a*Kcentred where P_2O_5* is the dependent variable (the concentration of P_2O_5), 'b' is the intercept (constant) of the model, 'a' is the regression coefficient associated with the Kcentred variable (the explanatory variable centred around its mean). By replacing with the estimated values: *P_2O_5=1,19+1,07×Kcentred*. This means that for each unit increase in Kcentred, the concentration of P_2O_5 increases by an average of 1.07 units. The intercept β=1.19 represents the mean value of P_2O_5 when *Kcentred =0,* i.e. when K is at its mean.

4 DISCUSSION

Based on the results obtained, it was concluded that potassium (K) content is a determining factor influencing the dynamics of assimilable phosphorus (P_2O_5) in the alluvial plain of the N'zoupri River. Although the effect of exchangeable base contents such as magnesium (Mg) and sodium (Na), as well as clay content, remains uncertain, their influence on phosphorus dynamics cannot be completely excluded. Furthermore, the positive multifactorial interactions observed between P_2O_5 and other nutrients such as calcium (Ca), magnesium (Mg), sodium (Na), and iron (Fe) suggest that phosphorus availability can be modulated by the presence of these cations. These cations can either compete with phosphorus for binding sites or stabilize certain forms of phosphorus in the soil.

As part of this study, soil surveys of topsoil (0-20 cm) were conducted to assess soil quality for growing cereals, particularly rice, following the example of those documented ([11], [12]). Potassium plays a crucial role in the dynamics of assimilable phosphorus, directly influencing its availability to plants, which is fundamental from a sustainable agriculture perspective. One of the mechanisms by which potassium exerts its influence is its ability to interact with other soil cations, such as calcium, magnesium, and iron (strong positive correlation between K and Fe, with $r = 0.50$, $p < 0.0001$), thereby altering the balance of electrical charges on the surface of soil particles. This process can release bound phosphorus, making it more accessible for uptake by plant roots. Potassium (K) is therefore recognized as one of the essential nutrients for crop growth [13].

The N'zoupri site is particularly important because of its arable land suitable for lowland rice production. This region, characterized by a high population density and a slight decrease in the area under cereals, favors optimized potassium fertilization to ensure optimal agricultural production ([14], [15]). In addition, the potassium present in the soil as a result of potassium fertilization can help regulate the enzymatic activity of roots, in particular those involved in phosphorus mobilization [16]. Thus, in the context of sustainable agriculture, where efficient nutrient management is paramount, adequate potassium availability can improve phosphorus use and reduce the need for external inputs, often from non-renewable sources. This helps to conserve natural resources and reduce environmental pollution caused by excess phosphorus in aquatic ecosystems.

The significant positive correlations between K and Fe suggest a possible interaction between these elements which, although essential, can influence phosphorus solubility. Their combined presence could therefore modify phosphorus dynamics by solubilizing or fixing it, depending on the soil conditions. These results highlight the fact that the amount of potassium assimilated by plants is influenced by several physicochemical soil properties. The multiple interactions identified make it possible to optimize potassium fertilization, taking into account the relationship between macronutrients such as nitrogen, potassium, and phosphorus [17]. Excessive potassium fertilization does not necessarily increase cereal yields but can lead to wasted resources and low use efficiency [18]. These interactions play an important role in soil development, both horizontally and vertically [19].

This study investigated the dynamics of assimilable phosphorus in soils of central Côte d'Ivoire to understand spatial variations and temporal changes over recent decades. Assimilable P_2O_5 at depths from 0 to 20 cm was studied after evaluating the performance of a widely used prediction technique: random forest [20].

5 CONCLUSION

In this study aimed at understanding the dynamics of assimilable phosphorus (P_2O_5) under upstream exposure in soils of central Côte d'Ivoire, it appears that potassium (K) content is a determining factor directly influencing spatial variations and temporal changes of this essential nutrient. The close relationship between potassium and phosphorus in the soil highlights the importance of optimized agronomic management, in which potassium not only plays a supporting role but also acts as a key element in the release and stabilization of phosphorus that is available to plants.

In the context of sustainable agriculture, the research highlights the importance of monitoring and regulating potassium levels in soil management practices to maximize phosphorus availability while reducing the environmental impacts associated with excessive fertilization. By integrating this knowledge into fertilization strategies, it is possible to promote a more resilient and efficient agriculture, able to adapt to the challenges posed by longitudinal and lateral soil variations, while meeting the growing demands of sustainable food production.

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