



Spatial distribution mapping of soil phosphorus adsorption-desorption characteristics in central Nepal using quantile regression forests algorithm

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ABSTRACT

Soil represents a major reservoir of phosphorus (P) in terrestrial ecosystems, and its adsorption-desorption behavior plays a critical role in regulating soil fertility and assessing potential environmental risks. However, these processes remain poorly characterized in Nepalese soils. In this context, the present study aimed to assess the spatial distribution of soil P adsorption-desorption characteristics in central Nepal. A total of 225 georeferenced soil samples were collected across central Nepal. Adsorption-desorption isotherm experiments were conducted to quantify P adsorption-desorption parameters using the Langmuir, Freundlich, and Temkin models. Furthermore, 122 environmental covariates were compiled, and spatial prediction maps were generated using a quantile regression forests method that integrated soil point data with these covariates. The results showed that several P adsorption parameters—namely, Langmuir P adsorption constant (Q_m), Langmuir P adsorption constant (K_L), Maximum P buffering capacity (MPBC), Freundlich P adsorption constant (K_F), Freundlich P adsorption constant (n), P buffering capacity (PBC), Standard P requirement (SPR), External P requirement (EPR), P sorption index (PSI), Degree of P saturation (DPS), and P eutrophication risk index (PERI)—were sparsely distributed across central Nepal. Similarly, P desorption parameters, including Langmuir P desorption constant (D_m), Langmuir P desorption constant (K_d), Freundlich P desorption constant (a_d), Freundlich P desorption constant (n_d), and Readily desorbable P (RDP), also exhibited wide spatial variability throughout the study area. The model's efficiency coefficients for predictions were highest for PSI (0.66), followed by K_F (0.59), EPR (0.59), SPR (0.54), MPBC (0.48), a_d (0.46), K_L (0.45), DPS (0.37), D_m (0.35), PBC (0.34), PERI (0.34), Q_m (0.31), n (0.31), RDP (0.26), K_d (0.19), and n_d (0.15), reflecting differences in spatial variability and sensitivity to environmental covariates. The generated spatial distribution maps provide a valuable foundation for developing sustainable P management strategies and guide future research efforts to optimize P availability in central Nepal.

Keywords: Digital mapping, Environmental covariates, Machine learning algorithm, Phosphorus adsorption, Phosphorus desorption

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INTRODUCTION

Nepal is a landlocked country in South Asia, bordered by China to the north and India on all other sides. The country lies between 26°22' to 30°27' N latitude and 80°4' to 88°12' E longitude, covering an area of 147,181 km² (Lamichhane et al 2021). Agriculture plays very important role in Nepal's economy, contributing 24.12% of the GDP and providing employment for approximately 57.3% of the population (MoALD 2023). Despite its economic importance, agricultural productivity remains relatively low, and the country continuous to experience a substantial agricultural trade deficit (MoALD 2025). Therefore, site-specific practices to increase agricultural productivity are essential for reducing the agricultural trade deficit and improving the national economy.

Proper nutrient management is essential for increasing agricultural productivity, as nutrients are crucial for the completion of the plant life cycle. Among these, phosphorus (P) plays a critical role throughout all stages of plant development, from early growth to maturity, and its functions cannot be substituted by any other nutrient (Goswami et al 2012). Therefore, maintaining sufficient soil P levels is essential for the long-term sustainability of agricultural systems (Sharpley et al 1994). Soil P is derived from both the weathering of parent materials and the application of inorganic and organic nutrient sources (Havlin et al 2010).

In Nepal, P is the second most widely used nutrient after nitrogen, which is typically supplied through urea. P is mainly applied in the form of diammonium phosphate (DAP) and single superphosphate (SSP) (Panta 2018). As Nepal does not produce fertilizers domestically, it depends entirely on imports to meet national demand. However, fluctuations in availability and pricing have affected DAP sales, with reported quantities of 140,982, 77,720, 110,120, and 184,046 metric tons in 2020/21, 2021/22, 2022/23, and 2023/24, respectively (MoALD 2024, MoALD 2025). The high cost of fertilizers, particularly in the absence of subsidies, remains a major challenge for farmers. To support farmers, the government provides a 61.4% subsidy on DAP, with approximately one-third of the Ministry of Agriculture and Livestock Development's budget allocated to fertilizer subsidies over the past decade (Kharel et al 2022). This allocation increased by 50.86% in 2023/24 (MoF 2023) and by 48.79% in 2024/25 (MoF 2024). Despite these efforts, many farmers continue to face delays in fertilizer supply and often do not receive the full quantity required.

Application of P without understanding the soil's indigenous mechanisms governing P availability can directly affect its use efficiency and, ultimately, sustainable P management. Adsorption of P refers to the chemical binding of plant-available P to soil particles, making it unavailable to plants, whereas desorption is the release of adsorbed P into the soil solution (Hyland et al 2005). These processes are key determinants of P bioavailability in soils, as they regulate the amount of P retained on soil surfaces (Sparks 2003). The P adsorption-desorption isotherm study is essential for understanding its adsorption-desorption behavior in soils. Various adsorption-desorption parameters, including P adsorption capacity, bonding energy, maximum P buffering capacity, sorption efficiency, standard P requirement, degree of P saturation, P buffering capacity, P desorption capacity, P desorption intensity, desorption rate, and readily desorbable P, can be derived from isotherm studies and significantly influence P management (Fanjana et al 2017).

Spatial soil information presented as maps is crucial for comprehensive soil quality evaluation, sustainable land management, and precision agriculture (Hateffard et al 2024). Soil mapping involves depicting the spatial distribution and variability of soil types and

properties within a given area. In recent decades, digital soil mapping (DSM) has emerged as an effective approach for estimating soil properties by converting point-based soil observations into continuous spatial surfaces using interpolation and predictive techniques (Sun et al 2014). Contemporary soil cartography largely adopts DSM within the SCORPAN framework, which integrates soil survey data with environmental covariates, advanced modeling approaches, and spatial interpolation methods (McBratney et al 2003). Among DSM methodologies, machine learning (ML) techniques are widely used to predict soil properties by capturing complex relationships between measured soil attributes and spatially continuous environmental variables (Wadoux et al 2020). In particular, the random forests algorithm has shown strong performance and reliability in predicting spatial patterns of soil properties across diverse landscapes (Kinoshita et al 2016, Hengl et al 2018).

Nepal's diverse soil properties are influenced by its variability in climate, topography, parent materials, and vegetation (Vaidya and Sah 2015). The climate ranges from sub-tropical to arctic, with moisture levels varying from arid to per-humid and distinct wet and dry monsoon seasons (Vaidya and Sah 2015, Karki et al 2016). Physiographically, the landscape transitions from alluvial plains to permanently snow-covered peaks, while vegetation spans from tropical Sal forests to tundra-like Nival zones (Vaidya and Sah 2015). These environmental gradients shape ecosystems, soil landscapes, land use, and P dynamics in soils. Despite this diversity, information on P adsorption-desorption characteristics in Nepalese soils remains limited. The spatial mapping of soil P adsorption-desorption parameters is largely unexplored, though such maps are crucial for sustainable P management and food security (Sanchez et al 2009). Therefore, this study aims to develop a digital soil map of P adsorption-desorption characteristics in central Nepal to support site-specific P management and informed decision-making.

MATERIALS AND METHODS

Study area

The study was conducted in central Nepal (Figure 1), covering the districts Dhading, Rasuwa, Sindhupalchok, Dolakha, Ramechhap, Sindhuli, Kavrepalanchok, Bhaktapur, Kathmandu, Nuwakot, Lalitpur, Makwanpur, Chitwan, Parsa, Bara, Rautahat, Sarlahi, Mahottari, and Dhanusha. Geographically, the area extends from 83.91863° to 86.57222° longitude and 26.56864° to 28.38619° latitude. This area spans three agro-ecological zones: high-hills, mid-hills, and Terai.

The high-hills region is mountainous, characterized by highly metamorphosed phyllites, schists, gneisses, and quartzites (Vaidya and Sah 2015). This zone experiences a temperate climate with mild summers and colder winters, where freezing temperatures are common at night and snow-covered landscapes are typical. The predominant soil types in these areas are Eutric Cambisols (CMeu), Humic Umbrisols (UMhu), and Leptic Umbrisols (UMle) (Vaidya and Sah 2015).

The mid-hills feature diverse topography of hills and valleys, with geological formations consisting of Cambrian to Precambrian phyllites, schists, quartzites, granites, and limestone of various ages (Vaidya and Sah 2015). This zone has a subtropical climate, with mild summers and cool winters, though certain valleys and river basins may experience higher temperatures. Eutric Cambisols (CMeu) and Chromic Cambisols (CMcr) are the predominant soil types in these areas (Vaidya and Sah 2015).

The Terai region lies in the southern plains, characterized by flat to gently sloping terrain. This zone primarily consists of recent and post-Pleistocene alluvium deposits, with soils that

are deep, fine-textured, and mostly stone-free (Vaidya and Sah 2015). The Terai has a tropical climate with hot summers and mild winters. Eutric Gleysols (GLeu) and Dystric Regosols (RGdy) are prevalent soil type in these areas (Vaidya and Sah 2015).

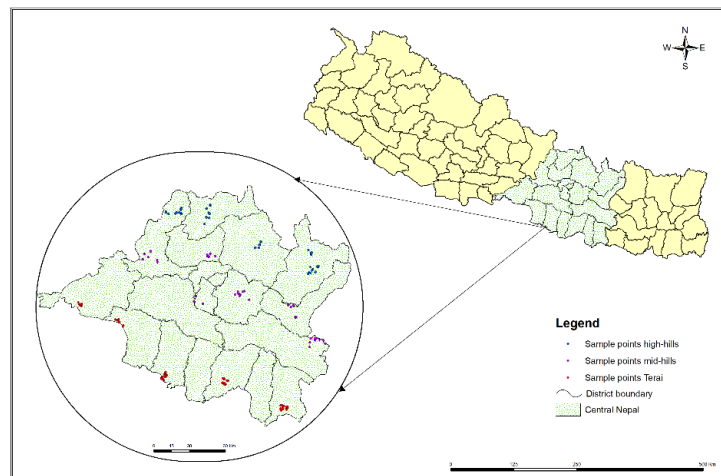


Figure 1. Location map of the study area (Source of base map: National Spatial Data Center under Survey Department, Nepal (<https://nationalgeoportal.gov.np/#/>))

Soil sampling and processing

A total of 225 soil samples were collected at a depth of 0-20 cm using a soil sampling auger across diverse locations in central Nepal (Figure 1). The sampling sites included Gaurishankar, Jugal, Gosaikunda, and Ruby Valley rural municipalities in the Dolakha, Sindhupalchok, Rasuwa, and Dhading districts, respectively. Additional sites included Phikkal, Bagmati, and Siddhalek rural municipalities in the Sindhuli, Lalitpur, and Dhading districts, respectively, as well as Manthali and Namobuddha municipalities in the Ramechhap and Kavrepalanchok districts, respectively. Furthermore, samples were also collected from Madi municipality in Chitwan and from Thori, Devtal, Chakkarghatta, and Aurahi rural municipalities in the Parsa, Bara, Sarlahi, and Dhanusha districts, respectively. The geographical coordinates of each sample point were recorded using a handheld GPS device. For P adsorption-desorption isotherm study, the air-dried soil samples were ground and sieved through a 2 mm sieve to obtain a homogeneous sample.

Laboratory analysis

For the P adsorption and desorption study, the method suggested by Pal (2011) was followed. First, the adsorption experiment was conducted, followed by the desorption experiment. Three grams of soil were equilibrated in an incubator at 25 °C for six days with 30 ml of 0.01 M CaCl₂ solution containing 3, 5, 10, 15, 20, 30, 50, and 75 µg P ml⁻¹, which was equivalent to 30, 50, 100, 150, 200, 300, 500, and 750 µg P g⁻¹ soil, respectively, as KH₂PO₄ with two drops of toluene to inhibit microbial activity. The soil was shaken for 30 minutes twice daily using a laboratory shaker. After equilibrium, the contents of the tube were centrifuged and filtered. The P content in the filtrate was determined by employing the ascorbic acid-molybdophosphate blue method (Kuo 1996).

Adsorbed P was calculated as the difference between added P and equilibrium P concentration. Then the adsorbed P (µg g⁻¹) and equilibrium P (µg ml⁻¹) were plotted to the adsorption isotherm equations:

Langmuir equation (Langmuir 1918): $\frac{C}{Q} = \frac{1}{Q_m} \times C + \frac{1}{(KL \times Q_m)}$

Where, C is the equilibrium P concentration ($\mu\text{g ml}^{-1}$), Q is the amount of adsorbed P ($\mu\text{g g}^{-1}$), Q_m and K_L are the constants related to maximum P adsorption capacity ($\mu\text{g g}^{-1}$) and bonding energy ($\text{ml } \mu\text{g}^{-1}$), respectively.

Freundlich equation (Freundlich 1926): $Q = K_F C^{1/n}$

$$\log Q = \frac{1}{n} \log C + \log K_F$$

Where, Q and C are the same as Langmuir equation, K_F and n are two constants. K_F indicates P adsorption capacity ($\mu\text{g g}^{-1}$), while n might also be considered same as K_L in Langmuir equation (Samadi 2006, Debicka et al 2016).

Tempkin equation (Tempkin and Pyzher 1940): $Q = b \ln C + a$

Where, Q and C are the same as Langmuir equation, a and b are two constants. The b value of Tempkin equation is considered as the P buffering capacity (PBC) of soil.

The maximum P buffering capacity (MPBC) which is the product of Q_m and K_L (Wang et al 2017) was determined by using the following equation.

$$\text{MPBC (ml g}^{-1}\text{)} = Q_m \times K_L$$

Phosphorus sorption index (PSI) was also calculated from the following relationship (Sims 2009).

$$\text{PSI (ml g}^{-1}\text{)} = \frac{Q_{75}}{\log C_{75}}$$

Where, Q_{75} and C_{75} represent the amount of P adsorbed and the equilibrium P concentration, respectively, at an addition of $75 \mu\text{g P ml}^{-1}$ in the adsorption isotherm study.

Degree of P saturation (DPS) was also calculated from the following relationship (Pautler and Sims 2000, Indiaty and Sequi 2004).

$$\text{DPS (\%)} = \frac{\text{STP}}{(\text{STP} + \text{PSI})} \times 100$$

Where, STP and PSI denotes soil test P (Olsen P) and P sorption index, respectively.

P eutrophication risk index (PERI) was also calculated from the following relationship (Huang et al 2004).

$$\text{PERI (\%)} = \frac{\text{DPS}}{\text{PSI}} \times 100$$

Where, DPS and PSI indicate the degree of P saturation and the P sorption index, respectively.

The standard P requirement (SPR) of the soil was determined as the quantity of P adsorbed when the solution P concentration reached $0.2 \mu\text{g P ml}^{-1}$ (Fox and Kamprath 1970, Juo and Fox 1977). Similarly, the external P requirement (EPR) was also determined as the quantity of P adsorbed when the solution P concentration reached $1 \mu\text{g P ml}^{-1}$ (Rashmi et al 2016, Yousuf et al 2019). The isotherm equation that provided a better fit to the data, either Langmuir or Freundlich, was used to calculate SPR and EPR.

For the P desorption study, soils from the adsorption study were initially washed with alcohol to remove soluble P. Subsequently, the washed soils were shaken with 0.5 M NaHCO_3 (pH 8.5) for a duration of 2 hours. After shaking, the suspensions were centrifuged and filtered. The samples were subjected to two successive desorption runs at 25°C . The P content in the filtrate was determined by employing the ascorbic acid-molybdophosphate blue method (Kuo 1996). The amount of P retained by the soil (pre-sorbed P) was calculated by taking the difference between the initially adsorbed P and the P content in desorption equilibrium solution. The data obtained on P desorption were fitted in accordance with a Langmuir and Freundlich equation.

Langmuir equation:
$$\frac{De}{S_{de}} = \frac{1}{D_m} \times De + \frac{1}{(K_d \times D_m)}$$

Where, S_{de} is the amount of pre-sorbed P ($\mu\text{g g}^{-1}$), De is the amount of P desorbed ($\mu\text{g ml}^{-1}$), D_m is the maximum P desorption capacity ($\mu\text{g g}^{-1}$) and K_d is a desorption constant that indicates P desorption intensity of soils ($\text{ml } \mu\text{g}^{-1}$).

Freundlich equation:
$$S_{de} = a_d De^{1/n_d}$$
$$\log S_{de} = \frac{1}{n_d} \log De + \log a_d$$

Where, S_{de} and De are as defined in the Langmuir equation, a_d and n_d are constants. a_d indicated P desorption capacity ($\mu\text{g g}^{-1}$), while n_d might be considered same to K_d , as in adsorption isotherm study.

Readily desorbable P (RDP), representing the amount of P transitioning from the soil solid phase to the liquid phase with $0 \mu\text{g ml}^{-1}$ P addition during the adsorption and desorption process (Wang et al 2017), was also calculated.

Various P adsorption-desorption parameters were determined from the adsorption and desorption isotherm study. The observed soil P adsorption-desorption parameters datasets used for prediction in mapping are presented in Table 1.

Table 1. Descriptive statistics of observed soil P adsorption-desorption parameters used in mapping of central Nepal

P adsorption-desorption parameters	Descriptive statistics				
	Mean	Minimum	Maximum	SEM	SD
Langmuir P adsorption constant (Q_m), $\mu\text{g g}^{-1}$	548.26	72.46	1428.57	12.36	185.45
Langmuir P adsorption constant (K_L), $\text{ml } \mu\text{g}^{-1}$	0.22	0.01	3.75	0.03	0.43
Maximum P buffering capacity, ml g^{-1}	122.68	4.47	2500.00	18.40	275.99
Freundlich P adsorption constant (K_F), $\mu\text{g g}^{-1}$	84.21	5.95	403.92	4.03	60.51
Freundlich P adsorption constant (n), g ml^{-1}	2.24	1.05	4.13	0.04	0.60
P buffering capacity, ml g^{-1}	64.32	26.94	126.71	1.16	17.45
Standard P requirement, $\mu\text{g g}^{-1}$	42.92	1.49	224.19	2.35	35.18
External P requirement, $\mu\text{g g}^{-1}$	84.21	5.95	403.92	4.03	60.51
P sorption index, ml g^{-1}	354.86	127.91	959.29	7.75	116.21
Degree of P saturation, %	3.45	0.02	34.56	0.29	4.31
P eutrophication risk index, %	1.20	0.004	12.58	0.11	1.66
Langmuir P desorption constant (D_m), $\mu\text{g g}^{-1}$	926.11	76.99	3532.45	44.02	660.34
Langmuir P desorption constant (K_d), $\text{ml } \mu\text{g}^{-1}$	0.24	0.02	2.52	0.02	0.25
Freundlich P desorption constant (a_d), $\mu\text{g g}^{-1}$	115.15	15.48	208.75	2.46	36.93
Freundlich P desorption constant (n_d), g ml^{-1}	1.09	0.50	2.54	0.02	0.30
Readily desorbable P, $\mu\text{g g}^{-1}$	9.74	0.30	69.25	0.65	9.80

SEM = Standard error of mean; SD = Standard deviation

Environmental covariates

Covariates are spatial datasets of environmental variables that are related to the soil forming factors (Van Egmond et al 2023). A total of 122 covariates (100 m resolution), representing soil-forming factors, were utilized for the spatial prediction of parameters, encompassing remote sensing data, terrain attributes, and climate variables (Table 2). All the covariates were projected to a common coordinate reference system (CRS). Soil point data (P adsorption-desorption parameters) and covariate layers were used as input for digital mapping.

Table 2. Covariate layers used for spatial prediction of soil P adsorption-desorption parameters in the central Nepal

Covariates	SCORPAN factor	Number	Reference
Ecoregion as biomes	O	14	Dinerstein et al (2017)
Yearly mean runoff over time period	R	1	CCCS (2024)
Yearly mean surface net solar radiation over	C	1	

time period			
Yearly mean temperature of air at 2m above the surface over time period	C	1	
Yearly total evaporation over time period	C	1	
Yearly total precipitation over time period	C	1	
Monthly precipitation over time period	C	12	
Mean year total precipitation	C	1	
GLiM - Global Lithological Map	P	16	Hartmann and Moosdorf (2012)
Normalized Burn Ratio 2	O	1	
Normalized Difference Drought Index	O, C	1	
Normalized Difference Snow Index	O, C	1	
Normalized Difference Vegetation Index	O	1	
Normalized Difference Water Index	O, C	1	
Radiance	O, P	1	
Band 1 (ultra-blue, coastal aerosol) surface reflectance	O, P, S	1	
Band 2 (blue) surface reflectance	O, P, S	1	
Band 3 (green) surface reflectance	O, P, S	1	
Band 4 (red) surface reflectance	O, P, S	1	USGS (2024)
Band 5 (near infrared) surface reflectance	O, P, S	1	
Band 6 (shortwave infrared 1) surface reflectance	O, P, S	1	
Band 7 (shortwave infrared 2) surface reflectance	O, P, S	1	
Tasseled cap transformation 1 st dimension	S, P	1	
Tasseled cap transformation 2 nd dimension	O	1	
Tasseled cap transformation 3 rd dimension	S, O, P	1	
Temperature land surface	C	1	
MODIS land cover type	O	17	Friedl and Sulla-Menashe (2022)
Radar backscatter in horizontal polarization	O, S	1	
Radar backscatter in horizontal-transmit and vertical-receive polarization	O	1	
Yearly Doppler data	O, S	1	JAEA (2024)
Yearly radar backscatter measurements	S, O	1	
Yearly radar-derived roughness metrics	R	1	
Yearly radar volume backscatter	O	1	
Landforms	R	15	CSP (2024b)
Continuous Heat-Insolation Load Index	C	1	CSP (2024a)
Multi-Scale Topographic Position Index	R	1	CSP (2024c)
Elevation	R	1	
Flow accumulation	R	1	
Gaussian curvature	R	1	
Gradient	R, N	1	
Horizontal curvature	R	1	Farr et al (2007)
Mean curvature	R	1	
Slope	R	1	
Topo diversity	R	1	
Topographic wetness index	R	1	
Vertical curvature	R	1	
Urban cover fraction	O	1	
Water permanent cover fraction	R	1	
Water seasonal cover fraction	C, P	1	
Bare cover fraction	O, R	1	Buchhorn et al (2020)
Crops cover fraction	O	1	
Moss cover fraction	O	1	
Snow cover fraction	O	1	

Quantile regression forests

The quantile regression forests method, an extension of the random forests (RF) approach proposed by Breiman (2001), was employed for spatial prediction. RF is a regression method that averages predictions from multiple decision trees to generate a final output. While RF provides specific predictive values, it does not account for the uncertainty of these predictions. To overcome this limitation, a probabilistic prediction framework was integrated with RF, resulting in the quantile regression forests model. This approach, introduced by Meinshausen and Ridgeway (2006), has become one of the most effective and widely used models for probabilistic forecasting. All analyses were conducted in the R and ArcGIS environment.

Model validation

For evaluating the model, a 10-fold cross-validation approach was employed (Hengl et al 2015). Five evaluation metrics were computed, including root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), concordance correlation coefficient (CCC), and model efficiency coefficient (MEC) as described by Genova et al (2024).

RESULTS

P adsorption parameters

Langmuir P adsorption constant (Q_m)

The spatial distribution of Langmuir P adsorption constant (Q_m) is shown in Figure 2, where values ranged from 325.43 to 964.88 $\mu\text{g g}^{-1}$, with a mean of 532.11 $\mu\text{g g}^{-1}$ (Table 3). Comparatively higher distribution was observed in the northern area of Rasuwa, Sindhupalchok, and Dolakha and the southern areas of Rautahat, Mahottari, Sarlahi, Bara and Parsa districts. Conversely, lower distribution was found in majority of mid-hills districts as well as Chitwan and Dhanusha districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC, and MEC for Q_m prediction were 150.88 $\mu\text{g g}^{-1}$, 91.97 $\mu\text{g g}^{-1}$, 0.31, 0.46, and 0.31, respectively (Table 4).

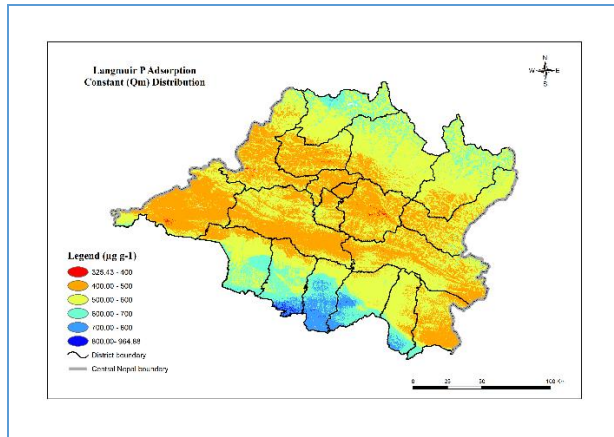


Figure 2. Spatial distribution of Langmuir P adsorption constant (Q_m) in central Nepal

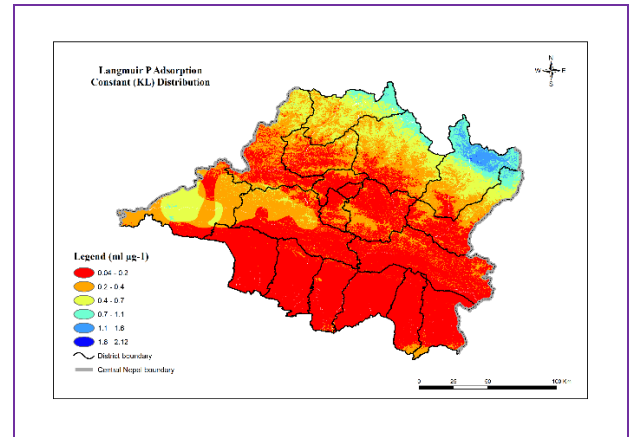


Figure 3. Spatial distribution of Langmuir P adsorption constant (K_L) in central Nepal

Langmuir P adsorption constant (K_L)

The spatial distribution of Langmuir P adsorption constant (K_L) is illustrated in Figure 3, with values that ranged from 0.04 to 2.12 ml μg^{-1} and a mean of 0.27 ml μg^{-1} (Table 3). A comparatively higher distribution was observed in the northern areas of Ramechhap, Dolakha, Sindhupalchok, and Rasuwa districts. In contrast, a lower distribution was noted in Dhanusha, Mahottari, Sarlahi, Rautahat, Bara, Parsa, Sindhuli, Kavrepalanchok, Kathmandu, Bhaktapur, Lalitpur districts, and their surrounding areas. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC, and MEC for K_L prediction were 0.32 ml μg^{-1} , 0.15 ml μg^{-1} , 0.46, 0.58, and 0.45, respectively (Table 4).

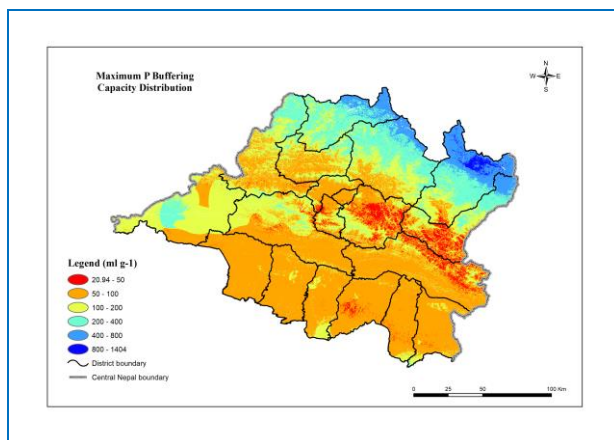


Figure 4. Spatial distribution of maximum P buffering capacity in central Nepal

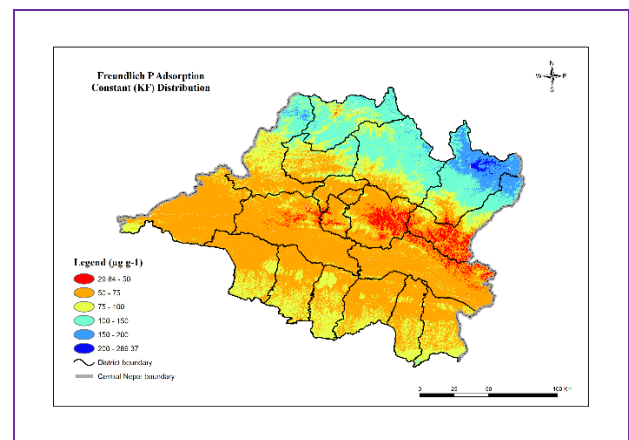


Figure 5. Spatial distribution of Freundlich P adsorption constant (K_F) in central Nepal

Maximum P buffering capacity

The spatial distribution of MPBC is shown in Figure 4, with values ranged from 20.94 to 1404.00 ml g^{-1} and a mean of 147.76 ml g^{-1} (Table 3). A comparatively higher distribution was observed in the northern areas of Ramechhap, Dolakha, Sindhupalchok, and Rasuwa districts. In contrast, a lower distribution was noted in the southern areas of Ramechhap and the northern areas of Sindhuli and Kavrepalanchok districts. The 10-fold cross-validation metrics RMSE,

MAE, R^2 , CCC, and MEC for MPBC prediction were 200.21 ml g⁻¹, 86.22 ml g⁻¹, 0.49, 0.60, and 0.48, respectively (Table 4).

Freundlich P adsorption constant (K_F)

The Freundlich P adsorption constant (K_F) spatial distribution map is shown in Figure 5, where values ranged from 29.84 to 289.37 $\mu\text{g g}^{-1}$ with a mean of 82.27 $\mu\text{g g}^{-1}$ (Table 3). Comparatively higher distribution was observed in the northern areas of Dhading, Rasuwa, Sindhupalchok, Dolakha, and Ramechhap districts. Conversely, lower distribution was found in the southern areas of Ramechhap and nearby sites of Kavrepalanchok district. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for K_F prediction were 38.76 $\mu\text{g g}^{-1}$, 27.85 $\mu\text{g g}^{-1}$, 0.61, 0.71 and 0.59, respectively (Table 4).

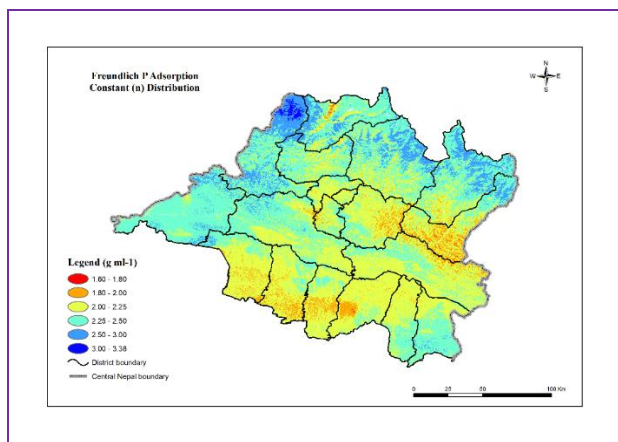


Figure 6. Spatial distribution of Freundlich P adsorption constant (n) in central Nepal

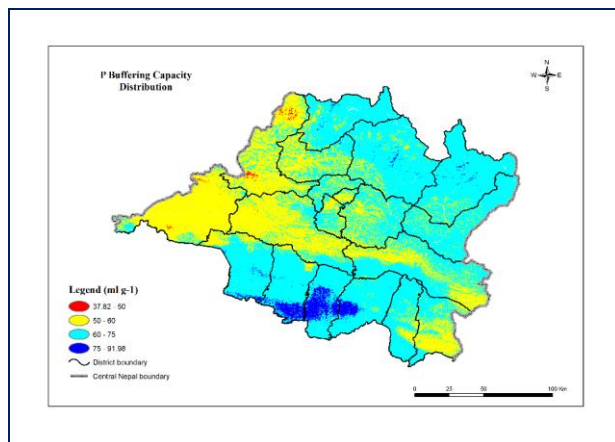


Figure 7. Spatial distribution of P buffering capacity in central Nepal

Freundlich P adsorption constant (n)

The spatial distribution of Freundlich P adsorption constant (n) is presented in Figure 6, where values ranged from 1.60 to 3.38 g ml⁻¹ with a mean of 2.27 g ml⁻¹ (Table 3). Comparatively higher distribution was observed in the Dhading, Rasuwa, Sindhupalchok, Dolakha, and Chitwan districts. Additionally, the northern areas of Ramechhap, southern areas of Dhanusha and western areas of Makwanpur also showed higher distribution. Conversely, lower distribution was found in the southern areas of Sarlahi, Rautahat, Bara, Parsa and Ramechhap districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for n prediction were 0.50 g ml⁻¹, 0.38 g ml⁻¹, 0.32, 0.44 and 0.31, respectively (Table 4).

P buffering capacity

The spatial distribution of PBC is illustrated in Figure 7, where values ranged from 37.82 to 91.98 ml g⁻¹ with a mean of 62.28 ml g⁻¹ (Table 3). Comparatively higher distribution was observed in some areas of Sarlahi, Rautahat, and Bara districts. Conversely, lower distribution was noted across most areas of Chitwan, Dhading and Makwanpur districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for PBC prediction were 13.79 ml g⁻¹, 10.58 ml g⁻¹, 0.35, 0.47 and 0.34, respectively (Table 4).

Standard P requirement

Figure 8 illustrates the spatial distribution of SPR, which ranged from 12.60 to 155.39 $\mu\text{g g}^{-1}$, with a mean of 42.66 $\mu\text{g g}^{-1}$ (Table 3). Comparatively higher distribution was observed in the northern areas of Dhading, Rasuwa, Sindhupalchok, Dolakha and Ramechhap districts. Conversely, lower distribution was observed in the southern areas of Ramechhap, the northern areas of Sindhuli, most parts of Kavrepalanchok, and some areas of Makwanpur and Lalitpur districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for predicted SPR were 23.77 $\mu\text{g g}^{-1}$, 17.08 $\mu\text{g g}^{-1}$, 0.56, 0.67 and 0.54, respectively (Table 4).

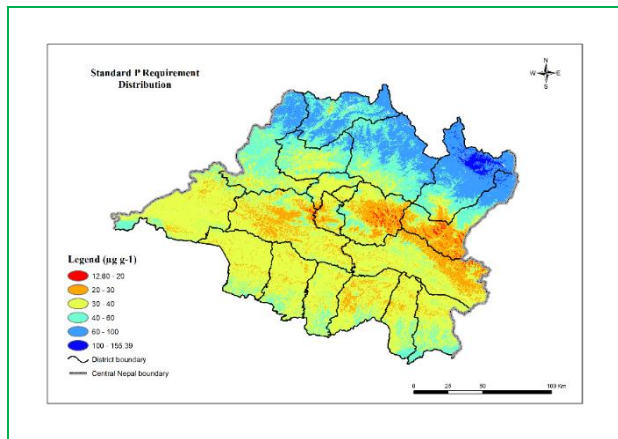


Figure 8. Spatial distribution of standard P requirement in central Nepal

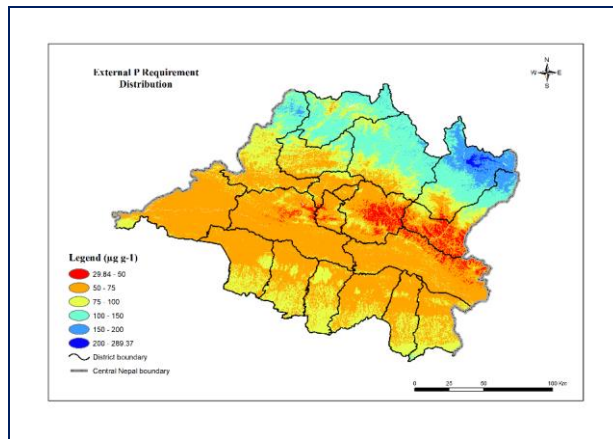


Figure 9. Spatial distribution of external P requirement in central Nepal

External P requirement

The spatial distribution of EPR is depicted in Figure 9, where values ranged from 29.84 to 289.37 $\mu\text{g g}^{-1}$ with a mean of 82.27 $\mu\text{g g}^{-1}$ (Table 3). The distribution was comparatively higher in the northern areas of Dolakha and Ramechhap districts. In contrast, lower distribution was observed in the southern parts of Ramechhap, the northern areas of Sindhuli, and the eastern areas of Kavrepalanchok districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for EPR prediction were 38.76 $\mu\text{g g}^{-1}$, 27.85 $\mu\text{g g}^{-1}$, 0.61, 0.71 and 0.59, respectively (Table 4).

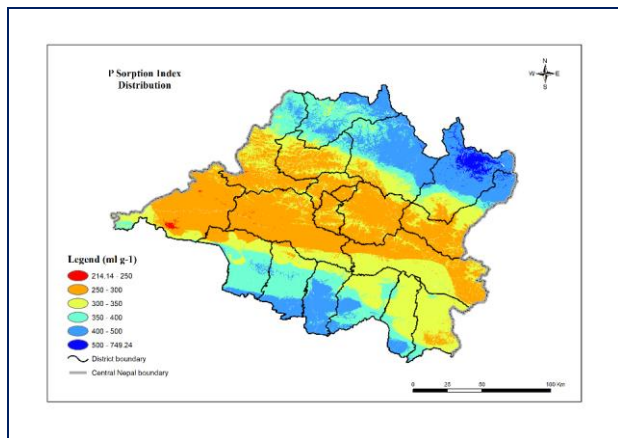


Figure 10. Spatial distribution of P sorption index in central Nepal

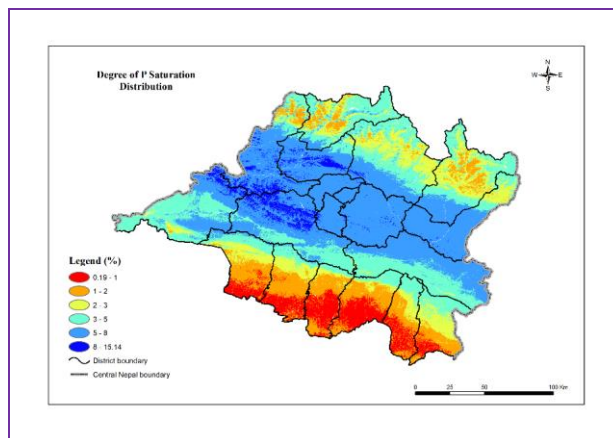


Figure 11. Spatial distribution of degree of P saturation in central Nepal

P sorption index

The PSI spatial distribution map is shown in Figure 10, where values ranged from 214.14 to 749.24 ml g⁻¹ with a mean of 338.12 ml g⁻¹ (Table 3). The distribution was comparatively higher in the northern areas of Ramechhap, Dolakha, Sindhupalchok, and the northeastern regions of Rasuwa districts, as well as in the southern parts of Bara and Rautahat districts. In contrast, lower distribution was observed across most areas of the Kavrepalanchok, Lalitpur, Bhaktapur, Kathmandu, Nuwakot, Makwanpur, Sindhuli, and Chitwan districts as well as in the southern areas of Dhading and Ramechhap districts. The 10-fold cross-validation metrics RMSE, MAE, R², CCC and MEC for PSI prediction were 67.96 ml g⁻¹, 44.40 ml g⁻¹, 0.67, 0.77 and 0.66, respectively (Table 4).

Degree of P saturation

The spatial distribution of DPS is illustrated in Figure 11, where values ranged from 0.19 to 15.14% with a mean of 4.36% (Table 3). Comparatively higher distribution was observed in the most areas of Kavrepalanchok, Bhaktapur, Kathmandu, Nuwakot, Dhading and Makwanpur districts, as well as in the southern areas of Dolakha and Sindhupalchok districts, and the northern areas of Chitwan and Sindhuli districts. Conversely, lower distribution was noted across southern areas of Dhanusha, Mahottari, Sarlahi, Rautahat, Bara, and Parsa districts. The 10-fold cross-validation metrics RMSE, MAE, R², CCC and MEC for predicted DPS were 3.42%, 1.90%, 0.37, 0.56 and 0.37, respectively (Table 4).

P eutrophication risk index

The spatial distribution of PERI is shown in Figure 12, where values ranged from 0.05 to 5.35% with a mean of 1.63% (Table 3). Comparatively higher distribution was observed in the most areas of Kavrepalanchok, Bhaktapur, Kathmandu, Nuwakot, Dhading and Makwanpur districts, as well as in the southern areas of Dolakha and Sindhupalchok districts, and the northern areas of Chitwan and Sindhuli districts. Conversely, lower distribution was noted across southern areas of Dhanusha, Mahottari, Sarlahi, Rautahat, Bara, and Parsa districts. The 10-fold cross-validation metrics RMSE, MAE, R², CCC and MEC for predicted PERI were 1.35%, 0.73%, 0.34, 0.53 and 0.34, respectively (Table 4).

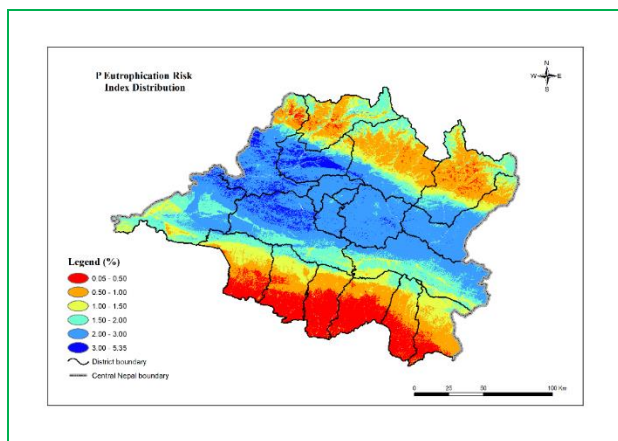


Figure 12. Spatial distribution of P eutrophication risk index in central Nepal

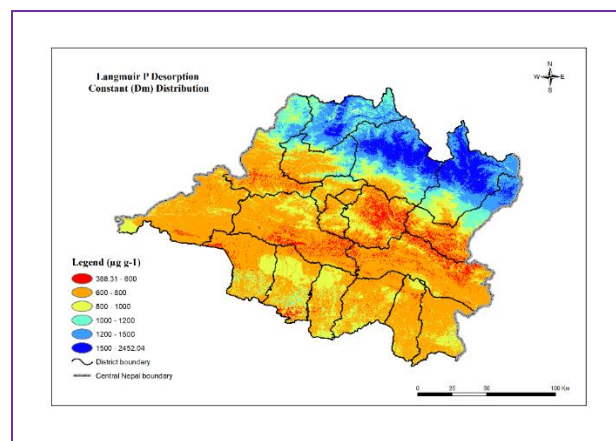


Figure 13. Spatial distribution of Langmuir P desorption constant (Dm) in central Nepal

P desorption parameters

Langmuir P desorption constant (Dm)

The Langmuir P desorption constant (Dm) spatial distribution map is presented in Figure 13, with values ranged from 368.31 to 2452.04 $\mu\text{g g}^{-1}$ and a mean of 881.39 $\mu\text{g g}^{-1}$ (Table 3). Comparatively higher distribution was observed in the northern areas of Rasuwa, Sindhupalchok, Dolakha, and Ramechhap districts. Conversely, lower distribution was found in the southern areas of Ramechhap, and Dhading districts, and eastern parts of Makwanpur. Moreover, northeastern areas of Kavrepalchok also showed lower distribution. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for Dm prediction were 531.06 $\mu\text{g g}^{-1}$, 402.91 $\mu\text{g g}^{-1}$, 0.35, 0.52 and 0.35, respectively (Table 4).

Langmuir P desorption constant (Kd)

The spatial distribution of Langmuir P desorption constant (K_d) is illustrated in Figure 14, where values ranged from 0.07 to 1.18 $\text{ml } \mu\text{g}^{-1}$ with a mean of 0.30 $\text{ml } \mu\text{g}^{-1}$ (Table 3). Comparatively higher distribution was observed in most areas of Kavrepalanchok district, the southern areas of Dhading and Lalitpur districts, and the northern areas of Makwanpur and Chitwan districts. Conversely, lower distribution was noted in smaller areas of Dolakha, and Sindhupalchok districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for predicted K_d were 0.22 $\text{ml } \mu\text{g}^{-1}$, 0.14 $\text{ml } \mu\text{g}^{-1}$, 0.19, 0.35 and 0.19, respectively (Table 4).

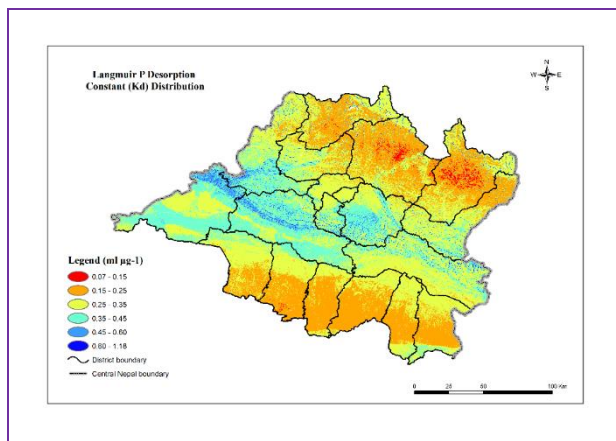


Figure 14. Spatial distribution of Langmuir P desorption constant (K_d) in central Nepal

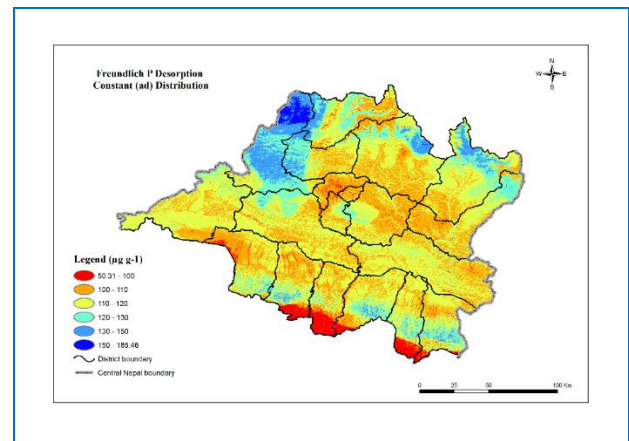


Figure 15. Spatial distribution of Freundlich P desorption constant (a_d) in central Nepal

Freundlich P desorption constant (a_d)

The Freundlich P desorption constant (a_d) spatial distribution map is shown in Figure 15, where values ranged from 50.31 to 185.46 $\mu\text{g g}^{-1}$ with a mean of 114.11 $\mu\text{g g}^{-1}$ (Table 3). Comparatively higher distribution was observed in the most areas of Dhading and nearby sites of Rasuwa and Nuwakot districts. Additionally, some northern areas of Sindhupalchok and Dolakha districts also exhibited higher distribution. Conversely, lower distribution was found in some southern areas of Dhanusha, Mahottari, Sarlahi, Rautahat and Bara districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for a_d prediction were 27.30 $\mu\text{g g}^{-1}$, 21.48 $\mu\text{g g}^{-1}$, 0.47, 0.58 and 0.46, respectively (Table 4).

Freundlich P desorption constant (n_d)

The spatial distribution of Freundlich P desorption constant (n_d) is illustrated in Figure 16, with values ranged from 0.70 to 1.71 g ml⁻¹ and a mean of 1.16 g ml⁻¹ (Table 3). Comparatively higher distribution was observed in most areas of Dhading, Rasuwa, and Makwanpur districts, as well as in the western regions of Nuwakot and the northern parts of Sindhupalchok, Dolakha, Ramechhap, and Chitwan districts. Conversely, lower distribution was found in some southern areas of Sarlahi, Rautahat and Bara districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for n_d prediction were 0.28 g ml⁻¹, 0.20 g ml⁻¹, 0.15, 0.31 and 0.15, respectively (Table 4).

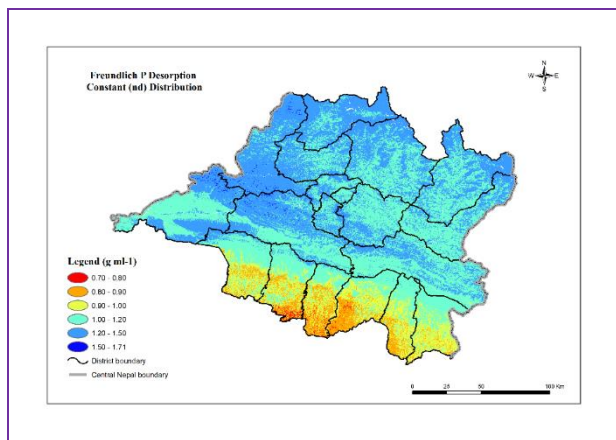


Figure 16. Spatial distribution of Freundlich P desorption constant (n_d) in central Nepal

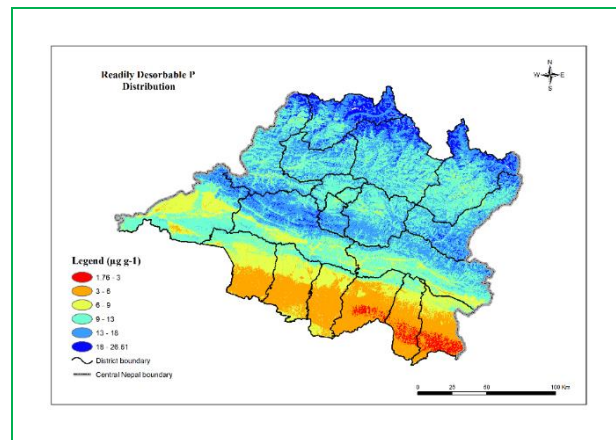


Figure 17. Spatial distribution of readily desorbable P in central Nepal

Readily desorbable P

The RDP spatial distribution map is shown in Figure 17, where values ranged from 1.76 to 26.61 µg g⁻¹ with a mean of 10.94 µg g⁻¹ (Table 3). Comparatively higher distribution was observed in the southern areas of Ramechhap, Kavrepalanchok, Lalitpur, and Dhading districts. Additionally, higher distribution was noted in the northern parts of Chitwan, Makwanpur, Sindhuli, Dhading, Rasuwa, Sindhupalchok, Dolakha, and Ramechhap districts. Conversely, lower distribution was found in the southern areas of Dhanusha, Mahottari, Sarlahi, Rautahat, Bara and Parsa districts. The 10-fold cross-validation metrics RMSE, MAE, R^2 , CCC and MEC for RDP prediction were 8.44 µg g⁻¹, 5.36 µg g⁻¹, 0.26, 0.43 and 0.26, respectively (Table 4).

Table 3. Descriptive statistics of predicted soil P adsorption-desorption parameters

P adsorption-desorption parameters	Descriptive statistics			
	Mean	Minimum	Maximum	SD
Langmuir P adsorption constant (Q _m), $\mu\text{g g}^{-1}$	532.11	325.43	964.88	68.59
Langmuir P adsorption constant (K _L), $\text{ml } \mu\text{g}^{-1}$	0.27	0.04	2.12	0.22
Maximum P buffering capacity, ml g^{-1}	147.76	20.94	1404.00	140.96
Freundlich P adsorption constant (K _F), $\mu\text{g g}^{-1}$	82.27	29.84	289.37	28.99
Freundlich P adsorption constant (n), g ml^{-1}	2.27	1.60	3.38	0.18
P buffering capacity, ml g^{-1}	62.28	37.82	91.98	5.51
Standard P requirement, $\mu\text{g g}^{-1}$	42.66	12.60	155.39	16.42
External P requirement, $\mu\text{g g}^{-1}$	82.27	29.84	289.37	28.99
P sorption index, ml g^{-1}	338.12	214.14	749.24	61.65
Degree of P saturation, %	4.36	0.19	15.14	2.24
P eutrophication risk index, %	1.63	0.05	5.35	0.85
Langmuir P desorption constant (D _m), $\mu\text{g g}^{-1}$	881.39	368.31	2452.04	298.30
Langmuir P desorption constant (K _d), $\text{ml } \mu\text{g}^{-1}$	0.30	0.07	1.18	0.08
Freundlich P desorption constant (a _d), $\mu\text{g g}^{-1}$	114.11	50.31	185.46	10.52
Freundlich P desorption constant (n _d), g ml^{-1}	1.16	0.70	1.71	0.14
Readily desorbable P, $\mu\text{g g}^{-1}$	10.94	1.76	26.61	4.17

SD = Standard deviation

Table 4. Cross-validation metrics for predicted and observed soil P adsorption-desorption parameters

P adsorption-desorption parameters	Statistics				
	RMSE	MAE	R ²	CCC	MEC
Langmuir P adsorption constant (Q _m), $\mu\text{g g}^{-1}$	150.88	91.97	0.31	0.46	0.31
Langmuir P adsorption constant (K _L), $\text{ml } \mu\text{g}^{-1}$	0.32	0.15	0.46	0.58	0.45
Maximum P buffering capacity, ml g^{-1}	200.21	86.22	0.49	0.60	0.48
Freundlich P adsorption constant (K _F), $\mu\text{g g}^{-1}$	38.76	27.85	0.61	0.71	0.59
Freundlich P adsorption constant (n), g ml^{-1}	0.50	0.38	0.32	0.44	0.31
P buffering capacity, ml g^{-1}	13.79	10.58	0.35	0.47	0.34
Standard P requirement, $\mu\text{g g}^{-1}$	23.77	17.08	0.56	0.67	0.54
External P requirement, $\mu\text{g g}^{-1}$	38.76	27.85	0.61	0.71	0.59
P sorption index, ml g^{-1}	67.96	44.40	0.67	0.77	0.66
Degree of P saturation, %	3.42	1.90	0.37	0.56	0.37
P eutrophication risk index, %	1.35	0.73	0.34	0.53	0.34
Langmuir P desorption constant (D _m), $\mu\text{g g}^{-1}$	531.06	402.91	0.35	0.52	0.35
Langmuir P desorption constant (K _d), $\text{ml } \mu\text{g}^{-1}$	0.22	0.14	0.19	0.35	0.19
Freundlich P desorption constant (a _d), $\mu\text{g g}^{-1}$	27.30	21.48	0.47	0.58	0.46
Freundlich P desorption constant (n _d), g ml^{-1}	0.28	0.20	0.15	0.31	0.15
Readily desorbable P, $\mu\text{g g}^{-1}$	8.44	5.36	0.26	0.43	0.26

RMSE = Root mean square error; MAE = Mean absolute error; R² = Coefficient of determination; CCC = Concordance correlation coefficient; MEC = Model efficiency coefficient

DISCUSSION

Distribution of P adsorption and desorption parameters

All the determined P adsorption and desorption parameters exhibited a wide distribution across the study area (Figure 2 to 17). The differences in adsorption sites and bonding energy, due to variations in climate, soil properties, nutrient management, and plant species, might have contributed to the wider distribution for the adsorption and desorption parameters of P. Soil P dynamics are strongly influenced by properties of soil, including pH, salinity, particle size distribution, organic matter (OM), metal oxide and wetland hydrology though affecting adsorption and desorption capacities of P (Li et al 2016, Reddy et al 2022).

Liu et al (2002) observed that phosphate adsorption on estuarine sediments was lowest at neutral pH (7-8) and increased under both acidic (pH < 7) and alkaline (pH > 8) conditions.

Du et al (2016) reported that P could be adsorbed by ligand exchange between P (in solution) and OH⁻ (on soil surface) at high pH values, since the ligand of OH⁻ would be replaced by HPO₄²⁻ or H₂PO₄⁻ in the aqueous solution. Similarly, Liu et al (2002) observed that P adsorption on the soils increased at low salinity, whereas decreased with increasing salinity (>5%). This could be due to negatively charged ions in the solution competes with phosphate ions (PO₄³⁻) in the soil colloids hence reduces P adsorption.

The presence of iron (Fe) and aluminum (Al) ions also plays a significant role in increasing P adsorption through binding of phosphate onto the active Fe and Al (Reitzel et al 2013, Huang et al 2016). However, the substrates with high Fe- and Al-oxide contents showed lower P adsorption at high pH values (Deng et al., 2017), since P would be liberated from the Al/FeOOH-P pool due to competition with OH⁻ ions at high pH values, influencing the shifting of the surface charge of the Fe/Al-oxides (Yan et al 2008). Moreover, Fe- and Al-OM complexes could play an important role in controlling P adsorption potential (Fink et al 2016), though OM can decrease P adsorption through competing for P adsorption sites and affecting the bonding energy of adsorbed P (Yang et al 2019).

Hydrological fluctuations, especially drying and wetting cycles, induce exposure and inundation of soils and change their oxidation and reducing potentials, which can influence P transformation between soil and its overlying water (Reddy et al 2022). Reddy et al (1999) reported that a reduced soil will adsorb a large amount of P with a low bonding energy, whereas an oxidized soil will adsorb less P but hold what it adsorbs more tightly. Moreover, changes in temperature would change soil P adsorption or desorption through influencing the ionic exchange strength at the soil and solution interface (Liu et al 2002). Increasing temperature would increase the bonding energy of P adsorption in soil and precipitation rates (Sah and Mikkelsen 1986, Reddy et al 2022) and high temperatures could decrease the time required to form crystalline forms (Reddy et al 2022).

Management practices, including different agricultural and tillage systems, also affect the amount of P adsorption in the soil by altering properties such as pH, calcium carbonate and OM content (Zafar et al 2016, Nobile et al 2018). Moreover, continuous fertilization can modify the soil properties, including the OM content, pH, and certain biological properties (Yan et al 2013), and this could affect the capacity of the soil to adsorb and desorb P. Among all the determined parameters, K_L, MPBC, DPS, and PERI exhibited a more dispersed spatial distribution. The sparse distribution of K_L, a key factor in MPBC estimation, might contributed to its variability. Additionally, DPS and PERI are derived from available P, and the uneven distribution of available P could be attributed to their broader spatial variation in the soil.

Significance of P adsorption and desorption parameters

The P adsorption capacity of a soil denotes its ability to adsorb P. Similarly, maximum adsorption capacity for P reflects the quantity of P binding sites per unit weight of soil, and is widely employed to assess the soil's ability to adsorb P (Hiradate and Uchida 2004, Yan et al 2013). The Langmuir constant (Q_m) denotes the maximum P adsorption capacity, while Freundlich constant (K_F) indicates P adsorption capacity of soil. The area with high maximum P adsorption capacity signifies low external P input applied, and vice versa (Abedin and Saleque 1998). Continuous cropping without P application may expose more adsorption sites due to the desorption of previously adsorbed P. Similarly, areas with high available P in the soil exhibited low maximum P adsorption capacity because most of their reactive sites had been saturated with the phosphate ions, and vice versa (Bekele et al 2020).

Additionally, a higher content of OM in soil also reflects a high maximum P adsorption capacity, and vice versa (Yang et al 2019).

The P bonding energy is a key factor representing the soil's ability to retain P, where higher values indicate stronger adsorption and a greater likelihood of spontaneous adsorption under limited P availability (Wang and Liang 2014). The Langmuir and Freundlich constants, K_L and n respectively, denote the bonding energy of P in soil. In areas with high P bonding energy, P is strongly adsorbed, whereas in areas with low bonding energy, P adsorption is weaker. Soils with high P bonding energy are less prone to P loss, while those with low bonding energy are more susceptible to P loss. In regions where the K_L value is below $0.4 \text{ ml } \mu\text{g}^{-1}$, P removal from the soil solution is predominantly governed by adsorption processes rather than precipitation (Ning et al 2022).

The MPBC is an integrated parameter that derived from Q_m and K_L (Wang and Liang 2014), and a higher MPBC indicates a greater potential for P adsorption, contributing to an increased soil P supplying ability. Therefore, areas with high MPBC exhibited higher P adsorption, and vice versa. Additionally, in areas with high P buffering capacity, P diffusion would be slowest, whereas in areas with low buffering capacity, P diffusion could occur rapidly (Khatun et al 2014).

Amount of P adsorbed at an equilibrium solution P concentration of $0.2 \text{ } \mu\text{g ml}^{-1}$ is generally accepted as the SPR for achieving optimum crop yield across a wide range of soils (Fox and Kamprath 1970). Beyond this threshold, further P application typically does not result in additional yield response (Rashmi et al 2016). Areas with high SPR require greater P fertilization to maintain optimal crop production, indicating a higher response to P application in the northern sites of the study area. However, continuous application of P fertilizers can lead to the accumulation of P in soil, this enhances their mobility and subsequent losses through non-point sources, which can contribute to eutrophication. This potential environmental risk is quantified as the EPR, defined as the quantity of P adsorbed when the solution reaches an equilibrium P concentration of $1 \text{ } \mu\text{g ml}^{-1}$. The eastern mid-hills appear to be more susceptible to P loss with increased P inputs. This could be attributed to their lower P adsorption capacity (Figure 5) as well as higher indigenous P supplying potential. In contrast, the northern areas are less likely to experience P loss with additional P application, could be due to their relatively higher P adsorption capacity (Figure 5).

The PSI, determined from a single-point isotherm, can be used to rapidly determine the soil's P adsorption capacity. The northern and southern areas exhibited higher PSI compared to other regions. The higher contents of OM, Al, and Fe, as well as the lower pH in the northern area, might have contributed to the high PSI. Similarly, the higher clay content and elevated Fe levels in the southern area could attributed to the high PSI. Additionally, the lower application of P inputs and the comparatively lower content of labile P in both northern and southern areas might be contributed to the increased PSI in these regions. Fe-Al oxides are the main carriers of variable charge in the soils. Lower pH is associated with a more positive charge on the surface of soil colloids, resulting in the stronger electrostatic bonding of phosphate anion and increased P adsorption (Xu et al 2016, Barrow 2017).

The DPS and PERI are considered an important indicator for assessing the risk of P loss from soils (Zhou et al 2015). A higher DPS indicates that a larger proportion of adsorption sites on the soil surface capable of binding phosphate from water have already been occupied (Xu et al 2022). Previous studies have suggested a critical DPS threshold of 25% for increased risk

of P loss (Zhou et al 2015). According to Huang et al (2004) PERI is classified into four risk levels: very high risk (>25%), high risk (20-25%), moderate risk (10-20%), and low risk (<10%). In all the studied areas, both DPS and PERI values were below 25% and 10%, respectively, indicating a low risk of P loss.

P release from soils occurs through desorption, which is essentially the reverse of adsorption. Desorption is more important than adsorption because of the importance of immobilized P in soil becoming available for reuse and also because of the environmental problems due to high P released from soil (Wang and Liang 2014).

The P desorption capacity of a soil indicates its ability to desorb previously adsorbed P. In addition, maximum P desorption capacity, represents the quantity of P released from a soil fully saturated with P, indicated the highest amount of P supplied within the soil (Ahmed et al 2021). The Langmuir constant (D_m) and Freundlich constant (a_d) indicate maximum P desorption capacity and P desorption capacity of a soil, respectively. These constants are widely used as indicators of the soil's ability to release adsorbed P. The area where have high content of these constant contains high capacity to release adsorbed P, and vice versa. The higher OM as well as sand content might attributed to higher maximum P desorption capacity in the respective area. Yang et al (2019) suggested that increasing soil OM content enhanced P desorption, as various anions released from OM compete with phosphate ions in the adsorption sites. The fine textured soil desorbed less P comparative to coarse textured soil (Sharma et al 2023).

Similarly, K_d or n_d values (a constant related to P mobility) are also indicative of P supply to crops. Sharma et al (2023) reported the desorption constant (K_d or n_d) measures the resistance to P desorbed, higher the value of K_d or n_d lower the potential of soil to release adsorbed P. Those area where have high desorption constant possess less soil potential to release adsorbed P, and vice-versa. Moreover, the lower content of readily desorbable P in the southern region suggests reduced P availability in these soils. Therefore, proper nutrient management practices should be adopted in this region to mitigate immediate P stress in crops compared with other areas.

Model efficacy among P adsorption and desorption parameters

The model's prediction efficiency for P adsorption-desorption parameters followed the order: $PSI > K_F = EPR > SPR > MPBC > a_d > K_L > DPS > D_m = PBC > PERI > n > Q_m > RDP > K_d > n_d$ (Table 4). This variation in prediction efficiency among P adsorption-desorption parameters reflects differences in their spatial variability and sensitivity to environmental covariates.

CONCLUSIONS

This study explored the distribution and accessibility of P adsorption-desorption parameters across the diverse regions of central Nepal, ranging from the southern plains to the northern high-hills. The findings underscore the role of P adsorption-desorption parameters as crucial intrinsic sources of available P over different time scales. All the studied parameters showed varying levels of distribution across the study area, as reflected in the mapped values. Most P adsorption parameters, except DPS and PERI, showed higher distribution in the northern region, whereas DPS and PERI were more prominent in the mid-hills region. Similarly, lower distribution of all P desorption parameters was observed in the southern areas. Areas with high Q_m , K_F , n , and PSI values indicated lower P use efficiency; therefore, appropriate P

management strategies should be developed for these regions. The study area did not exhibit P levels associated with eutrophication risk. Applying P fertilizer beyond the levels indicated in the spatial maps would not be economically viable for these soils. Overall, mapping the spatial distribution of P adsorption-desorption parameters can support the development of effective and sustainable P management strategies and for identifying priority areas for P related research in central Nepal.

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Authors' Contributions

Dinesh Khadka: Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Visualization, writing—original draft, Writing—review & editing. **Keshab Raj Pande:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing—review & editing. **Bhaba Prasad Tripathi:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing—review & editing. **Roshan Man Bajracharya:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing—review & editing.

Conflicts of Interest

The authors have no relevant conflict of interests.

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