Pak. J. Bot., 58(1) January 2026.

ARTICLE | DOI: http://dx.doi.org/10.30848/PJB2026-1(29)

INVESTIGATING THE IMPACTS OF PYROGENIC CARBON ON SOIL CHARACTERISTICS AND REGENERATION STOCK IN HIMALAYAN SUBTROPICAL PINE FORESTS EMPLOYING AI BASED ENSEMBLE-LEARNING TECHNIQUE

WAQAS UMAR[1], SAEED GULZAR[1], MUHAMMAD IRFAN ASHRAF[2]*, AZEEM KHALID[3] AND KHUZIN DINISLAM[4]

[1]Department of Forestry & Range Management, PMAS Arid Agriculture University, Rawalpindi, Pakistan
[2]Department of Forestry, University of Sargodha, Sargodha, Pakistan
[3]Institute of Soil and Environmental Sciences, PMAS Arid Agriculture University Rawalpindi, Pakistan
[4]Department of General Chemistry, Bashkir State Medical University, Ufa, Republic of Bashkortostan, Russia

*Corresponding author's email: mirfan.ashraf@uos.edu.pk; drirfancanada@gmail.com

Abstract

Wildfire driven ecological changes are a common phenomenon in Himalayan subtropical pine forests. These fires frequently alter the soil carbon pools and are major drivers of carbon losses and gains in these forests. Carbon losses due to wildfires had been studied in the past but detailed information on net carbon gains in the form of Pyrogenic Carbon (PyC) is limited. The present study was visualized to fill the information gap existing in this regard. The study was conducted using grid node sampling in a Himalayan subtropical pine forest in northeastern Pakistan. Over hundred soil samples were collected at two depths (0-15cm) and (16-30cm) in a composite manner. The soil samples were analysed and relationship of PyC with soil nitrogen, phosphorous, potassium, soil pH and soil EC was explored through use of ensemble-learning algorithms, a robust machine learning method based on artificial intelligence technology. We used Random Forest (RF) model which generates predictions from multiple decision trees built simultaneously and Extreme Gradient Boosting (XGBoost) algorithm in which decision trees are built in a sequence one after another leading to higher accuracy. Our results indicated that overall RF in spite of its ruggedness yielded models that are more promising. We found a significantly positive relationship of PyC with soil nitrogen and phosphorus, while PyC did not meaningfully explained variations in soil potassium, soil pH, and soil EC. We observed PyC stocks decreased with increasing soil depth. This study provided information on least studied carbon fraction in Himalayan forests by reporting its stock estimates and their relevance to selected soil characteristics. This will help in understanding the impacts of wildfire driven changes in Himalayan ecosystem.

Key words: Chir pine, Black carbon, Soil health, Supervised classification, Forest fire.

Introduction

Himalayan pine forests are adapted to repeated wildfires of low severity with majority of mature trees surviving frequent burns (Chandran *et al*., 2011; Fule *et al*., 2021). The south-west facing slopes, however, are more prone to fire ignitions (Kumar *et al*., 2015). Wildfires in subtropical pine ecosystem have wide-ranging ecological implications. They significantly alter understory with positive impacts on the floristic composition as less-frequent fires ensure rich diversity and more-frequent fires result in prevalence of fire tolerant species (Gupta *et al*., 2009; Kumar & Pandey, 2022; Bargali *et al*., 2022; Hussain *et al*., 2024). These fires are major driver of changes in aboveground and belowground carbon stocks as well as accumulate more soil carbon compared to aboveground stocks (Shah *et al*., 2014). Wildfire driven soil carbon dynamics has been extensively explored in Himalayan pine forests with major focus on soil organic carbon (SOC) which tends to decrease with the increasing age of stands and altitude (Sheikh *et al*., 2012; Amir *et al*., 2019). Soil organic carbon stocks decrease in post fire scenarios and subsequently recover over time (Kumar *et al*., 2013; Sharma *et al*., 2022). Soil carbon losses in these areas are recovered through variety of mechanisms including formation of pyrogenic carbon (PyC) or Charcoal (Vadrevu *et al*., 2012; Aryal *et al*., 2018;). However, the quantity of carbon added to soil as PyC by frequent biomass burning remains poorly estimated and demands investigations regarding its relevance to the soil characteristics and regeneration dynamics. As an important fraction of SOC in forested ecosystems across the globe, PyC influences soil properties. It influences nitrogen (N) cycling by adsorption of non-polar organic compounds in post fire scenarios although the effects may vary with ecosystem and soil depth (Butterbach-Bahl *et al*., 2011; Pingree & De Luca, 2017). The PyC-NH_3 covalent bonding is another significant mechanism in this regard (Hestrin *et al*., 2019). Pyrogenic carbon also influences the soil phosphorous (P) by facilitating its mineralisation processes, its effects on soil potassium (K) through entrapment of the nutrient rich water has also been documented (Fox *et al*., 2011; Sardans & Penuelas, 2015; Butler *et al*., 2018; Li *et al*., 2018; Zhang *et al*., 2019; Paramisparam *et al*., 2021). Significant changes in soil pH and electrical conductivity (EC) have been studied in response to varying PyC fluxes (Gundale & DeLuca, 2006; Li *et al*., 2018; Shahid *et al*., 2018; Neina, 2019; Gogoi *et al*., 2019).

Received: 04-05-2026 | Revised: 09-08-2025 | Accepted: 12-08-2025 | Online: 24-09-2025

Pyrogenic carbon has a profound effect on plant growth and functioning that is mainly dependent on its quantity and some other related factors like concentration of base cations, N immobilization and liming (Gale & Thomas, 2021). This combined effect results in improvement of photosynthesis rate (Licht & Smith, 2020). Generally, PyC strongly influence the germination of pines and oaks (Reyes *et al.*, 2015). Since, wildfires in the Himalayan subtropical pine forests is a common phenomenon there is no available information on wildfire derived PyC stocks and their relevance to soil and existing vegetation dynamics. The study provided the critical information for understanding how certain soil characteristics are influenced by PyC and how this, in turn, affects the regenerating pines in these forests. In this study, we employed systematic sampling and ensemble-learning algorithms to achieve the key objectives of understanding the influence of wildfire-derived PyC on vital soil characteristics and regeneration stock in the Himalayan subtropical pine forest ecosystem.

Material and Methods

Description of the study area: The study area was comprised of two sampling sites in the Himalayan foothills of northeastern Pakistan. One site was located in Margalla Hills National Park, and the other was in the adjacent Ghora-Gali Forest (Fig. 1). Margalla Hills National Park (MHNP) is in the easternmost foothills of the Himalayas Range, and covers an area of 17, 386 ha with an altitudinal range of 450-1580 m. The climate of Site-I was dry sub-tropical, with an annual average precipitation of 1200 mm, mostly falling in the monsoon season. The mean minimum temperature in January was 3.4°C and mean maximum temperature in July was 34.3° (Ali *et al.*, 2022). Geology is mostly Mesozoic to early Cenozoic (meta) sediments, including limestones, sandstones, slates and phyllites (Ali, 2014). Soils are principally moderately alkaline Entisols and Inceptisols, erosion rates are locally high (Ellis *et al.*, 1994). The vegetation of the national park consists of scrub vegetation at lower altitudes and pine stands at higher altitudes. Site-II is located in Ghora-Gali (forest subdivision in district Murree), which covers an area of 4606.61 ha. The average annual precipitation at Site-II is ~1640 to 1904 mm, with most falling during the July to August (Monsoon period). At both sites, vegetation was dominated by *Pinus roxburghii* (chir pine) and associated broadleaf species like *Quercus glauca*, *Quercus incana* and *Pistaciachinensis integerrima*. Understory vegetation was dominated by shrubs, with common species being *Myrsine africana*, *Carissa spinarum*, *Berberis lycium*, *Rubus ellipticus*, and *Dodonaea viscosa* (Rahman *et al.*, 2022). The herbage dominated by *Malvastrum coromandelianum, Podophyllum emodi* and *Pupalia lapacea* whereas most common grasses included *Tripogon filiformis*, *Chrysopogon aucheri*, *Phacelurus speciosus* and *Setaria glauca* (Siddiqui *et al.*, 2009; Bhatti *et al.*, 2017; Khan *et al.*, 2022).

Recurring fires are a common phenomenon in the pine-dominated stands and chir pine is believed to be adapted to frequent low severity burns mostly driven by the desire of locals for shifting cultivation and promoting forage production (Singh *et al.*, 2023). A study by Fule *et al.*, (2021) showed that these forests support a mean fire interval of less than 6 years. The ecosystem falls under the Fire Regime I category characterized by Garcia *et al.*, (2022) and is attributed by a short fire season, lower burned area, medium-low severity fires, small fire patches and high degree of variability over the years. Among the global fire pyromes identified by Archibald *et al.*, (2013) the study area falls under the ICS (Intermediate-cool-small) pyrome which is marked by the average FRI (Fire Return Interval) of 12 years.

Methods

The study was designed as a quasi-experiment due to lack of control on the treatment which is PyC produced from wildfires. Quasi-experimental design is widely applicable in studies related to fire ecology and is considered reliable for inferences (Butsic *et al.*, 2017).

Soil samples were collected systematically by employing grid node sampling scheme to minimize the selection bias in the experiment and grids of size 0.006° (664.48 x 664.48 meters Cartesian distance) were laid out by employing QGIS version 3.2.1, 2018. The sampling plan was an integration of grid and composite sampling to minimize experimental error (Carter & Gregorich, 2007).

The organic layer was removed and 10 subsamples were collected from marked one ha circular plot on each grid node at (0-15 cm) depth A and (16-30 cm) depth B (Palmer *et al.*, 2002; Cools & DeVos, 2016). These subsamples were mixed together to prepare a representative composite sample weighing one kilogram, sealed in polythene bags, and later transported to the laboratory for storage and further analysis. After compositing, the number of collected samples was 63 for Site-I and 39 for Site-II.

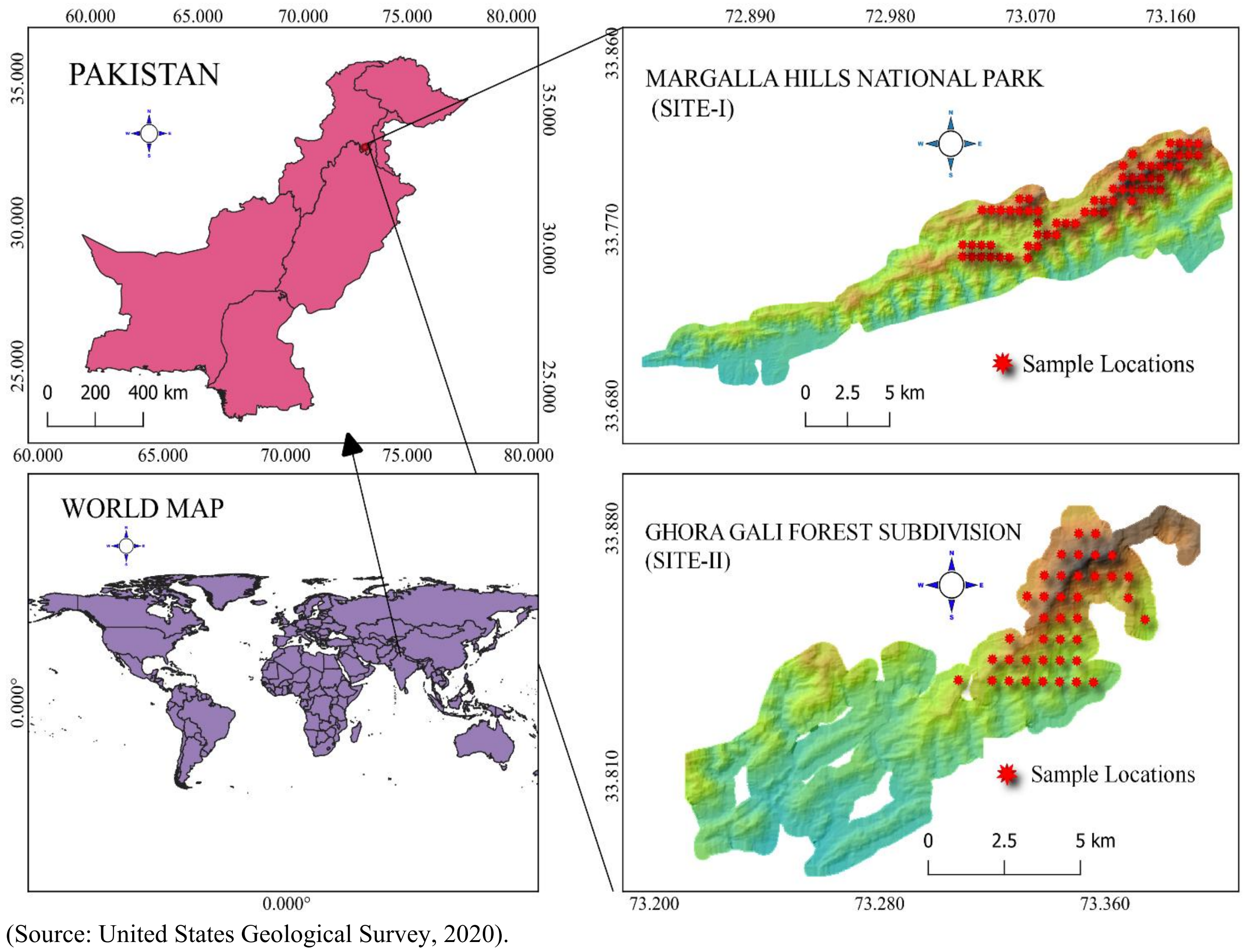
Pyrogenic carbon in the mineral soil samples was quantified through the weak digestion method (Kurth *et al.*, 2006). The soil samples were air-dried and passed through a 2mm sieve, pulverized and ball milled. One g of ball milled samples were digested in a solution of 10 milli-litres (ml), 1 molar (M) Nitric acid and 20 ml of (30%) Hydrogen peroxide. The digestion lasted around 16 hours at 100°C. The digested and undigested samples were subjected to elemental analysis for total carbon (TC) using an elemental analyzer (LECO-CS-300) at Hydrocarbon Development Institute Pakistan (HDIP), Islamabad. The quantity of PyC was calculated using the Eq. 1 (Abney *et al.*, 2019).

$$PyC(\%) = TCP \times PostDMass \div PreDMass \quad \text{Eq. 1}$$

Where: PyC = Pyrogenic carbon in percentage, TCP = Total carbon in digested samples (%), PostDMass = mass of soil sample after digestion (g), PreDMass = mass of soil samples before digestion (g).

Soil pH was measured by preparing a saturated paste of soil and employing a pH meter [Hanna Instrument HI 2211pH/ORP meter] (United States Salinity Laboratory Staff, 1954).

Total N was estimated using a three-gram soil sample that underwent wet oxidation with sulfuric acid and a digestion catalyst, converting organic nitrogen into ammonium. The ammonium was then quantified using the diffusion-conductivity method. The Kjeldahl method has a detection limit around 0.001% N (Isaac & Johnson, 1976; Horneck & Miller, 2019).



(Source: United States Geological Survey, 2020).

Fig. 1. Locality Map of study area and spatial distribution of samples across study sites.

Available K was extracted from the soil by treating a five-gram soil sample with a neutral ammonium acetate solution and agitating it on a shaker for five minutes. The contents were then filtered, and the filtrate was analysed using a flame photometer (GDV-DigiFlame2000) after appropriate calibration (Metson, 1956).

Available P was quantified using Olsen method on a five-gram sample. Phosphates (PO4-P) were extracted from soil using 0.5 M sodium bicarbonate solution. The hydroxides and bicarbonates result in desorption of phosphate from soil particles and high pH facilitated by the solution minimizes the absorption of phosphates. Ammonium molybdate and potassium tartrate reacts with orthophosphate ions. Ascorbic acid was used for the reduction of complex. The light absorbance of blue complex was observed using spectrometer (APEL-PD) 303S (Olsen & Sommers, 1982; Prokopy, 1995).

Soil EC was measured using a saturated soil paste and an EC meter (Selecta-CD2002). The detection limit of this method is around 0.01 ds m^{-1} (Rhoades, 1982). All soil fertility related analysis (NPK, pH and EC) were carried out at Soil and Water Testing Laboratory for Research, Rawalpindi, Pakistan.

Systematic sampling was carried out to gather data on the regeneration stock of *Pinus roxburghii* seedlings and saplings by demarking circular plots of nine-meter radius for counting seedlings and saplings. The plots were positioned on the same grids used for soil sampling and was nested inside the circular one ha plot (British Columbia Ministry of Forests, Lands, Natural Resource Operations and Rural Development, 2018; Wulfsohn, 2010). The age of seedlings and saplings was determined by whorl counts (DeYoung, 2016). The data collected from the sample plot was up-scaled to one ha.

Data processing and analysis: The number of observations (102) was found sufficient to fulfil the assumptions of normality and skewness (Dodge, 2008; Piovesana & Senior, 2018). Exploratory data analysis was performed using R software version 4.1.2 and Origin Pro (R core team, 2020; Originlab Corporation 2024), while the inferential stats were carried out in R using packages 'randomForest' and 'Xgboost' which are two distinct ensemble-learning methods for modelling non-linear relationships (Liaw & Weiner, 2002; Chen & Guestrin, 2016). Random Forest (RF) model constructed/trained 100 decision trees for each model through bootstrap aggregation or bagging to minimise the variance. Extreme Gradient Boosting (XGBoost) on the other hand built 500 decision trees in a sequence for each parameter through gradient boosting to avoid overfitting. For both approaches dataset was split into training (75%) and testing (25%) sets. Model performance was assessed through computation of performance metrices like R^2, root mean squared error (RMSE) and mean absolute error (MAE).

Results

Generally, the quantity of PyC decreased with increasing soil depth, with a mean value of 4.81±1.64 MG ha^{-1} for depth A and 3.49±1.23 MG ha^{-1} for depth B. Average N, P, K stocks decreased with increasing soil depth. Lower pH and EC values were recorded for depth B compared to depth A (Table 1). In regeneration stock survey, the average count of seedlings per hectare was higher (498.92) than that of saplings (199.18).

Application of ensemble-learning algorithms to analyse PyC-soil relationships indicated that overall RF through bootstrap aggregation produced higher R^2 values compared to XGBoost, which relies on gradient boosting for modelling relationships. Modelling PyC and N relationship through RF approach yielded R^2 values as 0.53 and 0.31 against depth A and B respectively, while R^2 from XGBoost were 0.36 and 0.26 (Table 2). Modelling through both approaches showed that soil P was also dependant on PyC as R^2 values emerging from RF model were 0.47 and 0.36 while through XGBoost they were 0.35 and 0.22 against depth A and B, respectively. Available Potassium on the other hand failed to exhibit any remarkable dependency on soil PyC as the R^2 values were lowest among macronutrients from both modelling approaches across both depths (Table 2). Pyrogenic carbon failed to exhibit any predictive power to explain variation in soil pH and soil EC through XGBoost approach while it did exhibit weak relationship when the data was subject to RF modelling. Random forest performed well by yielding comparatively lower RMSE and MAE values for all soil parameters across both depths.

Table 1. Descriptive statistics on Pyrogenic Carbon (PyC), soil characteristics and regeneration stock.

	Depth	PyC (MG ha^{-1})	N (MG ha^{-1})	P (mg kg^{-1})	K (mg kg^{-1})	pH	EC (ds m^{-1})	Seedlings (cnt ha^{-1})	Saplings (cnt ha^{-1})
Mean	A	4.81	0.79	3.56	112.03	7.24	1.01	498.92	199.18
	B	3.49	0.70	3.69	119.28	7.13	1.01		
SD	A	1.64	0.22	1.74	50.96	0.25	0.28	259.89	126.85
	B	1.23	0.17	1.88	53.96	0.24	0.23		
Skewness	A	0.95	0.62	0.90	0.84	-0.30	0.55	0.23	0.80
	B	1.20	0.09	0.31	0.14	-0.51	2.36		
Kurtosis	A	0.71	-0.43	0.39	2.46	-0.49	0.96	2.16	2.96
	B	1.05	-0.99	-0.85	-0.87	-0.62	10.11		
Min	A	2.05	0.45	1.2	32	6.66	0.49	78.59	39.30
	B	1.62	0.35	0.9	24	6.5	0.78		
Median	A	4.47	0.74	3.2	130.50	7.27	1.00	510.87	157.19
	B	3.24	0.68	3.6	132	7.18	0.94		
Max	A	10.55	1.39	8.7	312	7.7	1.92	1139.62	589.46
	B	7.12	1.07	7.5	264	7.6	2.39		

*Number of observations (N) = 102; cnt: count

Table 2. Model performance indicators for soil and regeneration stock.

		Xgboost			Random Forest		
	Depth	R^2	RMSE	MAE	R^2	RMSE	MAE
Nitrogen	A	0.36	0.19	0.16	0.53	0.17	0.14
	B	0.26	0.16	0.12	0.31	0.15	0.12
Phosphorous	A	0.35	1.73	1.27	0.47	1.54	1.11
	B	0.22	2.04	1.60	0.36	1.60	1.21
Potassium	A	0.09	60.71	44.91	0.18	51.50	40.76
	B	0.04	60.72	47.43	0.03	56.28	46.12
pH	A	0.07	0.28	0.24	0.06	0.27	0.23
	B	0.08	0.29	0.23	0.10	0.25	0.22
Electrical conductivity	A	0.05	0.37	0.28	0.12	0.24	0.21
	B	0.02	0.38	0.24	0.02	0.37	0.23
Seedlings	A	0.19	129.61	106.17	0.26	110.16	91.79
	B	0.11	145.74	120.68	0.23	106.13	94.63
Saplings	A	0.27	59.13	46.08	0.31	51.54	39.79
	B	0.24	62.04	47.49	0.36	49.52	33.41

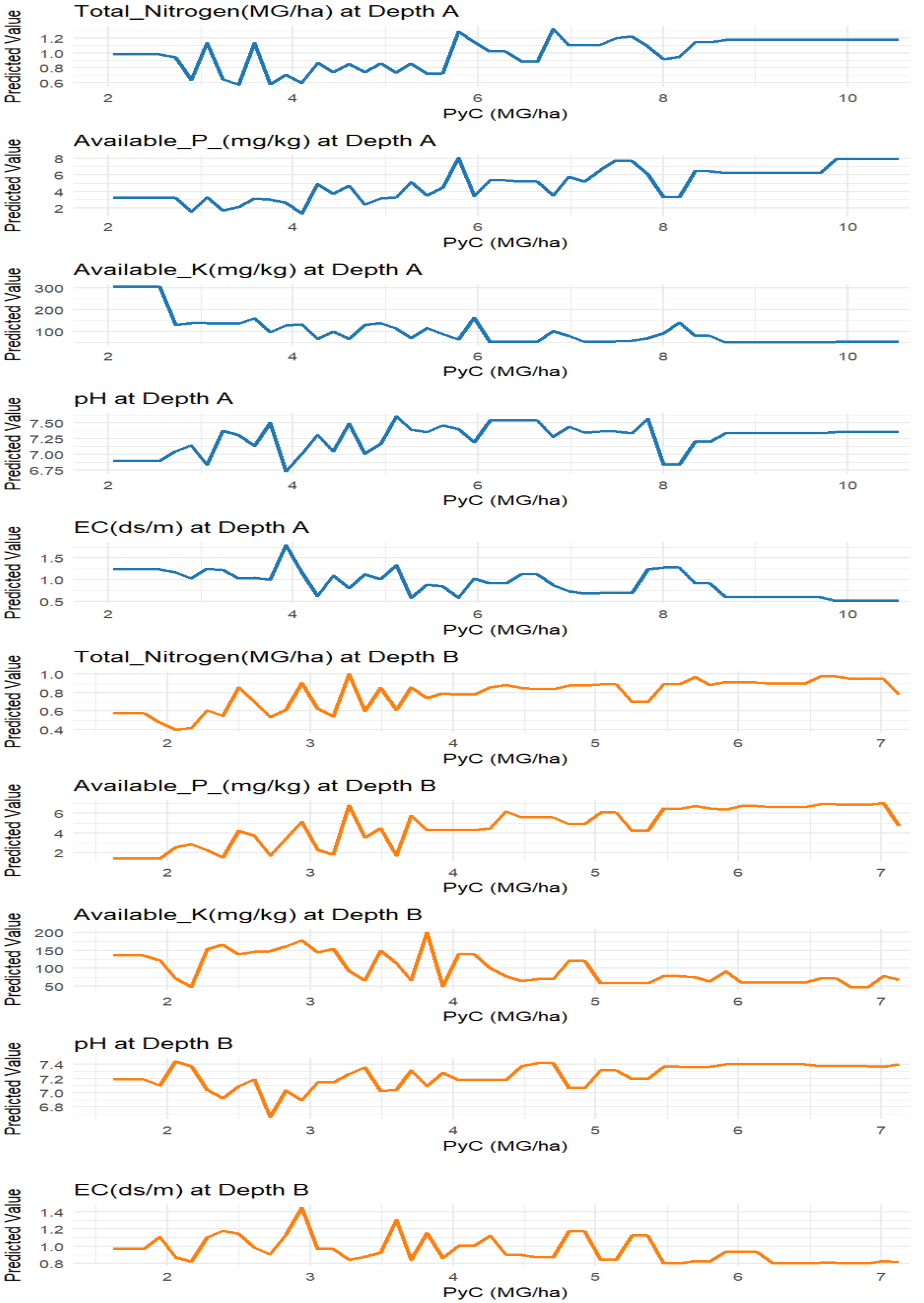


Fig. 2. Partial Dependence Plots (PDPs) from gradient boost (xgboost) for both soil depths A and B.

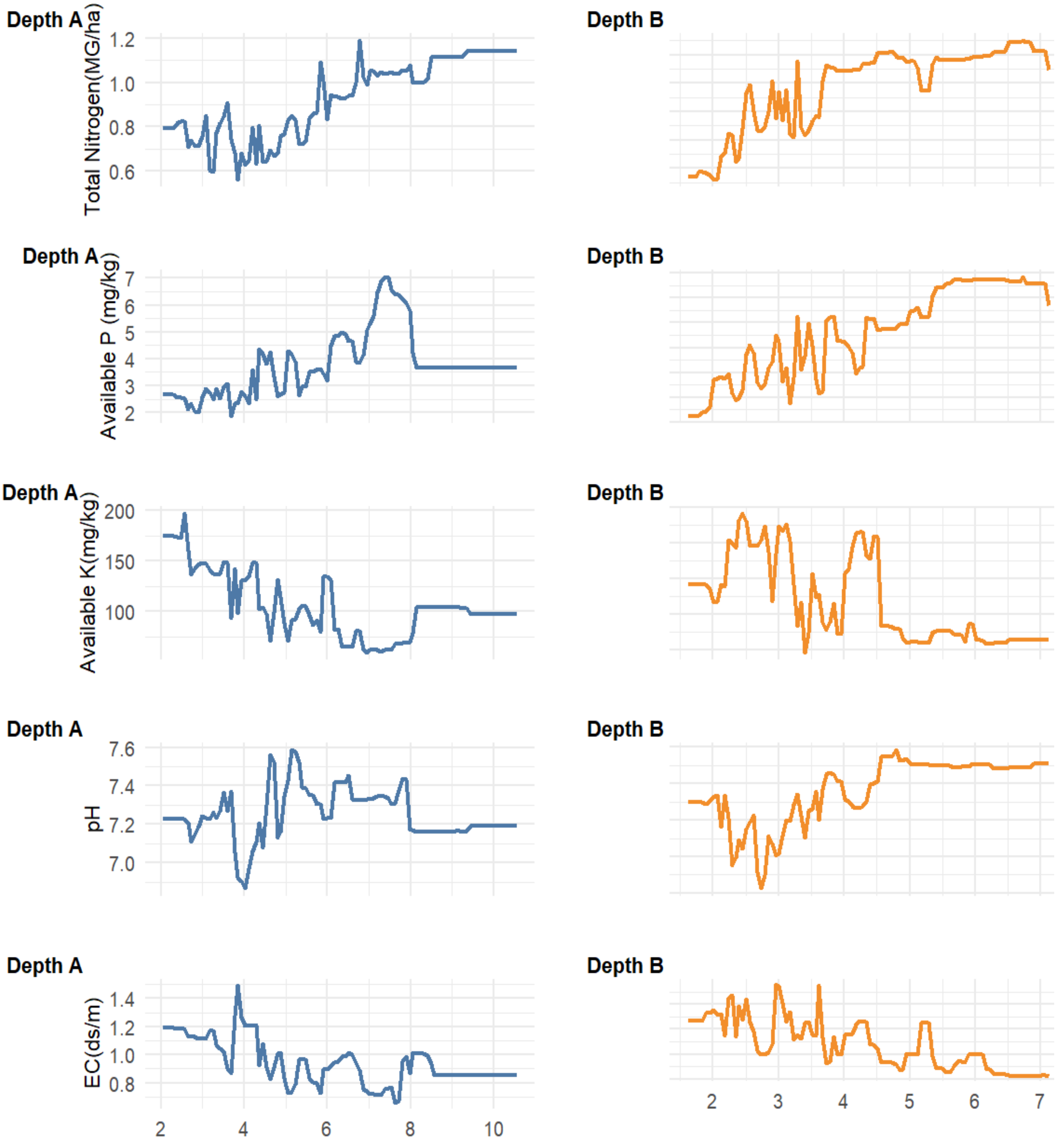


Fig. 3. Partial Dependence Plots (PDPs) from RF model for all soil variables across soil depths A and B.

The analysis also yielded partial dependence plots (PDPs) for visualising the non-linear trends among variables of interest for both models. Partial Dependence Plots from XGBoost indicated that soil N exhibited an increasing trend with the increase in PyC and peaked around 6-7 MG ha^{-1} and 3-4 MG ha^{-1} of PyC for depth A and B, respectively. Soil P achieved maximum values when PyC concentrations were 5-6 MG ha^{-1} against depth A and 3-3.5 MG ha^{-1} against depth B. Soil K showed a decreasing trend and its predicted values were the highest between 5-6 MG ha^{-1} of PyC at depth A and 3.5-4.0 MG ha^{-1} of PyC at depth B. Soil pH peaked when PyC readings were 5-6 MG ha^{-1} at depth A and 4-5 MG ha^{-1} at depth B. Soil EC didn't increase with increasing PyC and peaked at relatively lower concentrations of PyC (Fig. 2). The PDPs generated from RF indicated that with increase in PyC soil N stocks showed the increasing trend. Nitrogen stocks peaked When values of PyC were within range of 6-7 MG ha^{-1} at both depths. Soil P stocks also exhibited an increasing trend, with predicted values peaking at PyC levels of 7–8 Mg ha^{-1} at depth A and 6–7 Mg ha^{-1} at depth B. Potassium stocks predicted using the RF model showed a decreasing trend, indicating no significant influence of PyC. They peaked at comparatively lower PyC concentrations at both depths and declined with increasing PyC. The highest predicted values of soil pH were observed when PyC stocks ranged from 5-6 MG ha^{-1} at depth A and 4-5 MG ha^{-1} at depth B. Electrical conductivity values obtained from RF model were highest at the lower concentration of PyC (Fig. 3). The inconsistencies in PDP curves indicate that relationships among variables were complex and may involve other factors too, which are discussed in section 4.

Application of RF algorithm on seedlings and saplings data yielded better results compared to XGBoost model. Overall seedlings and saplings showed a weak dependency on PyC. Pyrogenic carbon concentrations at depth A merely explained variation in density of seedlings with R^2 values of 0.19 for XGBoost and 0.26 for RF model. Seedlings did not exhibit any dependency on PyC at depth B as the R^2 values were the lowest. Saplings on the other exhibited much stronger dependency on PyC across both depths with higher R^2 values from RF model observed as 0.31 against depth A and 0.36 against depth B (Table 2).

Predicted values of seedlings through RF model were highest when PyC values ranged between 5-6 MG ha^{-1} at depth A and 3.5-4 MG ha^{-1} at depth B while saplings were recorded the highest when PyC ranged from 7-8 MG ha^{-1} against depth A and 6.5-7 MG ha^{-1} at depth B (Fig. 4). Partial dependence plots from XGBoost model showed that seedlings numbers per hectare peaked with PyC values ranging from 5-6 MG ha^{-1} at depth A and 4.5-5 MG ha^{-1} at depth B. Predicted values for saplings were the highest when PyC was 2-3 MG ha^{-1} at depth A and 6.5-7 MG ha^{-1} at depth B (Fig. 5).

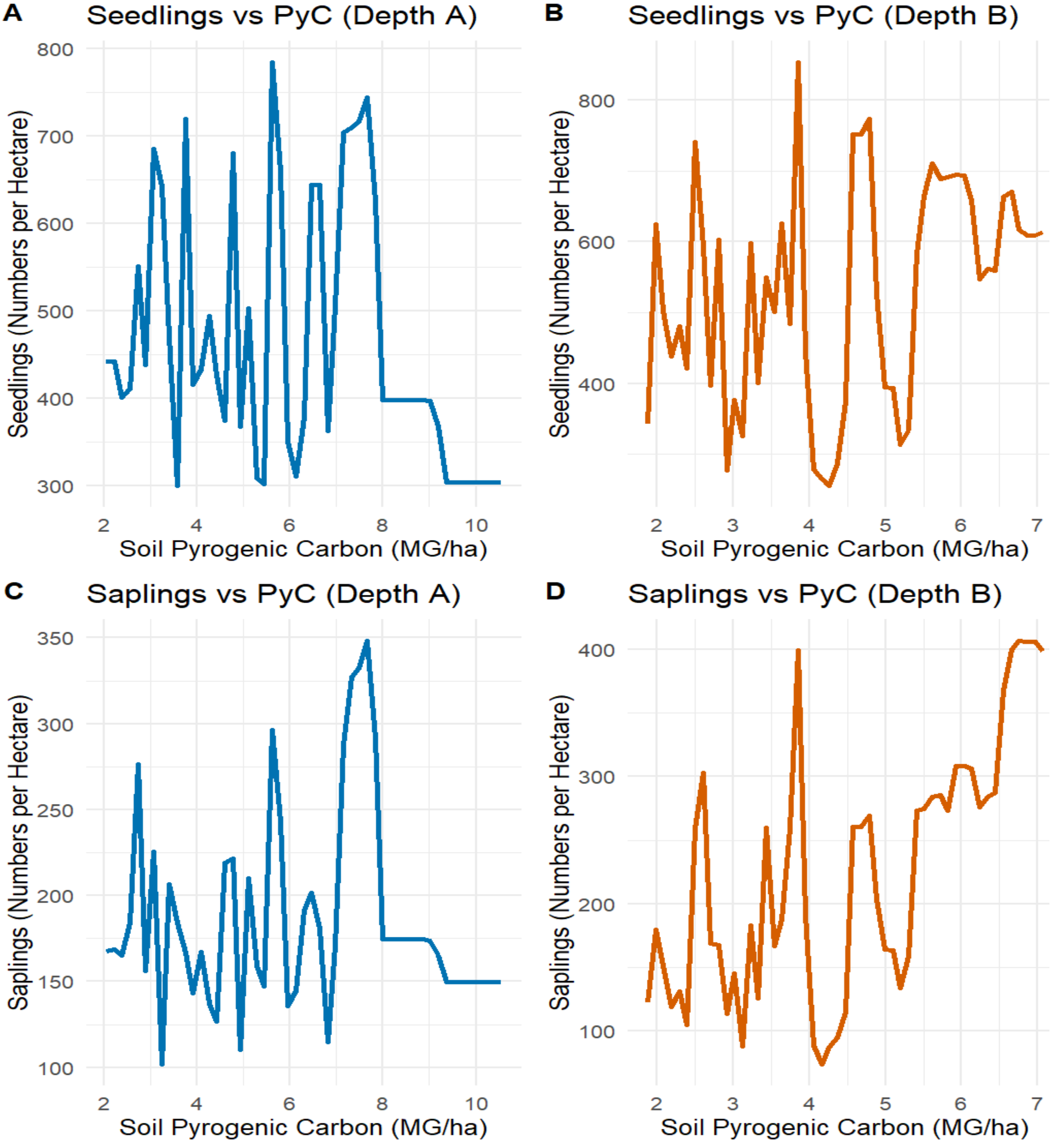


Fig. 4. Partial Dependence Plots (PDPs) from RF model for regeneration stock at depths A and B.

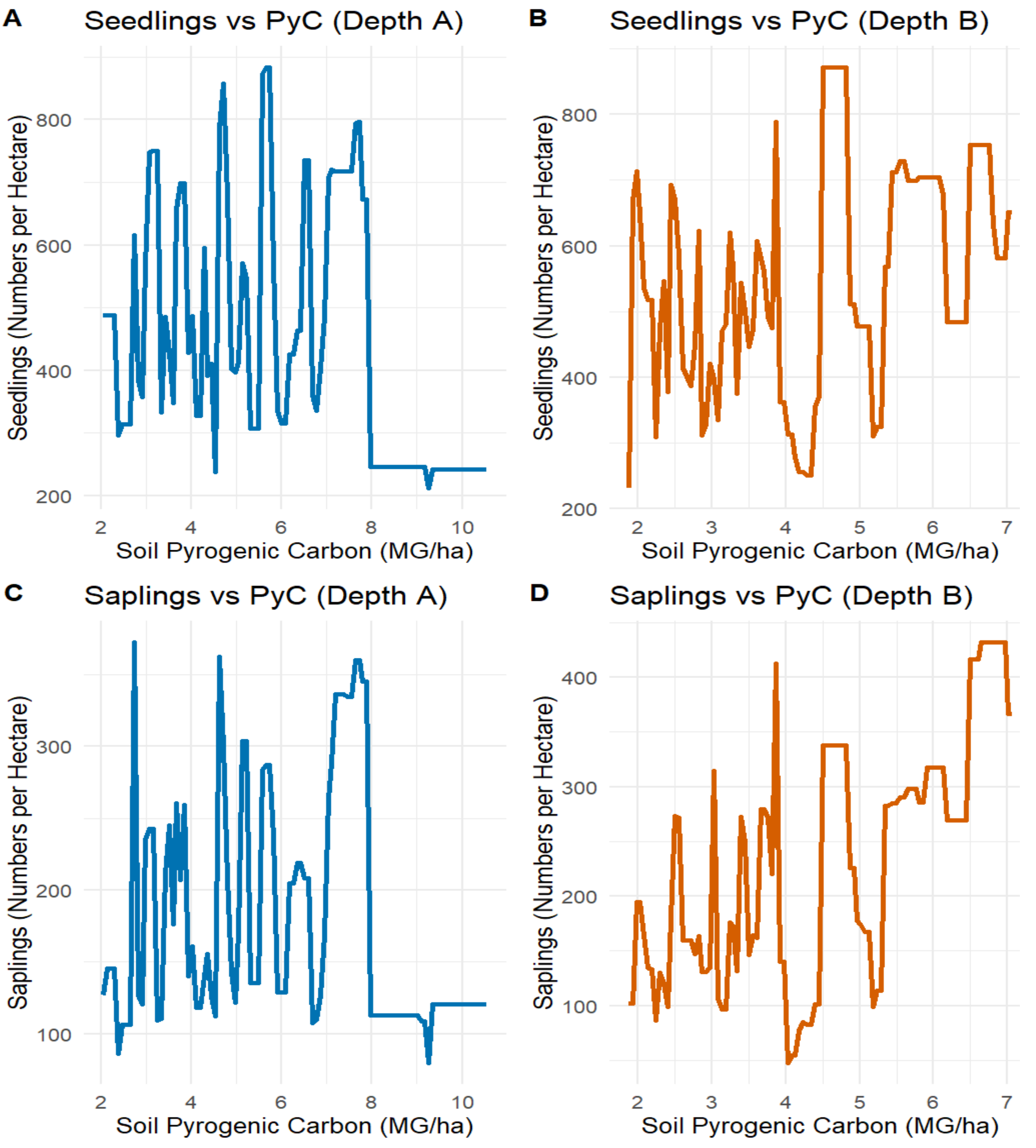


Fig. 5. Partial Dependence Plots (PDPs) from gradient boost (xgboost) for regeneration stock at soil depths A and B.

Discussion

Present study is first of its kind to report PyC-soil relationships in Himalayan subtropical pine forests ecosystem. We employed systematic sampling and ensemble-learning techniques based on artificial intelligence to investigate the effects of persisting PyC quantities on selected soil variables in wildfire affected pine forests. Pyrogenic carbon stock inventories from both sites exhibited a decrease with increasing depth and this observed decrease could be attributed to the fact that in fire prone forested ecosystems most of PyC detected in soil mineral horizons comes from the charring of organic layer and above ground biomass. The PyC later on adds up to mineral soil horizon through bioturbations (Santin *et al*., 2020). Consequently, PyC's vertical movement in soil is hindered by decreasing soil porosity in these forests as the clay content increases with depth resulting in less porous and more compacted soils below (Kumar *et al*., 2013). The observed decrease in PyC with increasing depth has been recorded in French coniferous forests (Soucémarianadin, *et al*., 2019), boreal forests of northeast China (Huang *et al*., 2018), Southeastern Australia (Wang *et al*., 2017), ponderosa pine dominated ecosystems of pacific northwest (Jauss *et al*., 2015) and temperate forests of northern China (Shi *et al*., 2025).

We found a significant relationship between PyC and N in the study area. The presence of significant relationships could be attributed to PyC's observed role in nitrogen cycling/nitrogen enhancement. Pyrogenic carbon induced nitrogen mobilization could be through adsorption of non-polar organic compounds (Klaus & Gundersen, 2011; Pingree & De Luca, 2017), formation of covalent bond with ammonia gas (NH_3), physical sorption or electrostatic interactions or precipitation of ammonium salts (Hestrin *et al.*, 2019). Our findings are consistent with previous studies under pine-dominated ecosystems where investigators studied post fire PyC-N dynamics on intermediate and long-term basis and recorded significant increase in ammonification nitrification and nitrogen mineralization (DeLuca *et al.*, 2006; Michelotti & Miesel, 2015). It is also worth mentioning here that PyC did not exhibit any significant effect on soil N pools on short term or immediate basis even after the observed enhanced enzyme activity (Stirling *et al.*, 2019; Lasota *et al.*, 2022).

The available P stocks increased with higher concentrations of PyC in soil profile horizontally and vertically. The PyC driven variation in P could be due to the fire driven biogeochemical shifts resulting in P rich soil-plant systems (Butler *et al.*, 2018). Pyrogenic carbon being common phenomenon in these ecosystems facilitates the availability of P as addition of PyC tends to enhance the sorption of P onto the sediments and the sorption capacity of P increases with the further increase in PyC concentrations (Zhang *et al.*, 2019). Our findings are consistent with numerous previous studies with observed enhancements or alterations in soil phosphorous levels in response to PyC additions although the effects varied based on fire histories and time since last fire and soil type (Makoto *et al.*, 2011; Borchard *et al.*, 2014; Mastrolonardo *et al.*, 2019; Dou *et al.*, 2025).

The Pyrogenic carbon and K relationship dynamics can be best explained by the porous nature of PyC which traps the water soluble K in soil (Paramisparam *et al.*, 2021). The increase in bio-available K happens immediately after the addition of PyC in two to six weeks period and the effect may fade with time due to leaching and active utilization of nutrients by plants justifying the weak relationship observed in our study (Li *et al.*, 2018). Borchard *et al.*, (2014) documented altered K levels against natural additions of PyC in Beech forests of Germany. Our findings are also supported by numerous other studies where investigators noted altered or significantly enhanced levels of soil K under natural settings (Mastrolonardo *et al.*, 2019; Gale & Thomas, 2021).

We did not find any significant relationship between PyC and soil pH. The lack of any significant effect of PyC on soil pH can be due the post fire leaching down of cations in these forests (Mastrolonardo *et al.*, 2019). Pyrogenic carbon and soil pH relationships have been studied extensively on the global scale and majority of the studies focused on alterations in soil pH in response to the application of PyC in laboratory or immediately after wildfires yielding conflicting results (Makoto *et al.*, 2011; Borchard *et al.*, 2014; Bryanin *et al.*, 2022). Significant changes in the behaviour of soil pH were recorded as a feedback to different concentration regimes of PyC and its physio-chemical properties (Gale & Thomas, 2021). It was noted that pH is more prone to changes when higher frequency of PyC amendments is added to soil as compared to additions with lower frequency (Wang *et al.*, 2017). The argument itself validates our results endorsing the fact that PyC do not affect the soil pH in long run and hence changes in soil pH in response to PyC applications are immediate and short lived which are harder to observe on spatial scale. Under natural settings on landscape scale, our results are consistent with a field study by Mastrolonardo *et al.*, (2019) from beech and birch forests of Belgium.

Pyrogenic carbon and soil EC relationships have been studied globally and most of the studies observed the immediate responses of soil salinity to PyC applications in the laboratory and in the field as well. Since, our study involved spatial component with complete disregard of time after PyC application therefore our results suggest no effect on soil EC in the long-run, since soil EC is controlled by a number of factors including weathering of rocks/parent material, soil drainage and wind borne salts yielding (Shabbir *et al.*, 2023), hence PyC-EC lack of correlation is plausible. Qi *et al.*, (2017) carried out a study in South Australian soils and found no robust correlation existing between PyC and soil EC endorsing our study findings.

The reported weak dependency of pine regeneration stock (seedlings and saplings) on PyC could be due to the enhanced levels of soil phosphorous (P) and water availability, which collectively help in the sprouting and establishment of regeneration (Makoto *et al.*, 2011). The findings from our experiment are consistent with Choi *et al.*, (2009) where elevated germination rates were observed in forest soils amended with charcoal (PyC) carbon in *Pinus densiflora* seedbeds. Makoto *et al.*, (2011) reported existence of positive correlation among *Larix gmelinii*/*Pinus sylvestris* number of seedlings and PyC stating it played significant contribution towards pine regeneration.

In a similar study by Makoto *et al.*, (2011), the application of charcoal enhanced the growth of Gamelin larch seedlings. Situmorang (2021) observed positive effect of charcoal PyC application on height and diameter of *Pinus merkusii* seedlings. Gale & Thomas (2021) well explained the dependency of seedlings and saplings on PyC in a temperate boreal forest study design, which concluded that PyC had profound effect on the physiology and tree foliar nutrients during early five years of growth. Five-year-old tree saplings were affected by PyC heterogeneity and were therefore well adapted to fires and fire related products in the ecosystem.

Pyrogenic carbon effects on early stages of regeneration was also observed in a meta-analytical study (Thomas & Gale, 2015). Licht & Smith (2020) reported similar explanations through a study designed to investigate the effect of PyC on the growth and vigor of pitch pine seedlings in the northerly forests of USA and observed increased water use efficiency and photosynthetic rates.

Conclusions

Present study indicated that wildfire derived PyC stocks in Himalayan pine forests decreased with increase in soil depth. The increase in PyC amount proved to enhance soil N and P stocks. Soil pH, EC, and K, however, did not exhibit any remarkable dependency on PyC quantities. Overall, RF model performed better in modelling relationships among variables of interest. Pine seedlings and saplings showed a weak dependency on PyC owing to our experimental design, which involved a coarse systematic sampling. Our findings suggested that addition of wildfire derived PyC is a potentially effective in enhancing soil fertility and improving regeneration stocks. Long-term observational studies and regular monitoring can further improve land management practices through provision of reliable data to forest managers for sustainable management decisions.

Acknowledgement

We thank the Miesel Ecosystems Lab, Michigan State University, USA for assistance in developing expertise on PyC quantification. Access to online resources and logistical and technical help during data analysis was provided by the Safford Lab, University of California, Davis, USA. The study was partially funded by the Higher Education Commission, Pakistan, under International Research Support Initiative Program (IRSIP). We are thankful to the reviewers for their insightful feedback, which helped improve our manuscript.

Authors Contribution: Planning and execution of the study: WU, SG, MIA. Research supervision: SG, MIA. Data acquisition, analysis, and interpretation: WU, AK, KD. Write-up of initial draft: WU, MIA. Review of final draft: WU, SG, MIA, AK, KD.

Conflict of Interest: The authors declare no conflict of interest.

References

Abney, R.B., L. Jin and A.A. Berhe. 2019. Soil properties and combustion temperature: Controls on the decomposition rate of pyrogenic organic matter. *Catena*, 182: 104127.

Amir, M., S. Saeed, X.D. Liu, A. Mannan, A. Khan, Z.Z. Li and M.A. Muneer. 2019. Soil organic content of stands of different ages in a subtropical Chir pine (*Pinus roxburghii*) forest of Pakistan. *Appl. Ecol. Environ. Res.*, 17(5): 11475-11487.

Ali, S., S.M. Khan, Z. Siddiq, Z. Ahmad, K.S. Ahmad, A. Abdullah and E.F. Abd_Allah. 2022. Carbon sequestration potential of reserve forests present in the protected Margalla Hills National Park. *J. King Saud Univ. Sci.*, 34(4): 101978.

Ali, F. 2014. Tectonic evolution of the Margalla Hills and a part of the southeastern Hazara Ranges, Pakistan. Ph. D. Thesis, University of Peshawar, Pakistan.

Aryal, B., B.P. Bhattarai, M. Pandey and A. Giri. 2018. Impact of forest floor fire on soil carbon sequestration of *Pinus roxburghii* forest in Langtang National Park, Nepal. *J. Nat. Hist. Mus.*, 30: 148-163.

Archibald, S., C.E. Lehmann, J.L. Gómez-Dans and R.A. Bradstock. 2013. Defining pyromes and global syndromes of fire regimes. *Proc. Natl. Acad. Sci.*, 110(16): 6442-6447.

Bargali, H., L.P.P. Calderon, R.C. Sundriyal and D. Bhatt. 2022. Impact of forest fire frequency on floristic diversity in the forests of Uttarakhand, western Himalaya. *Trees, For. People.*, 9: 100300.

Bhatti, M.F., M.I. Ashraf, Z. Masoom and S.U. Malik. 2017. Impact of industrial effluents on growth of dominant tree species of Islamabad, Pakistan. *Pak. J. Bot.*, 49(5): 1833-1839.

Borchard, N., B. Ladd, S. Eschemann, D. Hegenberg, B.M. Möseler and W. Amelung. 2014. Black carbon and soil properties at historical charcoal production sites in Germany. *Geoderma*, 232: 236-242.

British Columbia Ministry of Forests, Lands, Natural Resource Operations and Rural Development. 2018. Vegetation resources inventory: Ground sampling procedures. Resources Information Standards Committee, Forest Analysis and Inventory Branch, Version 5.5, Eberswalde, Germany. Available at: Government of British Columbia – VRI Procedures PDF.

Butler, O.M., J.J. Elser, T. Lewis, B. Mackey and C. Chen. 2018. The phosphorus-rich signature of fire in the soil–plant system: a global meta-analysis. *Ecol. Lett.*, 21(3): 335-344.

Butterbach-Bahl, K., P. Gundersen, P. Ambus, J. Augustin, C. Beier, P. Boeckx and S. Zechmeister-Boltenstern. 2011. Nitrogen processes in terrestrial ecosystems. In: (Eds.): Sutton, M.A., C.M. Howard, J.W. Erisman, G. Billen, A. Bleeker, P. Grennfelt, H. van Grinsven and B. Grizzetti (Eds.), *The European Nitrogen Assessment: Sources, Effects and Policy Perspectives*. Cambridge University Press, Cambridge, pp. 99-125.

Butsic, V., D.J. Lewis, V.C. Radeloff, M. Baumann and T. Kuemmerle. 2017. Quasi-experimental methods enable stronger inferences from observational data in ecology. *Basic Appl. Ecol.*, 19: 1-10.

Bryanin, S.V., A.V. Danilov, E.S. Susloparova and A.V. Ivanov. 2022. Pyrogenic carbon pools of the upper amur region. *Contemp. Probl. Ecol.*, 15(7): 777-786.

Carter, M.R. and E.G. Gregorich. 2007. *Soil sampling and methods of analysis*. 2nd ed. CRC Press, Boca Raton, Florida.

Choi, D., K. Makoto, A.M. Quoreshi and L. Qu. 2009. Seed germination and seedling physiology of *Larix kaempferi* and *Pinus densiflora* in seedbeds with charcoal and elevated CO_2. Landsc. *Ecol. Eng*., 5: 107-113.

Cools, N. and B. De Vos. 2016. Part X: Sampling and analysis of soil. In: Manual on methods and criteria for harmonized sampling, assessment, monitoring and analysis of the effects of air pollution on forests. Thünen Institute of Forest Ecosystems, Eberswalde, Germany, pp. 1-29.

Chandran, M., A.R. Sinha and R.B.S. Rawat. 2011. Replacing controlled burning practice by alternate methods of reducing fuel load in the Himalayan Long leaf Pine (*Pinus roxburghii* Sarg.) forests. In *5th International Wildland Fire Conference*, South Africa.

Chen, T. and C. Guestrin. 2016. XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785-794.

DeLuca, T.H., M.D. MacKenzie, M.J. Gundale and W.E. Holben. 2006. Wildfire-produced charcoal directly influences nitrogen cycling in ponderosa pine forests. *Soil Sci. Soc. Amer. J.*, 70(2): 448-453.

DeYoung, J. 2016. *Forest measurements: An applied approach*. Open Oregon Educational Resources, Mt. Hood Community College, Gresham, Oregon. Dodge, Y. 2008. The concise encyclopedia of statistics. Springer Science & Business Media.

Dou, X., J. Wang, K. Köster, C. Yu, Y. Ren, L. Sun and T. Hu. 2025. The role of pyrogenic carbon addition after wildfires in the boreal forest of China: Impact on plant–soil–microbial ecological stoichiometry. *Geoderma*, 455:117237.

Ellis, S., D.M. Taylor and K.R. Masood. 1994. Soil formation and erosion in the Murree Hills, Northeast Pakistan. *Catena*, 22: 69-78.

Fox, T.R., B.W. Miller, R. Rubilar, J.L. Stape and T.J. Albaugh. 2011. Phosphorus nutrition of forest plantations: The role of inorganic and organic phosphorus. In: (Eds.): E. Bünemann, A. Oberson and E. Frossard. *Phosphorus in action: Biological processes in soil phosphorus cycling*. Springer, Berlin, Heidelberg, pp. 317-338.

Fule, P.Z., S.C. Garkoti and R.L. Semwal. 2021. Frequent burning in chir pine forests, Uttarakhand, India. *Fire Ecol.*, 17(1): 1-11.

Gale, N.V. and S.C. Thomas. 2021. Spatial heterogeneity in soil pyrogenic carbon mediates tree growth and physiology following wildfire. *J. Ecol.*, 109(3): 1479-1490.

Garcia, M., M.L. Pettinari, E. Chuvieco, J. Salas, F. Mouillot, W. Chen and I. Aguado. 2022. Characterizing global fire regimes from satellite-derived products. *Forests*, 13(5): 699.

Gundale, M.J. and T.H. DeLuca. 2006. Temperature and source material influence ecological attributes of ponderosa pine and Douglas-fir charcoal. *For. Ecol. Manage.*, 231(1-3): 86-93.

Gupta, B., R. Mehta and V.K. Mishra. 2009. Fire ecology of ground vegetation in *Pinus roxburghii* Sargent plantations in North-West Himalaya—floristic composition and species diversity. *Casp. J. Environ. Sci*., 7(2): 71-78.

Gogoi, L., R. Narzari, N. Gogoi, M. Farooq and R. Kataki. 2019. Biochar production and application in forest soils-a critical review. *Phyton*, 88(4): 349.

Hussain, A., M.I. Ashraf, S. Hussain, M. Atif and B.A. Khan. 2024. Impacts of wildfire on soil characteristics in subtropical Chir Pine forests of Murree, Pakistan. *Int. J. Appl. Exp. Biol*., 3(1): 61-67.

Huang, W., Y. Hu, Y. Chang, M. Liu, Y. Li, B. Ren and S. Shi. 2018. Effects of fire severity and topography on soil black carbon accumulation in boreal forest of Northeast China. *Forests*, 9(7): 408.

Hestrin, R., D. Torres-Rojas, J.J. Dynes, J.M. Hook, T.Z. Regier, A.W. Gillespie and J. Lehmann. 2019. Fire-derived organic matter retains ammonia through covalent bond formation. *Nat. Commun.*, 10(1): 1-8.

Horneck, D.A. and R.O. Miller. 2019. Determination of total nitrogen in plant tissue. In: (Ed.): Kalra, Y.P. *Handbook of reference methods for plant analysis*. CRC Press, Boca Raton, Florida, pp. 75-83.

Isaac, R.A. and W.C. Johnson. 1976. Determination of total nitrogen in plant tissue, using a block digestor. *J. Assoc. Off. Anal. Chem.*, 59(1): 98-100.

Jauss, V., M. Johnson, E. Krull, M. Daub and J. Lehmann. 2015. Pyrogenic carbon controls across a soil catena in the Pacific Northwest. *Catena*, 124: 53-59.

Khan, K.A., S. Khan, M. Ahtasham, S.U. Malik, M. Saleem and M.I. Ashraf. 2022. Influence of tree species on soil characteristics in subtropical forest ecosystem: a case study in North-West Pakistan. *Soil Environ.*, 41(2): 135-141.

Kumar, R. and R. Pandey. 2022. Analyzing the impact of burning on vegetation in Himalayan chir pine (*Pinus roxburghii* Sarg.) forests, India. *Appl. Ecol. Environ. Res.*, 20(2).

Kumar, S., Meenakshi, G. Das Bairagi, Vandana and A. Kumar. 2015. Identifying triggers for forest fire and assessing fire susceptibility of forests in Indian western Himalaya using geospatial techniques. *Nat. Hazards*, 78: 203-217.

Kumar, M., H. Singh, J.A. Bhat and G.S. Rajwar. 2013. Altitudinal variation in species composition and soil properties of Banj Oak and Chir Pine dominated forests. *J. For. Environ. Sci.*, 29(1): 29-37.

Kurth, V.J., M.D. MacKenzie and T.H. DeLuca. 2006. Estimating charcoal content in forest mineral soils. *Geoderma*, 137(1-2): 135-139.

Lasota, J., T. Babiak and E. Błońska. 2022. C: N: P stoichiometry associated with biochar in forest soils at historical charcoal production sites in Poland. *Geoderma Reg.*, 28: e00482.

Li, Y., S. Hu, J. Chen, K. Müller, Y. Li, W. Fu and H. Wang. 2018. Effects of biochar application in forest ecosystems on soil properties and greenhouse gas emissions: A review. *J. Soils Sediments*, 18(2): 546-563.

Liaw, A. and M. Wiener. 2002. Classification and regression by randomForest. *R News*, 2(3): 18-22. Retrieved from https://CRAN.R-project.org/doc/Rnews/.

Licht, J. and N.G. Smith. 2020. Pyrogenic carbon increases pitch pine seedling growth, soil moisture retention, and photosynthetic intrinsic water use efficiency in the field. *Front. For. Glob. Change*, 3(31): 1-10.

Makoto, K., D. Choi, Y. Hashidoko and T. Koike. 2011. The growth of *Larix gmelinii* seedlings as affected by charcoal produced at two different temperatures. *Biol. Fertil. Soils*, 47: 467-472.

Mastrolonardo, G., C. Calderaro, C. Cocozza, B. Hardy, J. Dufey and J.T. Cornelis. 2019. Long-term effect of charcoal accumulation in hearth soils on tree growth and nutrient cycling. *Front. Environ. Sci.*, 7: 51.

Metson, A.J. 1956. Methods of chemical analysis for soil survey samples. New Zealand Soil Bureau Bulletin No. 12. Department of Scientific and Industrial Research, Wellington, New Zealand.

Michelotti, L.A. and J.R. Miesel. 2015. Source material and concentration of wildfire-produced pyrogenic carbon influence post-fire soil nutrient dynamics. *Forests*, 6(4): 1325-1342.

Michelotti, L.A. and J.R. Miesel. 2015. Source material and concentration of wildfire-produced pyrogenic carbon influence post-fire soil nutrient dynamics. *Forests*, 6(4): 1325-1342.

Neina, D. 2019. The role of soil pH in plant nutrition and soil remediation. *Appl. Environ. Soil Sci.*, 2019.

Olsen, S.R. and L.E. Sommers. 1982. Phosphorus. In: (Ed.): Page, A.L., *Methods of soil analysis. Part 2: Chemical and microbiological properties*. American Society of Agronomy and Soil Science Society of America, Madison, Wisconsin, pp. 403-430.

OriginLab Corporation. 2024. OriginPro (Version 2024) [Computer software]. OriginLab Corporation, Northampton, MA, USA. Available at: https://www.originlab.com

Palmer, C.J., W.D. Smith and B.L. Conkling. 2002. Development of a protocol for monitoring status and trends in forest soil carbon at a national level. *Environ. Pollut.*, 116: S209-S219.

Paramisparam, P., O.H. Ahmed, L. Omar, H.Y. Ch'ng, P.D. Johan and N.H. Hamidi. 2021. Co-application of charcoal and wood ash to improve potassium availability in tropical mineral acid soils. *Agronomy*, 11(10): 2081.

Pingree, M.R. and T.H. DeLuca. 2017. Function of wildfire-deposited pyrogenic carbon in terrestrial ecosystems. *Front. Environ. Sci.*, 5: 53.

Piovesana, A. and G. Senior. 2018. How small is big: Sample size and skewness. *Assessment*, 25(6): 793-800.

Prokopy, W.R. 1995. QuikChem Method 12-115-01-1-C.

Qi, F., R. Naidu, N.S. Bolan, Z. Dong, Y. Yan, D. Lamb and K.T. Semple. 2017. Pyrogenic carbon in Australian soils. *Sci. Total Environ.*, 586: 849-857.

R Core Team. 2020. R: *A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. Available at: https://www.R-project.org/.

Rahman, A., E. Gürbüz, S. Ekercin and S.M. Khan. 2022. Spatial dynamics of forest cover and land use changes in the western Himalayas of Pakistan. *Vegetation Index and Dynamics*, 193.

Reyes, O., J. Kaal, D. Arán, R. Gago, J. Bernal, J. García-Duro and M. Basanta. 2015. The effects of ash and black carbon (biochar) on germination of different tree species. *Fire Ecol.*, 11(1): 119-133.

Rhoades, J.D. 1982. Soluble salts. In: (Ed.): Page, A.L., *Methods of soil analysis*. Part 2. American Society of Agronomy, Madison, Wisconsin, pp. 167-179.

Shabbir, S., Q. Nazir, I. Saleem, R. Naz, S. Azhar, M. Rafay and M. Usman. 2023. Soil salinity hinders plant growth and development and its remediation-A review. *J. Agric. Res.*, 61(3): 189-200.

Shah, S., D.P. Sharma, P. Tripathi and N.A. Pala. 2014. Carbon partitioning in subtropical *Pinus roxburghii* forest, Solan, India. *J. Trop. For. Sci.*, 26(3): 355-361.

Shi, L., Y. Peng, X. Hou and Y. Zhang. 2025. Distribution of pyrogenic carbon in the soil of a cold temperate coniferous forest 13 years after a severe wildfire. *Land.*, 14(4): 851.

Sardans, J. and J. Peñuelas. 2015. Potassium: a neglected nutrient in global change. *Glob. Ecol. Biogeogr.*, 24(3): 261-275.

Santin, C., S.H. Doerr, M.W. Jones, A. Merino, C. Warneke and J.M. Roberts. 2020. The relevance of pyrogenic carbon for carbon budgets from fires: Insights from the FIREX experiment. *Glob. Biogeochem. Cycles*, 34(9): e2020GB006647.

Sharma, U., R. Kaushal and Y.P. Sharma. 2022. Effect of forest fires on soil carbon dynamics in different land uses under NW Himalayas. *Indian J. Ecol.*, 49(6): 2322-2329.

Shahid, S.A. and M. Zaman. 2018. Introduction to soil salinity, sodicity and diagnostics techniques. In: *Guideline for Salinity Assessment, Mitigation and Adaptation Using Nuclear and Related Techniques* (pp. 1-42). Springer, Cham.

Sheikh, M.A., S. Kumar and M. Kumar. 2012. Above and below ground organic carbon stocks in a sub-tropical *Pinus roxburghii* Sargent forest of the Garhwal Himalayas. *For. Stud. China*, 14(3): 205-209.

Singh, R.D., S. Gumber, R.C. Sundriyal, J. Ram and S.P. Singh. 2023. Chir pine forest and pre-monsoon drought determine spatial and temporal patterns of forest fires in Uttarakhand Himalaya. *Trop. Ecol*., 64(1): 1-11.

Situmorang, M.T.N. 2021. The effect of regosol soil mixed media, charcoal powder, and manure on the seedling growth of pine (*Pinus merkusii* Jungher de Vrieser). *J. Perbenihan Tanam. Hutan.*, 9(2): 143-156.

Stirling, E., R.J. Smernik, L.M. Macdonald and T.R. Cavagnaro. 2019. The effect of fire affected *Pinus radiata* litter and char addition on soil nitrogen cycling. *Sci. Total Environ.*, 664: 276-282.

Siddiqui, M.F., M. Ahmed, M. Wahab, N. Khan, M.U. Khan, K. Nazim and S.S. Hussain. 2009. Phytosociology of *Pinus roxburghii* Sargent (chir pine) in lesser Himalayan and Hindu Kush range of Pakistan. *Pak. J. Bot.*, 41(5): 2357-2369.

Soucémarianadin, L., M. Reisser, L. Cécillon, P. Barré, M. Nicolas and S. Abiven. 2019. Pyrogenic carbon content and dynamics in top and subsoil of French forests. *Soil Biol. Biochem.*, 133: 12-15.

Thomas, S. C. and N. Gale. 2015. Biochar and forest restoration: A review and meta-analysis of tree growth responses. *New For*., 46(5): 931-946.

United States Salinity Laboratory Staff. 1954. Diagnosis and improvement of saline and alkali soils (USDA Handbook No. 60). United States Department of Agriculture.

Vadrevu, K.P., E. Ellicott, L. Giglio, K.V.S. Badarinath, E. Vermote, C. Justice and W.K. Lau. 2012. Vegetation fires in the Himalayan region-Aerosol load, black carbon emissions and smoke plume heights. *Atmos. Environ.*, 47: 241-251.

Wang, R., Y. Zhang, A. Cerdà, M. Cao, Y. Zhang, J. Yin and L. Chen. 2017. Changes in soil chemical properties as affected by pyrogenic organic matter amendment with different intensity and frequency. *Geoderma*, 289: 161-168.

Wulfsohn, D. 2010. Sampling techniques for plants and soil. In: (Eds.): Upadhyaya, S., K. Giles, S. Haneklaus and E. Schnug., Advanced engineering systems for specialty crops: A review of precision agriculture for water, chemical, and nutrient application, and yield monitoring. Landbauforschung vTI, Braunschweig, Germany, pp. 3-30.

Zhang, H.H., X.Y. Cao, H. Wang, Z. Ma, J. Li, L.M. Zhou and G.P. Yang. 2019. Effect of black carbon on sorption and desorption of phosphorus onto sediments. *Mar. Pollut. Bull.*, 146: 435-441.