

The Relationship Between SOC and Soil Properties in Igneada Floodplain Forests National Park (NW Türkiye)

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Abstract

Floodplain forests are important ecosystems for biodiversity conservation and carbon storage, yet the relationships between soil organic carbon (SOC), soil physicochemical properties, and floodplain hydrological conditions remain insufficiently quantified in many protected wetland forests. This study evaluated the relationship between SOC and selected soil properties in the Igneada Floodplain Forests National Park (IFFNP) in northwestern Türkiye. A total of 52 soil samples were collected from the study area and analyzed for salinity, pH, lime, nitrogen, phosphorus, potassium, calcium, magnesium, sodium, iron, copper, manganese, zinc, and soil texture. Organic matter was determined using the modified Walkley-Black wet combustion method, and SOC was calculated from organic matter using the conventional Van Bemmelen conversion factor. Spatial patterns of soil properties were mapped using kriging interpolation, and relationships among variables were evaluated using Principal Component Analysis and Pearson correlation analysis. The first two principal components explained 62.16% of the total variance. PC1 was negatively correlated with SOC, whereas PC2 was positively correlated with SOC, indicating that SOC distribution was associated with a combined gradient of chemical and textural soil properties. Spatial maps showed that SOC and nitrogen tended to increase around wet and hydrologically influenced zones, particularly around Mert Lake. The results indicate that salinity, pH, magnesium, calcium, and textural characteristics are important factors associated with SOC variability in the study area. The results provide site-specific information for carbon-oriented soil conservation and floodplain ecosystem management.

Keywords: Igneada Floodplain, soil properties, SOC, GIS, PCA.



Received: 30/10/2025,

Accepted: 27/07/2026,

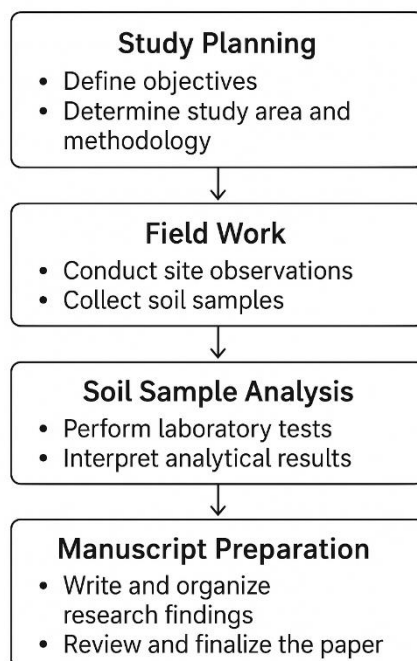
Available online: 01/08/2026

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Graphical abstract

Research Workflow:



1. Introduction

Floodplain forests are among the most dynamic, productive, and diverse forests in the world (Tockner and Stanford, 2002; Acosta *et al.*, 2017) and are one of the most endangered forest ecosystems (Valtera *et al.*, 2021). These ecosystems typically form in areas with high water levels, waterlogged soils, or areas subjected to flooding during certain times of the year (Kavgacı *et al.*, 2016). Although floodplain forests are often referred to as forests formed in temperate climate zones (Machar *et al.*, 2018; Machar, 2021), they are also found in many regions of the world (Tockner and Stanford, 2002; Romano, 2010; Flores *et al.*, 2017; Isaev and Demakov, 2023; Myster, 2025).

Several factors make floodplain forests important (Oswalt and King, 2005; Kowalska *et al.*, 2020). These factors include carbon sequestration capacity (Lininger and Polvi, 2020; Heger *et al.*, 2021; Scheunemann and Russell, 2023; Sarıyıldız and Tanı, 2024), biodiversity (Stammel *et al.*, 2022; Kra *et al.*, 2025), forestry (Schöngart, 2008; Sarıyıldız, 2024), hunting and fishing (Schöngart, 2008), and social activities (Ünal *et al.*, 2012; Dumlu and İhtiyar, 2017). Factors threatening floodplain forests, which are notable for their benefits, include habitat changes (Tockner and Stanford, 2002; Acosta *et al.*, 2017), temperature increase (Havrdová *et al.*, 2025) and the associated climate change (Jandl *et al.*, 2019; Kovařík *et al.*, 2025; Lenk *et al.*, 2024; Teng *et al.*, 2025) and pests and pathogens that threaten vegetation and soil.

These benefits and threats have prompted the study of floodplain forests in different disciplines (Rood *et al.*, 2005; Bozkaya *et al.*, 2015; Isaev and Demakov, 2023; Kovařík *et*

al., 2025; Myster, 2025). Forest protection, one of the fundamental components of floodplain forests, is essential for ecological area planning (Sürmen *et al.*, 2023). Therefore, soil and soil properties associated with forest ecosystems have been the subject of many studies (Wright *et al.*, 2001; Gallardo, 2003; Tecimen and Kavgacı, 2010; Kuschik-Maczollek *et al.*, 2024; Rychtecká *et al.*, 2023; Lenk *et al.*, 2024). This is because soil plays an important role in forest development and the carbon cycle (Ricker and Lockaby, 2015; Heger *et al.*, 2021). In addition, Gallardo (2003) stated that, in temperate wetland forests affected by flooding, floods can cause differences in soil properties by affecting biological and geochemical processes.

Soil Organic Carbon (SOC) sequestration is important for soil quality (Zhang *et al.*, 2025). This is because SOC has a positive effect on plant and soil productivity (Wu *et al.*, 2024). SOC, which also has a significant role in the global carbon cycle, plays an important role in combating climate change with an annual potential of 0.79-1.54 Gt (Yin *et al.*, 2025). Fluctuations in SOC dynamics are influenced by climatic conditions and vegetation cover (Wen *et al.*, 2025). Similarly, changes in SOC levels may also have uncertain effects on atmospheric CO₂ and the global carbon cycle (Wu *et al.*, 2024).

Recent advances in data acquisition and environmental monitoring have expanded the toolkit available for soil and land-use analysis. Remote sensing-based scene image classification, for example, has become increasingly effective in extracting land-cover information from satellite imagery, with deep transfer learning approaches such as the AI-Biruni Earth Radius

Optimization framework demonstrating strong performance in distinguishing forest, agricultural, and urban environments from high-resolution imagery (Sivasubramanian *et al.*, 2025), and vision-based deep learning systems enabling detailed phenological monitoring of crops such as coffee flowers (Sivasubramanian *et al.*, 2026). Similarly, Internet of Things (IoT)-enabled sensor networks and cloud-integrated platforms have enabled continuous, real-time collection of soil parameters such as moisture, pH, and nutrient content, supporting data-driven decision making in precision agriculture (Balaji *et al.*, 2026; Selvanarayanan *et al.*, 2024). Blockchain-based monitoring systems combining IoT sensing with decentralized data storage have further improved data integrity and traceability in field-scale agricultural applications (Vinayagam *et al.*, 2025). Although these technologies have been primarily developed in agricultural contexts, their underlying principles—spatial data integration, sensor-driven soil monitoring, and multivariate analysis—are directly relevant to ecosystem-scale soil carbon assessments in protected forest areas. The integration of such analytical frameworks with traditional field-based soil sampling offers promising directions for improving the spatial resolution and temporal continuity of SOC monitoring in floodplain ecosystems.

Despite increasing interest in carbon storage in floodplain and wetland forests, existing approaches to SOC assessment in forest ecosystems often rely on single-variable correlations or coarse-scale analyses that fail to capture local soil heterogeneity. Many studies focus primarily on agricultural or temperate upland soils, with limited attention to the specific hydrological and biogeochemical dynamics of protected floodplain forests (Gallardo, 2003; Heger *et al.*, 2021). Furthermore, the integration of spatial interpolation techniques with multivariate statistical frameworks remains underutilized in wetland forest soil research, limiting the ability to identify combined soil-property gradients that control SOC variability across the landscape. Site-specific evidence on how SOC is associated with soil chemical, textural, and hydrological gradients remains particularly limited for the Igneada Floodplain Forests National Park (IFFNP). Previous studies have mainly described the ecological, floristic, or general soil characteristics of the area, whereas quantitative integration of SOC, soil properties, spatial interpolation, and multivariate statistics has received less attention. Therefore, the objective of this study was to determine the relationships between SOC and selected soil physicochemical properties, to map their spatial distributions, and to identify the major soil-property gradients controlling SOC variability using PCA. The motivation for this work stems from the need to bridge the gap between general floodplain ecology and quantitative, spatially explicit soil carbon science in protected wetland ecosystems. The study contributes to floodplain soil carbon assessment by providing spatially explicit and statistically supported information for a protected wetland forest ecosystem, with the scope limited to the 0–20 cm soil layer

sampled across the national park during the 2025 spring season.

2. Literature review

Research on SOC in forest ecosystems has expanded considerably over the past two decades, yet several methodological and conceptual limitations remain unresolved, particularly for protected floodplain systems, and existing work relevant to the present study can be grouped into three broad strands. The first and most extensive strand relies on bivariate correlations or simple regression models linking SOC to one or two physicochemical variables at a time (Behera and Shukla, 2015; Yalçın *et al.*, 2018); while easy to implement and interpret, such univariate approaches cannot capture the combined influence of multiple, correlated soil properties on SOC accumulation and often yield contradictory results across studies — for instance, the positive SOC–calcium relationships reported in alkaline-cropped soils (Behera and Shukla, 2015) contrast with the weak or absent SOC–calcium relationships found in acidic floodplain soils — because these frameworks ignore the multivariate gradient structure that characterizes most soil systems, producing site-specific findings that are difficult to generalize. A second strand has applied geostatistical and deterministic interpolation methods, particularly kriging, to map SOC and related variables across landscapes (Bhunja *et al.*, 2016; Swinnen *et al.*, 2020; Wen *et al.*, 2025); these methods generate spatially continuous surfaces useful for visualization and management planning but, applied in isolation, describe spatial patterns without identifying the underlying soil-property gradients that drive them, while multivariate methods such as Principal Component Analysis (PCA) have separately been used to identify dominant gradients in soil-property datasets (Yalçın *et al.*, 2018; Ye *et al.*, 2022) — rarely, however, in combination with spatial interpolation in protected forest ecosystems — so that existing studies struggle to connect statistical gradients with the spatial domains in which they operate. A third, more localized strand consists of earlier work in IFFNP and adjacent areas addressing ecological, floristic, and general soil characteristics (Tecimen and Kavgaç, 2010; Cangir and Boyraz, 2009; Uslu, 2017; Yılmaz Dağdeviren and Karlioğlu Kılıç, 2023); these studies established valuable baseline information on vegetation composition, soil orders, pollen distribution, and ecological conditions, but none offered a quantitative, statistically integrated assessment of SOC variability in relation to multiple soil physicochemical properties across the park, leaving the absence of a site-specific multivariate SOC framework as the primary gap the present study aims to address. Taken together, these limitations — single-variable interpretations, the disjoint application of spatial and multivariate methods, and the absence of integrated SOC studies for IFFNP — define the methodological and contextual space in which this study is positioned.

3. Materials and methods

3.1. Study Area

The study area, İğneada Longoz Forests National Park, is located in northwestern Türkiye, within the borders of Kırklareli province, at coordinates 41° 46.4616'N and 41° 52.6633'N with 27° 55.2549'E and 28° 0.9262'E. It is situated on the Black Sea slope of the Istranca Mountains (**Figure 1**). The national park covers an area of 25 km². Ecologically and biologically rich, the study area has been the subject of research in many respects. In this study, the relationships between the soil properties of the national park, which is rich in SOC and has been proposed as a carbon sink in the past, were investigated.

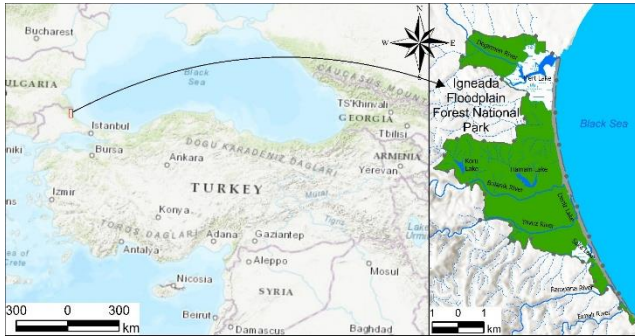


Figure 1. Location of the İFFNP study area in northwestern Türkiye and distribution of the soil sampling framework used in the study.

The study area is characterized by acidic, silt, and sand textures, no salinity problems (Cangir and Boyraz, 2009), and the distribution of Entisol and Inceptisol soil orders, which are young in nature and formed as a result of siltation activities. The study area hosts a floodplain forest established under the influence of five different streams (Çavuşköprü Stream, Elmalı Stream 1 and 2, Bulanık Stream, and Rampana Stream). Owing to their hydrological characteristics, soils continuously exposed to siltation do not develop profiles. The total annual rainfall in the area, which has a humid Black Sea climate, is approximately 802 mm. Because the study area is submerged for 4-6 months of the year, soil moisture is suitable for SOC accumulation (Toker and Sunar, 2018).

The study area, one of the most important areas in Türkiye, is home to rich vegetation (Yılmaz Dağdeviren and Karloğlu Kılıç, 2023) and animal species (Kaya, 2015). Favorable environmental conditions created by climate have ensured the survival of endemic plant species (Uslu, 2017). Its distance from metropolitan cities and protected status have also ensured the safety of these species. The İğneada floodplain, which is located on bird migration routes, hosts a high diversity of birds throughout the four seasons (Kaya, 2015).

3.2. Method

Before fieldwork, 750 × 750 m grids were created for soil sampling (Hazelton and Murphy, 2016). The locations of the soil samples collected within the prepared grids were randomly selected because the field consisted of dense forest and marshland areas, which restricted regular access to all grid cells. A total of 52 soil samples were collected from the 0–20 cm soil layer. Sampling was conducted during April 2025. At each sampling point, the geographic coordinates were recorded, and samples were transferred

to the laboratory in labelled bags for subsequent analysis. The use of a fixed sampling depth is important because SOC is strongly depth-dependent; therefore, all interpretations in this study refer only to the sampled soil layer.

The pH level was measured in saturated paste using a pH meter (Richards, 1954), and the salinity level was measured in saturated paste extract using an electrical conductivity meter (Tüzüner, 1990). Lime content was determined using volumetric calcimeter measurements. Nitrogen (%) content was measured according to FAO (1990), and available P (ppm) was measured using the Olsen method (Olsen *et al.*, 1954) with a spectrophotometer (FAO, 1990). K, Ca, Mg, and Na (ppm) were extracted with ammonium acetate and determined by ICP (FAO, 1990). Fe, Cu, Mn, and Zn (ppm) were extracted with DTPA and subsequently analyzed by ICP (FAO, 1990; Lindsay and Norvell, 1969; Follet, 1969).

Soil Organic matter (SOM) was determined using the modified Walkley-Black wet combustion method (Walkley, 1947). The method used to calculate SOC is the Van Bemmelen Conversion Factor. The SOC calculation is as follows:

Formula 1:

$$SOC\% = SOM\% \times 0,58$$

Where SOC is (%), SOM is (%), and 0.580 is the Van Bemmelen conversion coefficient (the reciprocal of 1.724) used to convert SOM to SOC (Pribyl, 2010; Jensen *et al.*, 2018).

Principal Component Analysis (PCA) was used to determine the multivariate relationships between SOC and other soil properties. PCA is a statistical method that reduces dimensionality and identifies groups of variables that explain the dominant patterns of variation in complex datasets. Sixteen soil variables obtained from 52 soil samples were included in the analysis. Prior to PCA, all variables were standardized to zero mean and unit variance to avoid scale effects among variables measured in different units. The number of important components was evaluated according to explained variance and interpretability. Correlations between principal component scores and SOC were tested using Pearson correlation analysis at a significance level of $p < 0.05$. This approach enabled the identification of the major soil-property gradients associated with SOC variability.

Formula 2:

RMSE (Root Mean Squared Error):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - Q_i)^2}$$

ME (Mean Error):

$$ME = \frac{1}{n} \sum_{i=1}^n (P_i - Q_i)$$

$P(P_i)$ — the estimated (LOOCV) SOC value for point i

$Q(Q_i)$ — the SOC value measured at point i

n — the number of sampling points (52)

RMSE (Root Mean Square Error): This is calculated by taking the square root of the average of the squares of the differences between the observed and predicted values, and measures the overall accuracy of the prediction (the magnitude of the error). As the errors are squared, it is more sensitive to large deviations or outliers than other metrics; it is therefore used as a standard metric for comparing the performance of different interpolation or modelling approaches — a low RMSE indicates high accuracy (Willmott, 1982; Isaaks and Srivastava, 1989).

ME (Mean Error): This is the average of the signed (directional) differences between the observed and predicted values, and reflects the model's tendency to systematically underestimate or overestimate, i.e. its bias. An ME value close to zero indicates that there is no systematic bias; however, as positive and negative errors may cancel each other out, it does not, on its own, provide information about the magnitude of the error (Isaaks and Srivastava, 1989; Webster and Oliver, 2007).

4. Results

Laboratory analyses showed spatial variability in SOC and soil physicochemical properties across the study area. Descriptive interpretation was based on the available laboratory results, spatial distribution maps, PCA outputs, and correlation analysis. The first two principal components and their relationships with SOC were used to summarize the dominant soil-property gradients in the study area.

4.1. Laboratory results

PCA was conducted using standardized values of 16 soil variables. The first two principal components explained 62.16% of the total variance, with PC1 explaining 39.00% and PC2 explaining 23.16%. Therefore, PC1 and PC2 captured the dominant gradients in soil properties in the study area. PC1 was mainly associated with salinity, magnesium, calcium, and texture-related variables, whereas PC2 was more strongly associated with pH, lime, phosphorus, and selected micronutrients. SOC showed a significant negative correlation with PC1 and a significant positive correlation with PC2, indicating that SOC variability was not controlled by a single soil property but by combined chemical and textural gradients. These results suggest that multivariate analysis provides a more comprehensive interpretation of SOC patterns than simple pairwise comparisons alone.

Table 1. Explained and cumulative variance of principal components derived from standardized soil physicochemical variables. The first five principal components accounted for 84.3% of the total variance.

Principal Component	Explained Variance (%)	Cumulative Variance (%)
PC1	39.00	39.00
PC2	23.16	62.16
PC3	9.52	71.68
PC4	7.37	79.05
PC5	5.25	84.30

The dominance of PC1 (39.00%) and PC2 (23.16%) in the variance structure indicates that the soil-property variability in the study area can be effectively summarized by two orthogonal gradients, with the cumulative variance of 62.16% exceeding the threshold commonly accepted for two-dimensional interpretation of environmental datasets. A pronounced decrease in explained variance after PC2 (PC3 = 9.52%, PC4 = 7.37%, PC5 = 5.25%) marks a clear scree-plot inflection between PC2 and PC3, supporting the decision to focus interpretation on the first two components. The first five components together account for 84.30% of the total variance, suggesting that the residual variability reflects local heterogeneity and minor random variation rather than systematic gradients. These results justify the use of a multivariate framework rather than univariate pairwise comparisons for the interpretation of SOC variability in the study area.

The principal component loadings are presented in **Table 2**. PC1 had a positive loading with salinity, magnesium, zinc, and clay content, and a negative loading with sand content. PC2 had a positive loading with pH, calcium, and sodium, and a negative loading with iron.

Table 2. Loadings of selected soil variables on PC1 and PC2, showing the main gradients controlling soil-property variation.

Variable	PC1	PC2
Salinity (dS/m)	0.333	0.247
pH	-0.139	0.451
Lime (%)	-0.239	0.291
Magnesium (ppm)	0.339	0.151
Calcium (ppm)	0.112	0.465
Sodium (ppm)	0.210	0.367
Iron (ppm)	0.147	-0.321
Zinc (ppm)	0.311	0.061
Sand (%)	-0.331	0.203
Clay (%)	0.316	-0.063

The loading structure of PC1 represents a salinity–base cation–texture gradient: salinity (0.333), magnesium (0.339), zinc (0.311), and clay (0.316) load positively, whereas sand (−0.331) loads negatively. This pattern reflects a textural–ionic contrast between fine-textured, magnesium- and salt-enriched soils on the one hand and sand-dominated soils on the other, which is consistent with sediment-sorting and solute-deposition processes typical of floodplain environments. PC2 is structured around an orthogonal pH–carbonate axis, with strong positive loadings of calcium (0.465), pH (0.451), sodium (0.367), and lime (0.291), and a negative loading of iron (−0.321). This configuration captures the well-established inverse relationship between soil alkalinity and iron solubility, indicating that the secondary axis of variation in the dataset is governed by acid–base buffering conditions. Taken together, the two components describe two independent and complementary controls on the soil chemical environment of the study area: a fluvially mediated salinity–texture gradient (PC1) and a pH–carbonate gradient (PC2).

The correlation results between the principal components and SOC are given in **Table 3**. Statistically significant correlations were detected among PC1, PC2, and SOC.

Table 3. Pearson correlation coefficients between principal component scores and SOC. Significant relationships indicate components associated with SOC variability.

Principal Component	Correlation Coefficient	P Value	Significance
PC1	-0.597	< 0.001	Significant
PC2	0.561	< 0.001	Significant
PC3	-0.189	0.180	Not significant
PC4	0.057	0.687	Not significant
PC5	0.031	0.829	Not significant

The Pearson correlation analysis demonstrates that SOC variability in the study area is jointly controlled by two independent gradients rather than by a single dominant soil property. The significant negative correlation between PC1 scores and SOC ($r = -0.597$, $p < 0.001$), combined with the positive loadings of salinity, magnesium, zinc, and clay on PC1, indicates that increasing salinity and fine-textured conditions are associated with reduced SOC accumulation, consistent with the inhibitory effect of salinity on the microbial decomposition–accumulation balance. Conversely, the significant positive correlation between PC2 and SOC ($r = 0.561$, $p < 0.001$), together with the positive loadings of calcium, pH, sodium, and lime on PC2, supports the role of organo-mineral interactions and polyvalent-cation-mediated stabilization mechanisms in preserving SOC. The remaining components (PC3, PC4, PC5) did not show statistically significant correlations with SOC ($p = 0.180$, 0.687 , and 0.829 , respectively), indicating that the lower-variance components do not contribute structurally to SOC variability. The opposing yet comparable magnitudes of the PC1–SOC and PC2–SOC relationships imply that SOC dynamics in the Igneada floodplain forest soils are governed by a balance between limiting (salinity–fine texture) and supporting (pH–calcium–carbonate buffering) processes, underscoring the need for a multivariate rather than single-variable interpretation of SOC patterns.

There were no salinity problems in the soils of the study area. However, the area showing an increasing trend in salinity levels was northwest of Mert Lake. Soils that are constantly washed under the influence of rivers do not experience salinity problems because of the drainage networks established by rivers. The absence of salinity problems supports SOC accumulation in the soil of the study area. Saline soils are known to hinder SOC mineralization.

SOC distribution showed an increase in the northwest and south of Mert Lake, while it tended to decrease in other areas. When SOC is evaluated in the study area, it is generally observed that SOC increases in areas where other elements also increase (Figure 2).

Calcium concentration increased in the northwest of Mert Lake and east of Saka Lake, while lower values were observed in other parts of the national park. The spatial coincidence between Ca and SOC in some areas may be related to the role of polyvalent cations in stabilizing organic matter through organo-mineral associations; however, this interpretation should be considered site-

specific because direct mechanism testing was not performed.

The distribution of potassium shows an increase in the north of Deniz Lake and in the area where Yavuz Stream, which feeds the lake, enters the national park (Figure 3). The soils in the study area also had sufficient K content.

Phosphorus concentration increased south of Mert Lake, north of Deniz Lake, and east of Koru Lake (Figure 3). Because the present study did not include a separate fertility classification or national-scale comparison, phosphorus was interpreted only in terms of its spatial pattern within the study area.

The distribution of magnesium increases in the northwest of Mert Lake, north of Deniz Lake, and south of Koru Lake in the area where Bulanık Stream enters the national park. Sufficient amounts of magnesium were found in the soils of the study area. The magnesium level originates from the Istranca Mountains, located in the western part of the study area. The area where the rivers originate has a mineralogical structure that contains Mg-bearing rocks.

The distribution of Mn shows an increase in the area northwest of Mert Lake, around Koru Lake, around Hamam Lake, and between Saka Lake and Yavuz Stream. It decreases south of Mert Lake, north of Lake Hamam, north of Koru Lake on the national park border, and south of Saka Lake. Like Mg, Mn increases along river courses, and siltation is an important factor in determining its content in the soil.

The nitrogen content also showed an increase around Mert Lake, similar to SOC, while it decreased in other areas. This pattern may reflect the close biogeochemical association between organic matter accumulation and nitrogen cycling in wet floodplain soils. Therefore, the spatial similarity between SOC and nitrogen was interpreted as an association rather than a direct causal relationship.

Iron concentration increased north of Koru Lake and south of Saka Lake (Figure 3). These areas correspond to zones affected by seasonal waterlogging. Under waterlogged and reducing conditions, iron can undergo redox transformations that influence its mobility and association with organic matter. Therefore, the observed spatial pattern of Fe was interpreted in relation to floodplain hydrology rather than as a simple oxidation effect.

Copper concentration increased northwest of Mert Lake and east of Hamam Lake. Because Cu can form complexes with organic matter, these spatial patterns may be associated with areas of higher organic matter accumulation. However, this relationship was treated as a possible explanation and not as direct evidence of causality.

Zinc concentration increased northwest of Mert Lake and between Hamam Lake and Deniz Lake (Figure 3). These areas partly correspond to stream-influenced zones, suggesting that fluvial deposition and local soil conditions may contribute to Zn distribution. Because this study did not directly test transport mechanisms, the Zn–river association was interpreted as a spatial hypothesis.

The distribution of sodium in the soils of the study area was homogeneous (**Figure 3**). The increase in the study area soils without excess sodium was not characterized by sharp lines.

The calcareousness of the study area soils showed a homogeneous distribution, which was normal, similar to that of sodium. A noticeable increase was observed only in a single area northwest of Mert Lake.

The sand distribution in the study area soils increased in the coastal section. Sandy soil was predominant throughout the study area. The clay distribution shows an increase in the northeast of Mert Lake and Deniz Lake, and between Hamam Lake and Koru Lake. Silt density also showed an increase in the northeast of Mert Lake and northeast of Saka Lake.

5. Discussion

In this study, the relationship between soil properties and SOC content was investigated using Principal Component Analysis (PCA). Sixteen soil properties (salinity, pH, lime, nitrogen, phosphorus, potassium, calcium, magnesium, sodium, iron, copper, manganese, zinc, sand, clay, and silt ratios) obtained from 52 soil samples were used in the analysis. PCA results showed that the first five principal components accounted for 84.3% of the total variance. A strong negative correlation ($r = -0.597$, $p < 0.001$) was found between PC1 (39.0% of the variance) and SOC, and a strong positive correlation ($r = 0.561$, $p < 0.001$) was found between PC2 (23.2% of the variance) and SOC. These findings indicate that combinations of specific soil properties are important for the accumulation of organic carbon in the soil.

Model performance evaluation revealed that the multiple linear regression model was able to predict SOC distribution in the study area soils with a moderate level of accuracy. According to the leave-one-out cross-validation (LOOCV) results, the parsimonious model incorporating iron, zinc, and phosphorus as predictors (RMSE = 0.722; ME = 0.009; $R^2 = 0.385$) outperformed the full model containing all nine soil parameters (RMSE = 0.746; ME = -0.002; $R^2 = 0.344$), indicating that the additional predictors contributed no meaningful improvement to predictive power but rather increased model complexity and the risk of overfitting. The higher observation-to-predictor ratio of the parsimonious model (17.3:1) further strengthens the statistical robustness of its predictions. In both models, the mean error (ME) values were very close to zero, demonstrating that the predictions were free of systematic bias (over- or under-estimation) and that the measured and predicted values were evenly distributed around the 1:1 line. The emergence of iron and zinc as the dominant predictors is geochemically consistent with the tendency of these elements to form complexes with organic matter and to accumulate in organic-rich sediments, suggesting that SOC accumulation in the floodplain environment is governed by processes linked to soil chemistry. Nevertheless, the moderate proportion of explained variance ($R^2 = 0.385$) indicates that SOC distribution

cannot be fully accounted for by the measured soil parameters alone, and that unmeasured environmental factors such as microtopography, climate regime, vegetation cover, and drainage conditions also contribute to its variability (**Figure 4**).

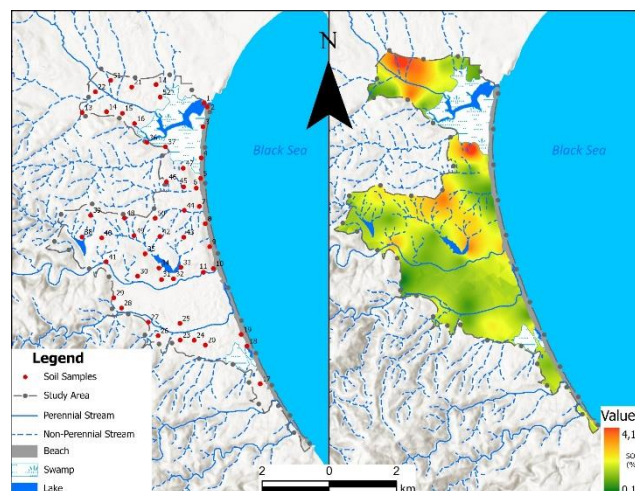


Figure 2. The distribution of soil samples taken from the study area and the distribution of SOC (%) within the study area.

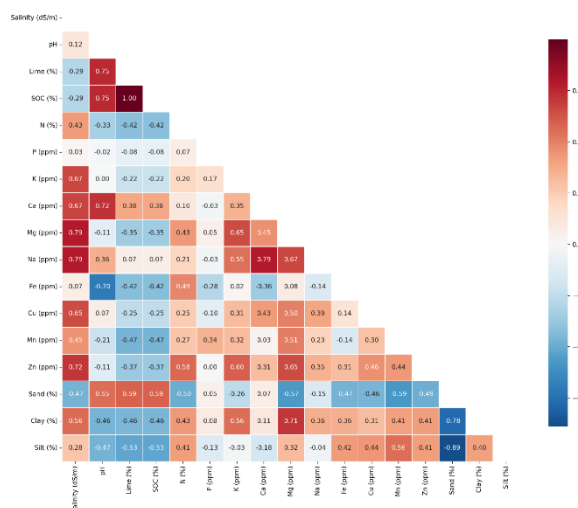


Figure 3. Correlation matrix showing pairwise relationships among SOC and selected soil physicochemical properties.

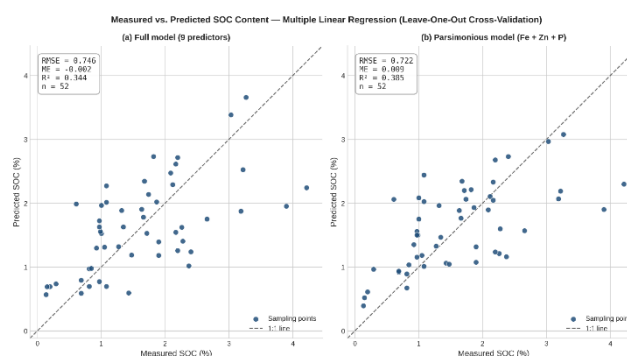


Figure 4. Measured versus predicted SOC content (LOOCV): (a) full model (RMSE = 0.746; $R^2 = 0.344$); (b) parsimonious model with Fe, Zn, and P (RMSE = 0.722; $R^2 = 0.385$).

When evaluating the correlation between soil properties in the study area, there was a very strong positive correlation between pH and SOC ($|r| = 0.75$). As the lime content of the soil increased, pH and organic carbon levels also increased. There is a strong positive relationship between salinity, K, Ca, Mg, and Na ($|r| = 0.67$ - 0.79). As the salinity increased, these elements also increased. A very high correlation was observed between Mg and Ca ($|r| = 0.45$). There is a strong negative correlation between Fe and pH ($|r| = -0.70$). As soil pH increased, the availability of Fe decreased. There was an expected strong negative correlation between clay and sand ($|r| = -0.78$). As the sand content in the soil increased, clay content decreased. Silt and sand ($|r| = -0.89$) had a very strong negative correlation. As the sand content increased, silt content decreased. There was a positive correlation between N and salinity ($r = 0.43$). As salinity increased, the nitrogen levels also increased. A strong positive correlation was observed between Zn and salinity ($|r| = 0.72$). A positive correlation was observed between Cu and salinity ($|r| = 0.65$).

The soils of the İğneada floodplain forest are acidic (Öztürk, 2025). Gross and Glaser (2021) stated that acidic soils have more SOC stocks than neutral and alkaline soils do. However, Shaaban (2024) stated that soil acidification is a growing concern for both plant growth and health. The decomposition of organic matter has also been reported to increase soil acidity. Supporting this information, a relationship between SOC and pH was detected in the soils of the study area (Figure 5). Consistent with this observation, moist forest soils are generally acidic in character (Ye *et al.*, 2022). Therefore, they are considered to be potentially suitable areas for SOC accumulation.

When the relationship between Ca and SOC was evaluated in the study area, no significant correlation was observed (Figure 5). The irregular distribution of calcium stems from its general characteristics (Burstrom, 1968). In a study conducted in India, it was determined that SOC and pH have a positive and significant relationship with calcium, potassium, and magnesium, along with the current state of the soils (Behera and Shukla, 2015).

No correlation was observed between potassium and SOC (Figure 5). The unrelated equation of K (Karaoluk Esençay and Korkmaz, 2019), which plays an important role in plant health and growth and is an absolute requirement, may be due to its small size and leaching (Qiu *et al.*, 2018). This view was supported by the ineffectiveness of potassium in the PCA results (Table 2).

No correlation was observed between phosphorus and SOC (Figure 3).

A negative relationship was observed between Mg and SOC (Figure 5). The PC1 loading seen in Table 2 as positive loading and the negative correlation of PC1 with SOC also strengthened the relationship by showing that organic carbon content tended to be low in soils with high Mg content (Table 3). Mg deficiency is likely to occur in acid-reactive soils (Gupta *et al.*, 2025). Dash *et al.* (2025) reported Mg deficiency in acidic soils in their study. However, no Mg deficiency was observed in the soils of the

study area. This may be due to the transport of Mg, which is present in mineral form such as olivine, dolomite, and serpentine, to the study area.

A negative relationship was observed between Mn and SOC (Figure 5). Conversely, Yalçın *et al.* (2018) found a positive relationship between manganese and organic matter in their studies. Obrador *et al.* (2007) reported that Mn deficiency is a distinct condition in acidic sandy soils. However, the reason for this inverse situation observed in the study area may be that organic matter determines the distribution of nutrient elements (Obrador *et al.*, 2007). The PCA results indicated no relationship (Table 2). This situation may be influenced by pH. Indeed, Yalçın *et al.* (2018) conducted their study in an area with slightly alkaline soil. When the relationship between Mg, Mn, and lime and SOC observed in the study area is evaluated in the context of flooding-induced changes in biogeochemical processes (Gallardo, 2003), a more accurate interpretation can be obtained.

The relationship between nitrogen and SOC should be interpreted cautiously. Although nitrogen is commonly associated with organic matter accumulation, the observed pattern in this study may reflect local hydrological conditions, salinity effects, texture, or spatial heterogeneity among sampling points. Therefore, this result was not interpreted as evidence that nitrogen reduces SOC; rather, it indicates that SOC and nitrogen did not show a simple positive relationship across all sampled locations.

There was a negative correlation between Cu and SOC in the study area (Figure 5). However, this relationship was not evident in PC1 and PC2 loadings (Table 2). When the soils of the site were evaluated, it was observed that there were no salinity problems (Öztürk, 2025). We can interpret this relationship observed in the field as salinity affecting the mobility of Cu, a heavy metal, rather than SOC (Acosta *et al.*, 2011).

In the study area soils, the Fe-pH relationship was stronger than the Fe-SOC relationship (Figure 5). Similarly, PC2 loading was also negative (Table 2). In acidic forest soils, Fe and dissolved organic matter significantly affect soil pH and pedogenesis (Jansen *et al.*, 2003). This situation observed in the study area soils, where both Fe sufficiency and excess are present, is a shift from a direct Fe-C relationship to a pH-Fe relationship, as reported by Ye *et al.* (2022). In the same study, when the hypothesis that pH, not Fe, was the driving force in the relationship between Fe and C in soil (Ye *et al.*, 2022) was tested, supporting findings were obtained.

Zinc showed relatively high values in selected parts of the study area (Figure 3). Because Zn may interact with organic matter and salinity-related soil processes, its distribution was discussed as a spatial association rather than a confirmed causal mechanism.

6. Conclusions

This study evaluated the relationship between SOC and selected soil physicochemical properties in the IFFNP using

laboratory analyses, spatial interpolation, PCA, and correlation analysis. The findings indicate that SOC variability in the study area is associated with salinity, pH, magnesium, calcium, and textural properties, and that the first two principal components explain an important proportion of the total soil-property variation. Spatial patterns also suggest that hydrologically influenced areas, particularly zones around lakes and stream corridors, may support higher SOC accumulation through moisture availability, sediment deposition, and reduced decomposition under periodically waterlogged conditions. However, the results should be interpreted as site-specific and limited to the sampled soil depth and sampling period. The study provides useful information for soil carbon assessment and conservation planning in protected floodplain forests. Future studies should include seasonal sampling, detailed hydrological measurements, bulk density, and SOC stock calculations to better quantify carbon storage potential in floodplain ecosystems.

The soils in the floodplain areas are alluvial and essentially formed under the influence of rivers. The fact that they are generally flat or nearly flat also accelerates river deposition. This means that floodplain forests experience increased sediment deposition and mineral properties of the soil. Similarly, Beer *et al.* (2010) and Luo *et al.* (2017) reported that the quality and quantity of carbon entering the soil are determined by vegetation cover that develops under the influence of climatic characteristics. This process results in the storage of large amounts of sediment and SOC (Swinnen *et al.*, 2020; Heger *et al.*, 2021). This storage affects the regional sediment and carbon dynamics (Cole *et al.*, 2007). Approaches supporting this thesis have described floodplain forests as areas that function as global carbon reservoirs and are important for carbon mineralization (Alderson *et al.*, 2019; Swinnen *et al.*, 2020).

When evaluating the relationship between the SOC content and other soil properties in the study area, it was found to be a suitable site for organic carbon storage. The findings revealed that salinity, pH, magnesium, calcium, and textural properties play an important role in SOC storage. Furthermore, the absence of a negative situation for SOC accumulation in other element properties also strengthens the potential of the site. These findings provide important information for the development of soil management strategies and conservation of organic carbon stocks. The PC1 and PC2 results indicated that organic carbon accumulation is difficult in soils with high salinity, pH, calcium, sodium, magnesium, and clay content. To increase organic carbon accumulation, areas where salinity, pH, calcium, sodium, magnesium, and clay contents are elevated can be rehabilitated using drainage systems in addition to rivers. This will result in both soil rehabilitation and a healthy forest ecosystem.

Beyond the methodological contributions of this study, the spatially explicit SOC–soil-property associations identified here provide a basis for real-time, in-situ monitoring frameworks in protected floodplain ecosystems. The hotspot zones identified around Mert Lake, where SOC, nitrogen, and hydrologically influenced gradients

converge, represent priority locations for the deployment of IoT-based soil sensor networks measuring pH, electrical conductivity, soil moisture, and temperature at high temporal resolution. The PCA-derived gradients (PC1 and PC2) can be operationalized as composite indicators in such monitoring systems, allowing changes in soil quality to be tracked using a small number of sensor-measurable proxies rather than the full set of sixteen variables analyzed here. When integrated with periodic remote-sensing-based land-cover classification and blockchain-enabled data integrity protocols for field-scale environmental data, this framework could support continuous, transparent, and protected monitoring of SOC dynamics in IFFNP and comparable floodplain systems. For protected-area managers, such an implementation would enable early detection of carbon-loss anomalies, evidence-based prioritization of conservation interventions in salinity- or fine-texture-stressed sub-areas, and integration of SOC monitoring with national climate-reporting commitments. In this respect, the present site-specific evidence is intended as a baseline from which scalable, sensor-driven SOC monitoring frameworks for protected floodplain forests can be developed.

The results of this study can serve as a guide for researchers and managers in creating healthy and sustainable ecosystems and soil research. This study also demonstrated that PCA is an effective method for understanding the relationship between soil properties and soil organic carbon.

Acknowledgment and/or disclaimers, if any

We would like to thank Prof. Dr. Emre ÖZŞAHİN and Berk YAVAŞER for their support and assistance during the fieldwork.

This study was supported by the Scientific Research Projects Coordination Unit at Tekirdağ Namık Kemal University. Study Project No. NKUBAP.03.YL.24.620 “Determination of Soil Properties of Igneada Floodplain Forests National Park by Using GIS Techniques” was prepared as part of a Master’s thesis entitled.

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