Quantile Regression for Soil Organic Carbon: A Distributional Analysis of Soil Variability

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Abstract. Climate change is affecting more places around the world, making it even more important to take new steps to stop it. In this context, soil organic carbon (SOC) not only plays a key role in biochemical cycles and soil fertility, but it also helps control the climate by taking in and/or releasing CO2 into the air. However, SOC data show a lot of variation, which makes it hard to estimate because of the complicated interactions between soil-forming factors. Standard regression models that use the mean usually don't show how complex SOC variability really is. This article examines the relationship between soil color and SOC through a distributional model employing quantile regression. This method helps in understanding how soil color affects different parts of the soil organic carbon (SOC) distribution, mainly its values along the distribution quartiles, allowing the identification of extreme values below 10% and above 90%. The Brazilian Agricultural Research Corporation (Embrapa) made the data available, which comes from different biomes and land use systems. This makes sure that the data is not all the same. The findings demonstrate that linear regression can only identify a general correlation between soil color and SOC, yielding a low R^2 value of approximately 0.53. This means limited explanatory power and the existence of heteroscedasticity, as corroborated by piecewise linear regression analysis. Quantile regression, on the other hand, proved more effective in identifying non-linear patterns and differences in distribution, obtaining an R^2 of 0.94 for the 90% quantile.

Keywords: Soil Organic Carbon · Quantile Regression · Environmental Modeling

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1 Introduction

Soil is one of the largest carbon reservoirs on the Earth's surface, storing more carbon than the air and plants. Thus, proper soil management is an important part of policies to combat climate change. Soil organic carbon (SOC) is an essential component of the environment, as it influences biogeochemical cycles, soil fertility, and climate regulation. In turn, soil organic carbon has a direct effect on water retention, nutrient availability, biological activity, and soil structural stability, affecting agricultural productivity and ecosystem resilience [1,2].

Accurately monitoring soil organic carbon (SOC) is an important task for sustainability and mitigating the effects of climate change, being directly associated with the United Nations Sustainable Development Goals (SDGs), especially SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 15 (Life on Land) [3].

Despite its importance, common practices for estimating soil organic carbon (SOC) involve laboratory techniques, including dry combustion and wet oxidation, which are expensive, time-consuming, and logistically complex for extensive use [4].

To overcome these limitations, over the years, several researchers have investigated statistical and computational methods to estimate SOC from more accessible attributes, such as soil color, texture, and depth, in addition to environmental variables. Among the soil attributes associated with SOC, soil color is recognized as a good indicator, as it is closely linked to the accumulation of organic material and mineral composition.

Despite recent advances in machine learning methods, much of the research still uses mean-based regression models, ranging from simple linear regression to approaches with linear regression trees [5,6]. These models offer an initial approximation; however, they often do not adequately represent the complexity of pedological processes, since soil organic carbon (SOC) data typically exhibit non-linearity, asymmetry, and heteroscedasticity [8,10].

In this context, a single global relationship may be inadequate to characterize the variability of SOC under different environmental and soil conditions. In this context, quantile regression appears as an alternative method, evaluating several quantiles of the distribution, including the lower and upper extremes, instead of just the mean. This suggests an interesting alternative, especially in the context of SOC, since the extremes of the distribution are frequently associated with soils poor or rich in carbon [8–10].

Even though this seems like an advantage, soil scientists don't often use quantile regression, especially when they are looking into the link between soil color and soil organic carbon (SOC). Most current research emphasizes predictive performance or utilizes advanced modeling techniques rooted in machine learning, whereas the distributional characteristics of soil organic carbon (SOC) are inadequately investigated.

This study examines the correlation between soil color and SOC using quantile regression. The main objective is to examine variations in this relationship

across different regions of the SOC distribution, which may contribute to understanding its variability.

This work makes two important contributions. First, it offers an empirical examination of the soil color–SOC relationship from a distributional viewpoint. Second, it shows that quantile regression is a strong and easy-to-understand tool for analyzing soil data that can be used for digital soil mapping and environmental monitoring.

The remainder of this paper is organized as follows. Section 2 presents some aspects of quantile regression. Section 3 presents the related work on SOC estimation and soil color analysis. Section 4 describes the dataset and the methodological approach, including the regression models employed. Section 5 presents and discusses the experimental results. Finally, Sect. 6 concludes the paper and outlines directions for future research.

2 Theoretical Background

Modeling soil organic carbon (SOC) is quite hard because soil systems are naturally very different from each other. Climate, parent material, topography, organisms, time, and land use are all examples of soil-forming factors that interact in complicated ways to change SOC [7]. Consequently, SOC data frequently display nonlinearity, asymmetry, and heteroscedasticity, thereby constraining the efficacy of conventional regression methods predicated on the conditional mean.

Ordinary least squares (OLS) and other classical regression models try to find the conditional expectation $\mathbb{E}(Y \mid X)$ by minimizing the squared errors. Researchers like these models because they are simple to use and understand, but they rely on assumptions such as linearity and constant variance. In environmental and pedological datasets, these assumptions are often not met, which can lead to pictures of the processes that are going on that are biased or not complete.

Quantile regression extends classical regression by facilitating the estimation of conditional quantiles of the response variable. Quantile regression does not just model the mean; it also estimates the conditional quantile function $Q_Y(\tau \mid X)$ for a given $\tau \in (0, 1)$. This lets us look at the relationship between predictors and response in a more complete way.

Given a dataset $\{(x_i, y_i)\}_{i=1}^n$, where $x_i \in \mathbb{R}^p$ denotes the explanatory variables and $y_i \in \mathbb{R}$ signifies the response variable, the quantile regression estimator is formally defined as:

$$\hat{\beta}_\tau = \arg\min_{\beta \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^\top \beta), \tag{1}$$

where $\rho_\tau(u)$ is the asymmetric loss function, known as the pinball loss:

$$\rho_\tau(u) = \begin{cases} \tau u, & \text{if } u \geq 0, \\ (\tau - 1)u, & \text{if } u < 0. \end{cases} \tag{2}$$

This loss function treats underestimating and overestimating differently, which lets the model focus on certain parts of the distribution. When $\tau = 0.5$, the model is median regression, which is better at dealing with outliers than mean-based methods.

One of the best things about quantile regression is that it can show how things affect different people in different ways. Classical regression assumes a constant relationship between predictors and response, while quantile regression allows model parameters to vary across quantiles. This feature makes it easier to find different regimes in the data, where explanatory variables may have different effects depending on the level of SOC.

Another important thing about quantile regression is that it can easily handle heteroscedasticity. The method doesn't assume that the variance is always the same. Instead, it models how the response variable's dispersion changes with the predictors. Diverging quantile curves show that things are becoming less stable, while converging curves show that things are becoming more stable.

These characteristics are crucial in soil science. SOC is known to change a lot based on the environment, and the processes that affect soils with low carbon may be different from those that affect soils with high carbon. Quantile regression provides a distributional perspective that goes beyond average trends by modeling several quantiles at once.

Classical quantile regression is generally characterized as a linear model; nonetheless, extensions such as polynomial formulations can proficiently depict nonlinear relationships between predictor and response variables. Quantile regression offers a robust and comprehensible method for analyzing complex environmental data, even in its simplest form.

In general, quantile regression is a way to model distributions that gives a better picture of how SOC behaves. It helps us understand soil processes better by letting us look at variability, asymmetry, and extreme values. It is also a useful alternative to traditional mean-based models.

3 Related Work

There have been a lot of different ways to study how to figure out how much soil organic carbon (SOC) there is. Some of these methods are pedological knowledge, field measurements, and computer-based methods. People have known for a long time that the color of soil can help you guess how much organic matter it has. Initial research showed that both field and lab tests of soil color can give very accurate estimates of SOC [18]. More research confirmed this link, showing that soil color can show how the environment is doing, such as where wetlands are located [11].

Better sensing technologies have made it possible to use a lot more data sources to figure out SOC. A lot of work has been done to figure out soil organic carbon (SOC) from soil reflectance characteristics using spectroscopy-based methods [14]. Satellite images, especially the Sentinel-2 time series, have also made it possible to map SOC and other soil properties in great detail [13,25].

Researchers have also looked into how unmanned aerial systems and multispectral images can help improve spatial resolution in landscapes that aren't all the same [16]. Low-cost sensing methods like mobile phone images and color sensors have also become useful for estimating SOC in places where there aren't many resources [19,20,27].

At the same time, machine learning methods have been increasingly used to predict SOC, often obtaining better results by finding non-linear relationships between environmental variables, especially when associated with spectral data and remote sensing data [12,15]. However, these methods often function as black boxes, which makes it difficult to understand the processes that are actually occurring and driving that soil state.

Numerous studies have shown that the correlation between soil color and soil organic carbon (SOC) is affected by different factors besides organic matter content. Changes in mineral composition, soil texture, and environmental variables can alter soil color without altering SOC, making modeling a somewhat more complicated process [23,26,30]. Geospatial analyses have demonstrated that the distribution of SOC is strongly influenced by land use and landscape characteristics, thus pointing to the need for methodologies capable of accommodating heterogeneous data [29].

A common limitation across much of the literature is the dependence on mean-based modeling methods, which assume a homogeneous relationship between predictors and SOC. However, SOC data are frequently characterized by asymmetry, nonlinearity, and heteroscedasticity, making average-based models insufficient to fully describe the underlying processes [7]. In this context, models that focus solely on the conditional mean may overlook important distributional patterns.

Quantile regression provides an alternative scheme to examine different regions of the conditional distribution of SOC. Through modeling multiple quantiles, this approach makes it possible to investigate how explanatory variables influence not only typical values as well as extreme conditions, which are particularly relevant in environmental applications [8–10]. In spite of these advantages, its application in soil science remains relatively limited, particularly in studies explicitly studying the relationship between soil color and SOC.

Consequently, the literature lacks a comprehensive distributional analysis of the soil color–SOC relationship. This paper aims to bridge the gap by using quantile regression to examine how the relationship varies across different parts of the SOC distribution. This gives a more detailed and understandable picture of soil variability.

4 Methodology

This section describes the dataset, preprocessing steps, and modeling strategies adopted to investigate the relationship between soil color and soil organic carbon (SOC). The proposed approach combines exploratory data analysis with mean-based and distributional regression models, enabling a comprehensive evaluation of how soil color influences SOC under varying conditions.

4.1 Dataset and Preprocessing

The dataset used in this study comprises soil profiles collected across Brazilian biomes, including agricultural, forest, and pasture areas. The data include measurements of soil organic carbon (SOC) and associated pedological attributes, with particular emphasis on soil color, which is used as the main explanatory variable in this study.

Due to the skewed nature of SOC data, a logarithmic transformation was applied to stabilize variance and reduce asymmetry. This transformation is commonly used in soil studies to improve the suitability of statistical modeling. After preprocessing, the dataset was analyzed to assess the distribution of SOC across land-use classes and to verify the absence of severe multicollinearity.

4.2 Exploratory Analysis

An exploratory data analysis was conducted to characterize the distribution of soil organic carbon (SOC) and investigate its relationship with available attributes, including soil color. Histograms were used to examine the distribution and variability of SOC across land-use classes. Furthermore, correlation coefficients were calculated to assess associations between SOC and other variables. This step aimed to support the selection of modeling approaches best suited to the data's characteristics.

4.3 Linear Regression Models

As a baseline approach, a simple linear regression model was fitted to describe the relationship between soil color index and SOC:

$$Y = \beta_0 + \beta_1 X + \varepsilon, \tag{3}$$

where Y represents the log-transformed SOC and X the soil color index.

To further investigate potential structural changes in this relationship, a segmented (piecewise) linear regression model was also considered. This approach allows different linear relationships to be estimated in distinct regions of the data, enabling the identification of possible regime shifts.

4.4 Quantile Regression

To capture the heterogeneous and distributional behavior of SOC, quantile regression was applied. Unlike classical regression, which estimates the conditional mean, quantile regression models the conditional quantile function:

$$Q_Y(\tau \mid X) = X^\top \beta_\tau, \tag{4}$$

where $\tau \in (0, 1)$ represents the quantile of interest.

The model parameters are estimated by minimizing the pinball loss function:

$$\hat{\beta}_\tau = \arg\min_{\beta} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^\top \beta), \tag{5}$$

which allows different regions of the SOC distribution to be modeled independently.

In this study, quantile regression was used to analyze how the relationship between soil color and SOC varies across low-, median-, and high-carbon conditions. A polynomial specification was adopted to account for potential nonlinearities in the relationship.

4.5 Model Evaluation

We looked at the coefficient of fit (R^2) for linear models to see how well the model worked. This made it possible to see how well different specifications explained the data.

The focus of the quantile regression analysis was on how well the model could capture distributional patterns, including nonlinearity and heteroscedasticity. We checked the model by looking at the difference between the predicted and observed values and the shape of the estimated quantile curves.

5 Results and Discussion

This section presents the results obtained using the described methodology. Initially, we present a brief exploratory analysis of the data and examine the degree of asymmetry and kurtosis. In the following analysis, we evaluate the correlation matrix in the context of the three land uses: pasture, forest, and agriculture. The final step involved the use of regression models, namely linear, piecewise linear, and quantile. This allowed us to verify the relationship between soil color and soil organic carbon (SOC).

5.1 Exploratory Analysis

The exploratory analysis showed that SOC values varied significantly between land use classes, both in the different variables compared and after applying a logarithmic transformation. Figure 1 shows that the distributions present different patterns of asymmetry and dispersion. Forest areas tend to present higher SOC values, while agricultural and pasture systems present wider and more dispersed distributions. These patterns demonstrate that the soil is not homogeneous everywhere, which implies that modeling strategies must take this into account.

Table 1 presents the distribution of observations among biomes and land use types, demonstrating that the database has considerable diversity, despite a higher concentration of samples in the Atlantic Forest, Cerrado, and Caatinga biomes. This diversity contributes to the difficulty in determining the distribution of soil organic carbon (SOC), indicating heterogeneity in soil formation,

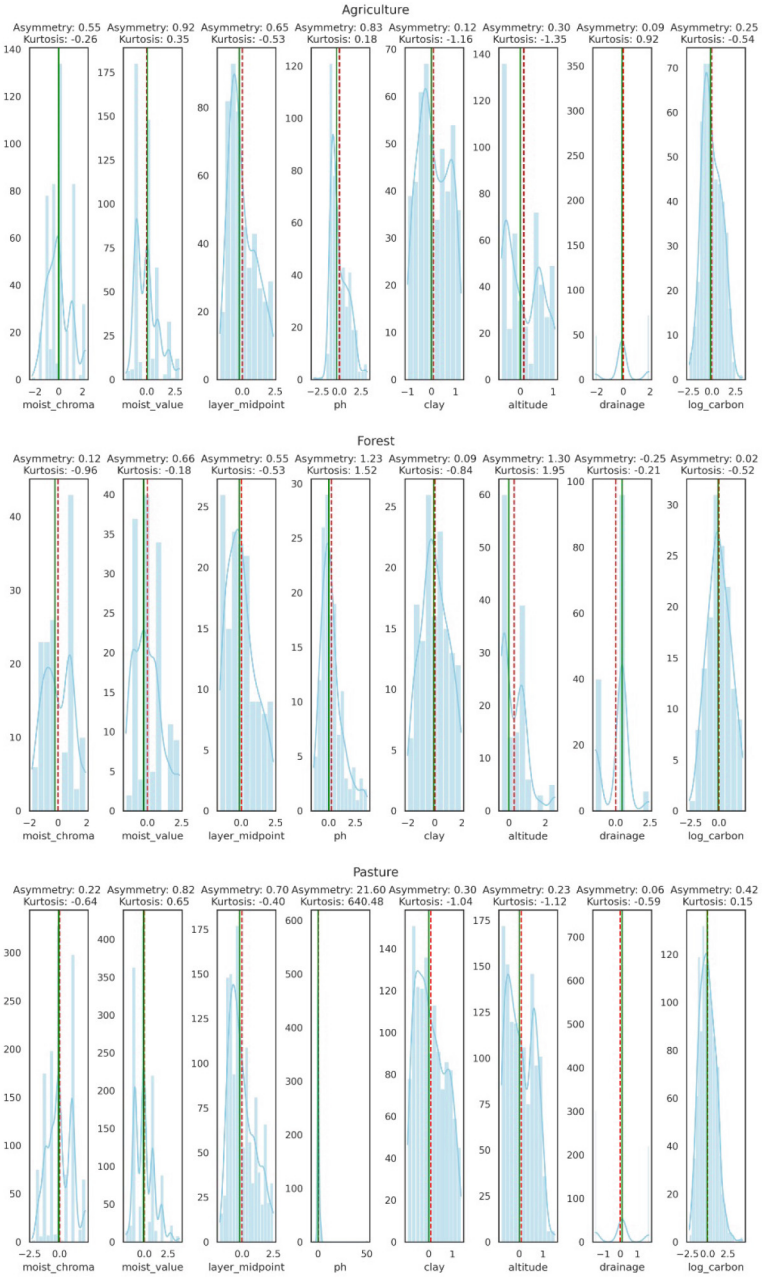

Fig. 1. Distribution of soil organic carbon content per land use.

which influences the relationship between the explanatory variables and our target variable.

Table 1. Number of records by biome and land use.

Biome	Agricultural	Forest	Pasture
Amazon	63	153	452
Caatinga	1050	38	1203
Cerrado	218	127	1681
Atlantic Forest	1136	405	1886
Pampa	39	12	96
Pantanal	0	5	0

The correlation analysis (Fig. 2) indicates that the relationships among the available attributes are generally moderate, suggesting the absence of severe multicollinearity. This supports the validity of the regression analysis and allows the use of soil color as a meaningful explanatory variable in the subsequent models.

5.2 Regression Models

As mentioned earlier, a simple linear regression model was fitted to describe the relationship between soil color index and soil organic carbon (SOC). Figure 3 shows the evaluation performed. The model demonstrates limited explanatory power, with a coefficient of determination of $R^2 = 0.53$. However, the pattern of residuals suggests heteroscedasticity, with increased dispersion at higher SOC values.

A complementary analysis was performed by individualizing the main color-related variables that influence SOC. Figure 4 shows that the model captures a general decreasing trend, indicating that darker soils tend to have a higher carbon content.

To investigate whether structural changes occur in the relationship between color and soil organic carbon, we used a piecewise linear regression model represented in Fig. 5. With this approach, we performed adjustments in different regions, aiming for the best linear relationship for each of them and thus trying to identify transition points where the system's behavior changes, or rather, where changes occur in the relationships between color and SOC.

As can be seen, the results indicate the presence of distinct regimes, characterized by different slopes along the intervals of the soil color index. This indicates that the influence of color on SOC is not uniform, but varies according to the range analyzed. In certain intervals, small variations in color are associated with more significant changes in SOC, while in others the relationship is weaker or more stable. This behavior shows that the relationship between

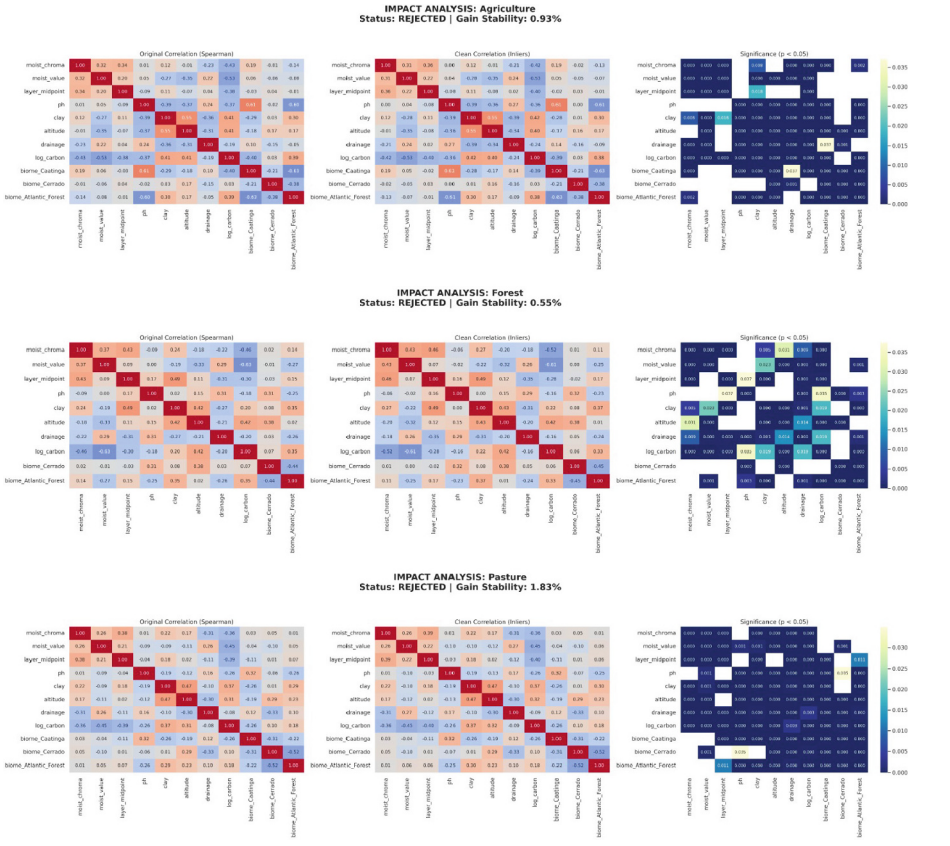

Fig. 2. Correlation matrix and statistical significance among the attributes.

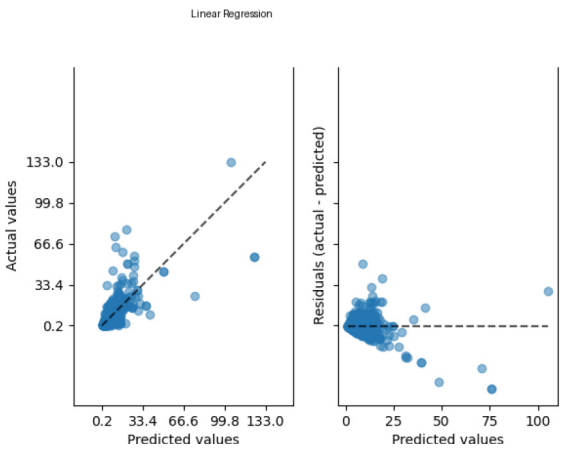

Fig. 3. Linear regression.

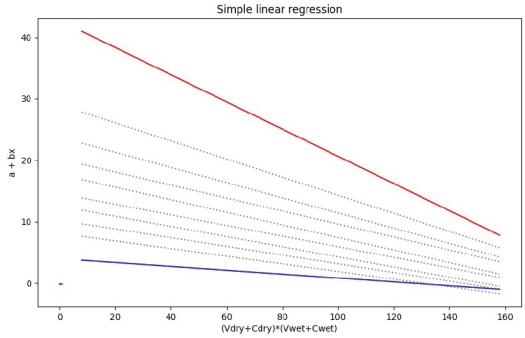

Fig. 4. Linear regression between soil color index and carbon content.

color and SOC is heterogeneous, probably due to other pedological and even environmental factors. For example, in some color ranges, the hue may be more directly associated with the accumulation of organic matter, while in others it may be strongly influenced by factors such as the presence of minerals, as already mentioned.

In order to better investigate this variation, quantile regression was employed. Figure 6 shows the result of the quantile regression adjustment; a coefficient of determination of $R^2 = 0.94$ was obtained. Furthermore, through the analysis of the quantile curves, it is observed that the relationship between soil color and SOC differs along the distribution.

In lower quantiles, the relationship seems to be more stable and less affected by changes in soil color. Higher quantiles, on the other hand, show more variability and stronger nonlinear patterns. This means that high SOC values are affected by more than just soil color. This behavior is in line with heteroscedasticity and backs up the idea that SOC is a distributional phenomenon.

Comparing the three approaches presented, important differences are observed in the ability of each to represent the relationship between soil color and SOC. Simple linear regression captures only a global trend, providing limited explanatory power, probably due to the presence of heteroscedasticity. In turn, the piecewise linear model achieves better results, as it can discern distinct regimes in the relationship between color and carbon, suggesting that the relationship is not uniform across all soil color possibilities. As already mentioned, not all dark soil is rich in carbon; it may have a high presence of minerals that give it a darker character. The problem is that this piecewise linear model still imposes linearity assumptions, limiting its flexibility. In contrast, quantile regression offers a more complete and robust structure, simultaneously modeling different regions of the SOC distribution. It obtained the best degree of fit, in addition to representing both the intensity and the variation of the relationship that differ between conditions through the divergence between the quantile curves. Thus, by comparing the three approaches, we get the impression that the dynamics of soil organic carbon (SOC) are so complex that they cannot

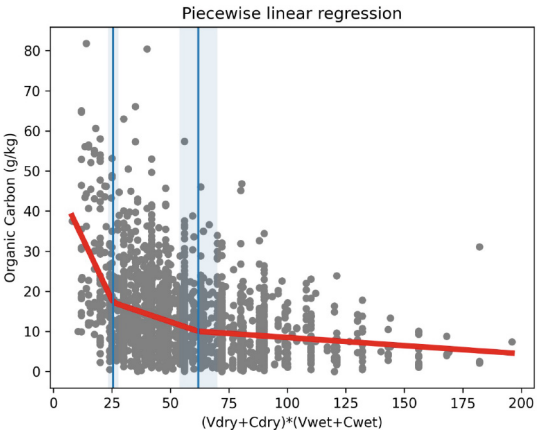

Fig. 5. Segmented linear regression between soil color index and carbon content.

be adequately described by a single functional relationship and, instead, must be interpreted from a viewpoint of distributions, in which different factors may prevail under conditions of low, medium, and high carbon content.

Overall, the results suggest that mean-based models provide only a partial description of the relationship between soil color and soil organic carbon (SOC). In contrast, quantile regression offers a more complete representation, being able to capture the variability, non-linearity, and even heterogeneity of the distribution.

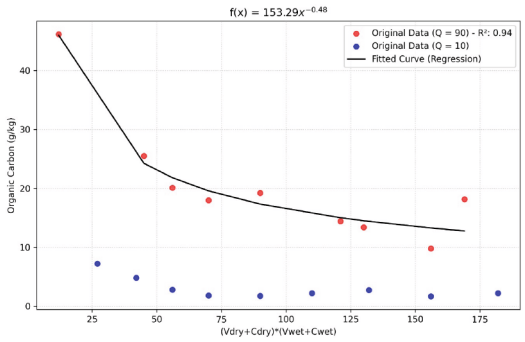

Fig. 6. Polynomial quantile regression between soil color index and carbon content.

6 Conclusion

Climate change has increasingly impacted the planet. Hurricanes, intense heat waves, and snowstorms have become more and more present in society's daily

life. Research that can assist in initiatives to help mitigate these climate effects is becoming increasingly important. In this context, soil plays a fundamental role, being able to help reduce polluting gases in the atmosphere.

This work examined the correlation between soil color and soil organic carbon (SOC) using approaches based on regression techniques focused on both the mean and the probability distribution itself. The results obtained indicate that linear regression identifies a general inverse correlation between soil color and SOC; however, its explanatory capacity is limited and insufficient to capture the heterogeneity of the data, due to the presence of heteroscedasticity. The more carbon in the soil, the greater the uncertainty of the relationship, which can be explained by factors that influence color, such as the presence of minerals that make the soil darker but without a significant presence of carbon.

The piecewise linear model improved our understanding of the relationship between color and carbon by defining specific regimes within this relationship. This result indicates that different processes can regulate the dynamics of soil organic carbon (SOC) in different soil color ranges. However, this approach relies on segmented assumptions, which compromises its ability to capture more complex patterns, especially in the presence of heteroscedasticity.

The use of quantile regression confirmed what the piecewise linear regression indicated about soil color not being uniform across all SOC levels. This quantile approach allowed modeling different parts of the conditional distribution; that is, the quantiles were able to capture the upper part of the distribution, where variability is greater and non-linearity is more prevalent, indicating that environmental and other pedological factors can affect SOC accumulation.

These results corroborate the literature, indicating that soil organic carbon (SOC) is a phenomenon of variability, and uncertainty is predominant. Another interesting result of this work is that it highlights the limitations of exclusively using mean-based models, emphasizing the effectiveness of quantile regression as a reliable and understandable alternative for soil data analysis. In this way, quantile regression proves to be a helpful technique for decision-makers in the agricultural, land management, and climate sectors, potentially providing a clearer view of soil organic composition (SOC) behavior.

As future work, we believe that incorporating other data, such as remote sensing data, in addition to climate data, could yield more accurate results for SOC estimation, especially with the use of quantile regression. Another possibility would be the use of quantile machine learning methods, which could provide greater explainability and robustness for understanding the problem.

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the use of this tool, the authors reviewed and edited the manuscript as necessary and assume full responsibility for its content.

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