

Faculty of Sciences

Quantifying the influence of soil forming factors on carbon stock in the High Fens region and predicting its spatial distribution

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Abstract

This study investigates the environmental factors controlling Soil Organic Carbon (SOC) stocks in the High Fens peatlands and evaluates the potential of spatial modelling approaches to predict their distribution. An integrated approach combining field sampling, laboratory analyses, remote sensing, and statistical modelling was applied across the plateau. A total of 36 soil pits were sampled in contrasting environmental settings.

SOC stocks were estimated using carbon concentration, dry bulk density, and soil depth measurements. Environmental predictors including topography, hydrology, vegetation indices, soil type, and land cover were analyzed to assess their influence on SOC variability. Results indicate that land cover and soil type are the main factors controlling SOC distribution. Peaty wetland environments displayed significantly higher SOC stocks than forested silty-stony soils. While topographic and hydrological variables contributed to explaining peatland dynamics, their direct statistical influence remained secondary.

A Gamma Generalized Linear Model proved more suitable than classical linear regression due to the skewed distribution of SOC values. In parallel, a Random Forest model successfully predicted the spatial distribution of SOC and highlighted the importance of non-linear environmental interactions. Overall, the study demonstrates that combining field observations with remote sensing and machine-learning approaches provides an effective framework for assessing SOC dynamics in peatland ecosystems. The results also emphasize the importance and vulnerability of the High Fens as a major long-term carbon reservoir under increasing anthropogenic and climatic pressures.

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1. Introduction

Peatlands are unique ecosystems defined by the accumulation of partially decayed organic material, peat, that forms over centuries or millennia (Gorham, 1957). This process occurs in environments where waterlogged and anoxic (oxygen-poor) conditions significantly limit the rate of organic matter decomposition (Dargie et al., 2017). These conditions are typically found in humid zones with cool temperatures and specific topographic features that facilitate water retention in and over the soil. Physically, peat is characterized by its high porosity, high water content, low pH, and low bulk density (Andersen et al., 2011; Walter et al., 2018).

On a global scale, peatlands play a disproportionately large role in the terrestrial carbon cycle (Keiser et al., 2024). While they cover approximately 3% of the Earth's land surface (Xu et al., 2018), they are estimated to store roughly one-third of the world's soil organic carbon (Dargie et al., 2017 ; Li et al., 2024), written SOC. This carbon reservoir, estimated to be between 455 and 600 Gt (Yu et al., 2010), contains around twice the amount of carbon stored in the biomass of all global forest ecosystems combined (Minasny et al., 2024). Peatlands are mostly present in northern latitudes, where climate conditions range from cool to cold, facilitating water retention under adequate topography (Wastiaux and Schumacker, 2003 ; Henrion et al., 2024).

In the specific context of the High Fens, the highest plateau in Belgium (Province of Liège), these peatlands have served as active carbon sinks for approximately 14,000 years, following the end of the last glaciations (Demoulin and Hallot, 2009). The efficiency of this sink is driven by cold, wet, and acidic conditions that limit the microbial decomposition of plant material, such as *Sphagnum* mosses and *Molinia caerulea* (Wastiaux and Schumacker, 2003). Peatland ecosystems are vital carbon sinks under natural conditions, though they are highly sensitive to disturbances like drainage or climate warming, which can trigger the release of stored carbon as CO₂, and other greenhouse gases such as CH₄ and N₂O (Holden et al., 2004 ; Alm et al., 1999).

In ombrotrophic (mostly rain-fed) systems like the High Fens' bog, peat accumulation exceeds multiple meters in depth in specific locations, representing a massive, time-integrated store of organic matter (De Vleeschouwer et al., 2012). However, these carbon stocks are highly vulnerable to anthropogenic disturbances, including artificial drainage and land-use changes like spruce afforestation, which can initiate peat oxidation (Holden et al., 2004). Studies indicate that a lowering of the water table allows oxygen to penetrate the soil, stimulating oxidation activity, therefore accelerating the release of CO₂ into the atmosphere (Holden and Connolly, 2011).

As global temperatures rise, northern peatlands risk shifting from net carbon sinks to significant carbon sources, potentially releasing billions of tons of carbon and creating a positive feedback loop for climate change (Minasny et al., 2024). Understanding the interplay between micro-topography, such as hummocks and hollows and moisture levels is essential for accurately predicting the future stability of these critical global carbon reservoirs (Keiser et al., 2024 ; Li et al., 2024). Existing research on these stocks reveals that SOC stock can range reach several hundred tons per hectare across the landscape (Dargie et al., 2017).

Despite extensive research on peatland carbon dynamics, relatively few studies have investigated SOC variability at broader spatial scales in the High Fens using a combination of field measurements, remote sensing, and predictive spatial modelling. Most previous studies either

focus on local-scale experimental observations or long-term monitoring approaches, while fewer studies attempt to combine conceptual understanding of peatland functioning with spatial modelling based on heterogeneous environmental data. In particular, the relative influence of topography, hydrology, vegetation, and soil characteristics on SOC distribution within the plateau remains insufficiently quantified.

To address these limitations, this study aims to investigate the environmental controls of SOC stocks and predict their spatial distribution across a broad study area. The main research questions are as follows :

- *Which environmental factors are strongly associated with the spatial variability of SOC stocks on the High Fens plateau?*
- *To what extent can SOC spatial distribution be accurately assessed using a broader-scale sampling strategy combined with remote sensing and spatial modelling approaches?*
- *How accurately can SOC stocks be predicted across the study area using limited field observations and environmental predictor variables?*

2. Literature review

2.1. Peatlands biogeochemical functioning in cold and temperate Environments

Peatlands are unique biogeochemical systems defined by the long-term imbalance between primary productivity and microbial decomposition (Tonks et al., 2017 ; Swinnen et al., 2019 ; Dargie et al., 2017). Morphologically, a peatland is typically a diplotelmic structure, meaning that it is divided into two distinct vertical horizons: the acrotelm and the catotelm (Swinnen et al., 2019). The acrotelm, or the "active layer," resides at the surface and is characterized by a fluctuating water table, high hydraulic conductivity, and relatively rapid aerobic decay (Tonks et al., 2017 ; Swinnen et al., 2019 ; Givelet et al., 2004). In contrast, the underlying catotelm remains permanently saturated and anaerobic (De Vleeschouwer et al., 2012). In this deeper horizon, the weight of accumulating organic matter collapses the pore spaces, significantly reducing water movement and slowing decomposition to a near-halt, effectively sequestering carbon for millennia (Tonks et al., 2017 ; Holden et al., 2004 ; Minasny et al., 2024). The bottom horizon essentially acts as an aquiclude (confining layer), keeping the bog wet by maintaining the water table high (Swinnen et al., 2019). Below these organic layers sit mineral layers, transitioning into bedrock that does not hold significant carbon concentration as opposed to bog layers (Allan et al., 2013).

Peatlands are fundamentally classified based on their hydrological and nutrient status:

- Ombrotrophic bogs are "rain-fed" systems that receive water and nutrients almost exclusively from atmospheric depositions (Givelet et al., 2004). Because they are isolated from groundwater, they are typically highly acidic ($\text{pH} < 4$) and nutrient-poor (Givelet et al., 2004).
- Minerotrophic fens are fed by both atmospheric inputs and terrestrial sources transported by groundwater or surface runoff (Holden et al., 2004 ; Minasny et al., 2024). These systems typically have higher concentrations of dissolved ions and salts compared to bogs (Holden et al., 2004 ; Henrion et al., 2024). These peatlands also have higher nitrogen content and are more susceptible to N_2O emissions compared to "poor" ombrotrophic peatlands (Martikainen et al., 1993).

A minerotrophic environment can turn into an ombrotrophic system through a natural successional process often referred to as paludification (Schaffhauser et al., 2017 ; Wastiaux and Schumacker, 2003). This transition occurs as peat accumulates over centuries or millennia, eventually raising the peatland surface until it is topographically higher than the surrounding points where surface runoff or groundwater can enter (Givelet et al., 2004). Once the surface becomes hydrologically isolated from these terrestrial water and nutrient inputs, the system becomes exclusively dependent on precipitation, completing the transition from a fen into an ombrotrophic bog (Schaffhauser et al., 2017 ; Givelet et al., 2004).

The dynamics of these ecosystems are governed by a complex feedback loop between the biological community and the physical environment (Brantley et al., 2011). As pioneer vegetation, such as bryophytes, colonize an area, they influence and change the local hydrology and chemistry to create an acidic, nutrient-poor, and waterlogged habitat (Clymo, 1984 ; Andersen et al., 2011).

This "ecosystem engineering" ensures that the litter entering the soil profile is highly recalcitrant (Ritson et al., 2017). Once submerged below the water table, this organic matter enters a state of metabolic arrest, where the lack of oxygen forces microbes to rely on inefficient anaerobic respiration, such as methanogenesis, that produces additional methane (Gatis et al., 2020 ; Yu et al., 2010). Peatlands are therefore also methane sources as well as carbon sinks (Gatis et al., 2020 ; Xu et al., 2018 ; Holden and Connolly, 2011). Peatlands are characterized by a sensitive hydrological equilibrium: excessive water saturation induces anaerobic conditions that drive methane production, while water table drawdown exposes organic matter to oxygen, triggering rapid decomposition and the release of carbon dioxide. In contrast to CO₂ and CH₄ dynamics, saturated peatlands have typically very low N₂O emissions (Evans et al., 2021). Anaerobic conditions completely convert nitrates all the way to harmless nitrogen gas (N₂) rather than stopping at N₂O (Alm et al., 1999). However, similarly to CH₄, drained peatlands experience seasonal drying, and oxygen enters the profile, which stimulates nitrification, and the production of N₂O, which is a greenhouse gas (Holden et al., 2004).

On top of natural interactions, these inherent dynamics are being highly disrupted by human intervention (Minasny et al., 2024). The structural integrity of a peatland is fundamentally tied to its "eco-hydrological" stability, a state easily compromised by anthropogenic land-use changes (Gatis et al., 2020 ; Holden et al., 2004). Activities such as drainage for agriculture or forestry, peat extraction, and infrastructure development fundamentally alter the double structure by artificially lowering the water table (Holden et al., 2004 ; Li et al., 2024). This transition exposes the long-sequestered catotelm to oxygen, which "reverse" the peat-forming process and shift these systems from global carbon sinks to atmospheric sources (Minasny et al., 2024). Critically, this degradation does not only manifest itself by gaseous losses ; it also strongly enhances the mobilization of Soil Organic Carbon (SOC) into water pathways. While physical erosion is often low in stable peatland topographies, the biochemical transformation of particulate SOC into Dissolved Organic Carbon (DOC) represents a far more potent transport mechanism (Kalbitz et al., 2000, Moore et al., 2026). Once the peat structure is exposed to drainage, increased microbial activity accelerates the breakdown of organic matter into soluble forms, allowing DOC to leach into water streams at rates that can exceed losses from physical soil transport (Kalbitz et al., 2000). Considering the quantity of carbon and methane contained in peatlands, as highlighted earlier, this reversal is strongly harmful for global climate dynamics (Brantley et al., 2011).

Furthermore, human influence extends beyond direct physical disturbance to include the indirect effects of atmospheric deposition and climate change (Allan et al., 2013). Climate-driven temperature increases and altered precipitation patterns significantly modulate the ratio of CO₂ to CH₄ released from the peat profile. While CO₂ is released in higher volumetric quantities during aerobic decomposition, CH₄ is a far more potent greenhouse gas, it possesses a global warming potential (GWP) approximately 28 to 34 times greater than that of CO₂ over a 100-year horizon, and over 80 times greater over a 20-year horizon (Myhre et al., 2013; Pachauri et al., 2014). Consequently, even minor increases in methanogenesis due to warmer, waterlogged conditions can disproportionately accelerate positive climate feedbacks, offsetting the peatland's capacity for carbon sequestration.

Increased nitrogen loading from industrial and agricultural sources can alter the competitive balance between mosses and vascular plants, potentially accelerating decomposition rates (Del

Giudice and Lindo, 2017). Even more considering that ombrotrophic peatlands are dystrophic and oligotrophic, meaning that they are generally acidic and are poor in nutrients and nitrogen (Holden et al., 2004). When peatlands are disturbed, they can transition from negligible nitrogen sources into significant atmospheric pollutants (Del Giudice and Lindo, 2017).

Because the accumulation of Soil Organic Carbon (SOC) is such a slow process often occurring at rates of less than a millimeter per year, the system is particularly vulnerable to rapid anthropogenic shifts (Moore et al., 2026 ; Dargie et al., 2017 ; Swinnen et al., 2019). Understanding how specific variables like slope, drainage and vegetation patterns interact with human pressures is therefore critical for predicting the resilience of these massive carbon reservoirs in the Anthropocene (Andersen et al., 2011).

2.2. Environment control on peatland dynamics

2.2.1. Temperature influence

Temperature is a fundamental control of the peatland carbon balance, acting as a climatic filter that dictates the rates of both organic matter production and microbial decomposition (Swinnen et al., 2019 ; Wang et al., 2023). Northern peatlands are characteristically formed in humid zones with cool temperatures where the thermal regime limits the efficiency of decomposers, allowing for the long-term accumulation of partially decayed material (Andersen et al., 2011).

The accumulation of peat is governed by the net balance between Net Primary Production (NPP) and the rate of decay (Swinnen et al., 2019). Process-based models of long-term blanket peatland development indicate that Early Holocene warming was a primary driver of peatland initiation (Swinnen et al., 2019). In these models, a temperature increase, for example of 3.74 °C (observed between 10–8.5 kyr BP) is estimated to have boosted biomass production to a degree that outweighed the simultaneous increase in decomposition caused by higher evapotranspiration and aerobic decomposition. This created an imbalance that triggered lateral peat expansion and increased its surface area (Swinnen et al., 2019).

The sensitivity of SOC to temperature change is disproportionately higher in cold regions than in warm ones (Wang et al., 2023). This sensitivity is often quantified using the Q10 multiplier, which represents the factor by which microbial respiration increases for every 10 °C rise in temperature. Global estimates for SOC decomposition often cite a Q10 value of approximately 1.43 (Wang et al., 2023). However, research in temperate peatlands suggests that decomposition is more sensitive at lower temperature thresholds; for instance, Q10 values can reach 3.7 for temperatures between -4 and 5 °C (-4°C is the minimum limit for decomposition), as small increases above freezing activate specific microbial groups (Wang et al., 2023).

Rising temperatures are threatening stored carbon by ramping up soil respiration and the runoff of DOC (Brantley et al., 2011). As soil warms up, microbial activity surges and triggers oxidation processes. This effect shifts vegetation type ; Sphagnum moss gives way to vascular plants like shrubs and grasses, meaning that the soil is supplied with easily degradable litter (Del Giudice and Lindo, 2017). This effect tends to boost microbial activity, leading to the breakdown of deep, ancient peat layers that had been stable for centuries (Del Giudice and Lindo, 2017).

2.2.2. Topographic factors

Topographic factors, including slope gradient, altitude, and broader topographic features, are primary determinants of peatland development, thickness, and carbon storage potential (Nasrul et al., 2020 ; Li et al., 2024). The influence of relief factors can be divided in two categories ; direct and indirect influences.

First, slope gradient exerts a fundamental control on peat thickness, typically following a well-established inverse relationship where steeper slopes are characterized by shallower peat layers (Nasrul et al., 2020 ; Brosens et al., 2020). This is a direct influence, driven by gravity, which increases lateral soil and water movement and physical erosion rates on steeper gradients (Brosens et al., 2020). Erosion itself has a relatively weak impact in peatlands, with most of the soil movements related to solifluction and creep displacement caused by gravity (Matthews et al., 2005).

Consequently, the thickest peat deposits are typically found on flatter areas, such as plateaus or footslopes positions (Keiser et al., 2024 ; Li et al., 2024). Research indicates that in many upland environments, peat development is functionally restricted on slopes exceeding 25°, as these gradients facilitate rapid drainage and erosion rather than organic matter accumulation (Holden and Connolly, 2011). In contrast, on gentle slopes (<15°), lateral fluxes are much lower, and soil thickness becomes more dependent on local vertical processes such as soil production and chemical weathering (Brosens et al., 2020).

Topography serves as the primary regulator of the hydrological processes that sustain peatlands (Nasrul et al., 2020). Its indirect role dictates the movement of water and biogeochemical fluxes downslope (Brosens et al., 2020). Areas of topographic convergence, such as depressions or footslopes act as zones of water accumulation that favour peat development by maintaining saturated, anaerobic conditions (Hasan et al., 2012). An example of how to quantify this phenomenon is the Terrain Wetness Index (TWI), a metric used to quantify this control; it generally shows a positive correlation with peat thickness because high-index areas create the waterlogged environments essential for peat to form (Hasan et al., 2012).

Furthermore, subsurface topography and the nature of the soil-bedrock interface play important roles in hydrological routing (Lin, 2010). Interactions between soil horizons or between peat and relatively impermeable mineral layers (like clay-rich soils) can impede vertical percolation and promote lateral flow, keeping the upper organic layers saturated (Fraser et al., 2001).

Finally, altitude and elevation also regulate the climatic conditions, such as high precipitation and cool temperatures, that drive peat formation (Walter et al., 2018). However, an elevation threshold can exist where excessively low temperatures at high altitudes limit the primary productivity of vegetation, thereby capping the maximum possible peat depth that can accumulate (Holden and Connolly, 2011). This goes in hand with the vegetation depreciation with altitude. While macro-topographical factors such as elevation are strong controllers the local climate, vegetation growth and subsurface hydrology (which influence peat formation and presence in a region), they are often less predictive of the spatial variability in topsoil organic carbon content, that are more influenced by micro-topography (Keiser et al., 2024 ; Li et al., 2024 ; Nasrul et al., 2020).

2.2.3. Hydrological and vegetation dynamics

Despite an extensive overview of hydrological dynamics in section 2.1, some important notions are still needed to fully cover water dynamics in peatlands. The concept of the mean annual effective water table depth (WTDe) is identified as the primary determinant on greenhouse gas fluxes in managed peatlands (Evans et al., 2021). Every 10 cm of reduction in WTDe (deepening the aerated layer) can increase net warming impacts by the equivalent of at least 3 tons of CO₂ per hectare per year (Evans et al., 2021).

Furthermore, while macro-topographical features like altitude and elevation regulate the climatic conditions such as high precipitation and cool temperatures (that drive large-scale peat accumulation), macro-topography is often less predictive of spatial variability in Soil Organic Carbon (SOC) stocks (Gross and Harrison, 2019 ; Ritson et al., 2017). Instead, these stocks are heavily influenced by micro-topography, where hummocks and hollows create local variations in moisture levels and microbial activity (Keiser et al., 2024). The combination of all types of plants present is highly important, as measurements from aerated hummocks only can underestimate carbon turnover by an average of 25%, while measurements from hollows alone can overestimate it by 40–56% (Keiser et al., 2024). Macro-topography completely overlooks the micro-topographic vegetation-related dynamics.

In parallel, vegetation composition strongly regulates peatland hydrology, carbon inputs, and decomposition rates through both direct and indirect mechanisms (Andersen et al., 2011 ; Del Giudice and Lindo, 2017). Plant communities determine the quantity and chemical quality of litter entering the soil profile, thereby influencing both peat accumulation and microbial activity.

Sphagnum mosses are widely recognized as ecosystem engineers in ombrotrophic bogs because of their important water-holding capacity, low decomposition rates, and ability to acidify their surroundings (Clymo, 1984 ; Ritson et al., 2017). In comparison to Sphagnum moss, vascular plants decompose organic matter faster than mosses. Their root systems can also alter peat structure and facilitate oxygen penetration. For example, a shift from moss-dominated communities toward vascular vegetation often increases soil aeration and accelerates decomposition ; though this effect is less important in wet and cold environments (Del Giudice and Lindo, 2017). This vegetation shift is commonly observed in disturbed or drained peatlands, where *Molinia caerulea*, shrubs, or tree species progressively replace Sphagnum communities (Wastiaux and Schumacker, 2003). Such transitions are particularly relevant in temperate peatlands, where drainage, nitrogen deposition, and climatic warming can trigger long-term ecological succession toward drier vegetation assemblages (Holden et al., 2004).

2.2.4. Bedrock and soil type influence

Beyond surface hydrology and vegetation dynamics, subsurface geological conditions exert a strong control on peatland development, hydrological behavior, and long-term carbon accumulation. The lithological characteristics of the underlying parent material influence topography, weathering rates, soil texture, permeability, lateral water flow, and nutrient availability, all of which control peatland formation and persistence (Lin, 2010 ; Fraser et al., 2001).

The most fundamental role of parent material in peatland environments is its influence on drainage conditions. Peat accumulation requires long-term water saturation, which is strongly favored by relatively impermeable substrates that limit vertical percolation and promote water retention in upper soil horizons (Holden et al., 2004 ; Minasny et al., 2024). Geological materials such as clays, shales, or weathered schists often act as hydraulic barriers, reducing infiltration and maintaining high water tables favorable to anaerobic conditions (Fraser et al., 2001).

On the opposite side, highly permeable substrates such as coarse sands, or gravels facilitate rapid drainage, lowering water retention capacity and making long-term peat accumulation less likely (Walter et al., 2018). In this case, organic matter is more exposed to oxygen, increasing aerobic decomposition rates and limiting the formation of thick peat deposits. The hydraulic conductivity of subsurface materials therefore directly regulates whether an environment functions as a long-term carbon sink or remains mineral-dominated.

Bedrock composition also influences peat chemistry through mineral weathering. This process comes from below the organic horizon, where bedrock releases dissolved ions and nutrients into the soil and its groundwater (Andersen et al., 2011).

For example, silicate-rich bedrock tends to favor ombrotrophic environments because of their acidic and nutrient-poor conditions ; whereas lithologies such as carbonates or clays are more reactive and favor minerotrophic systems instead (Givelet et al., 2004 ; Holden et al., 2004).

The interface between mineral soil and peat also plays an important structural role in peatland hydrology. Transitions between organic horizons and underlying mineral layers can create zones of reduced permeability, especially where silts or clays are present, because of their fine grain and reduced hydraulic conductivity (Lin, 2010). These interfaces can redirect water laterally rather than vertically, keeping saturation in upper peat horizons and reinforcing anaerobic conditions, favorable for carbon soils accumulation (Fraser et al., 2001).

In addition, the soil type material developed on the weathered parent material influences carbon storage through its physical and chemical properties. Soil texture influences porosity, water retention, and oxygen diffusion, with finer-textured soils generally retaining more moisture than coarse materials because of capillary forces (Su et al., 2022 ; Brady and Weil, 2016). In mineral soils underlying peatlands, clay and silt fractions may additionally stabilize organic matter through organo-mineral interactions, physically protecting carbon compounds from microbial decomposition (Gross and Harrison, 2019).

However, in deep peat systems, the direct influence of mineral soil properties progressively decreases with distance from the mineral substrate. In these cases, the main influence of bedrock and soil type becomes hydrological rather than biochemical, as they primarily determine whether conditions are suitable for peat initiation and maintenance over long timescales (Minasny et al., 2024).

2.2.5. Land cover and human intervention

While peatlands are naturally regulated by interactions between climate, hydrology, vegetation, topography, and parent material, human activities have become one of the most significant drivers of peatland degradation worldwide (Minasny et al., 2024 ; Li et al., 2024). Anthropogenic disturbances alter the eco-hydrological equilibrium required for peat accumulation, often shifting these systems from long-term carbon sinks to net carbon sources (Holden et al., 2004).

Among all land use modifications, drainage is widely recognized as the most disruptive intervention in peatland environments. Artificial drainage systems are commonly installed to improve land suitability for forestry, agriculture, peat extraction, or infrastructure development by lowering the water table and increasing soil aeration (Holden et al., 2004 ; Evans et al., 2021). However, this hydrological alteration directly exposes previously saturated organic matter to oxygen, which stimulates aerobic microbial decomposition and accelerates the mineralization of centuries or millennia of accumulated carbon (Holden and Connolly, 2011).

The lowering of the water table triggers a sequence of physical and biogeochemical changes. First, as discussed earlier, increased oxygen penetration enhances microbial respiration, resulting in higher CO₂ emissions from peat oxidation (Alm et al., 1999). Second, the drying and compaction of upper peat layers causes structural collapse, increasing dry bulk density and leading to land subsidence over time (Holden et al., 2004 ; Moore et al., 2026). Subsidence rates of 1 to 2 cm per year have been reported in drained peatlands in the Anglian Fens, which alters natural surface topography and hydrological pathways (Holden et al., 2004).

In addition to carbon losses in gaseous state, disturbed peatlands often experience increased mobilization of DOC. As decomposition accelerates under oxic conditions, organic compounds become more soluble and are exported through lateral water fluxes into streams and drainage networks (Kalbitz et al., 2000).

Human influence is not limited to direct physical interventions. Atmospheric nitrogen deposition resulting from agriculture, industry, and fossil fuel combustion can also modify peatland nutrient dynamics (Del Giudice and Lindo, 2017). Because many peatlands are naturally oligotrophic and nutrient-poor, even moderate nitrogen enrichment can alter species competition by favoring vascular plants over Sphagnum mosses, thereby indirectly increasing decomposition rates and reducing carbon sequestration efficiency (Del Giudice and Lindo, 2017 ; Holden et al., 2004).

Climate change itself can be considered an indirect anthropogenic pressure interacting with all previously described disturbances. Rising temperatures, altered precipitation regimes, and more frequent drought periods intensify peatland vulnerability by lowering water tables, increasing evapotranspiration, and enhancing microbial activity (Wang et al., 2023 ; Minasny et al., 2024). In already disturbed peatlands, these climatic pressures amplify degradation processes and reduce ecosystem resilience.

2.3. Critical Zone, a new way of studying complex environments

Similarly to how human activity influences every aspect of bog dynamics, natural factors influence themselves, reaching a dynamic equilibrium according to the forcing of each component, as seen in the literature review. Integrating every part that compose the whole environment in a unique model allows to study the processes under a multidisciplinary spectrum, rendering the results much closer to reality than what can be achieved in a controlled environment reviewing the role of variables independently. In recent decades, a new holistic concept was introduced to address this problem, acting as a paradigm shift in Earth Science, called the Critical Zone.

The Critical Zone (CZ) is the vertical area ranging from the top of the vegetation to the aquifers in the subsurface. To rephrase it in a more precise way ;

The critical zone is defined as “*heterogeneous, near surface environment in which complex interactions involving rock, soil, water, air, and living organisms regulate the natural habitat and determine the availability of life-sustaining resources*” (National Research Council, 2001).

This conceptual topic is getting more and more attention due the important role of the interactions between the hydrological, lithological, pedological and atmosphere systems. These domains have for long been studied independently, in laboratory, with controlled parameters. However, this sort of “ideal” environment has limited applications in the outside world considering that parameters from varied domains are constantly present together and influencing the behavior of other fields of study (Lin, 2010).

Despite being only a few meters thick, the interactions observed in the CZ cannot be ignored when studying Earth system sciences. In his article, Lin describes the critical zone as the “most heterogeneous and complex region of the Earth”, and emphasizes the fact that it can be permanently changed by human-induced actions, reaching a new equilibrium after an irreversible evolution. It is important to point out that the term of critical zone does not describe a precise type of environment. Analyzing the Critical Zone in its whole could bring new ways to understand how all of these well-researched fields interact together.

The main objective of the study concept “Critical Zone” is to characterize relationships between many study fields elements to simulate outside environments interactions as precisely as possible. Considering the dynamic aspect of the CZ, taking human actions and impacts into account is itself required to accurately describe the processes influencing said study elements. This can be applied to various natural settings, the concept is not framed to a single type of environment.

2.4. High Fens plateau characteristics

2.4.1. Overall environmental conditions specific to the plateau

The site sits on a Cambrian-Ordovician base, and was folded during the Caledonian and later Hercynian orogenies. The bedrock lithology is mainly made with quartzites, phyllites, and quartzophyllites. Local intrusions from the Revinian are also found in the area (Demoulin, 1980). Following the orogenies, two transgressions have happened, the first one during the High Cretaceous, and the second one was during the Oligocene. Signs of these littoral transgressions can be found in the form of sand deposits and flint clay, though most are only lingering remains today (Demoulin, 1986). Quaternary periglacial processes have left scars such as cryogenic mounds, and silt deposits from aerial origin also accumulated on topographic heights during colder phases (Demoulin, 1986).

In temperate upland peatlands such as those of the High Fens, bedrock composition is particularly relevant because peat deposits often develop on shallow mineral substrates or directly over bedrock. In these systems, the interaction between relatively impermeable lithologies, shallow slopes, and abundant precipitation creates the hydrological conditions necessary for sustained peat accumulation despite moderate climatic conditions (Wastiaux and Schumacker, 2003 ; Henrion et al., 2024).

The development of the peatlands on the High Fens plateau began approximately 14,000 years ago following the Late Glacial Maximum. Multiproxy studies, integrating pollen analysis, macrofossils, and geochemical signatures, describe a transition from a glacial tundra to the ombrotrophic bogs that define the region today (De Vleeschouwer, 2012, Davis et al., 2003). Palaeo-environmental data from the Belgian High Fens reveals that many ombrotrophic massifs began as minerotrophic depressions during the early Holocene that gradually filled with peat and shifted towards Sphagnum-dominated environments as they lost contact with groundwater (Damblon, 1996).

The mean annual temperature of the High Fens plateau, approximately 6.7 °C, falls within a relatively temperate-cool range, providing the necessary conditions for the development of massive peat reservoirs over the last 14,000 years (De Vleeschouwer et al., 2012). This temperature is also in the range characterized by high value of Q10, meaning that in the High Fens, even minor climatic warming could significantly accelerate the turnover of the acrotelm because of the activation of certain microbial groups (Wang et al., 2023 ; Keiser et al., 2024).

Temperature fluctuations are recorded through various proxies in the peat stratigraphy, such as testate amoebae, pollen, and dust deposition (Allan et al., 2013, Davis et al., 2003). Analysis of the Misten bog core shows that periods of maximum dust flux often correspond to cold events. For example, a strong climatic deterioration between 3300 and 2500 BP, marked by cold and dry conditions, coincided with a shift in vegetation and microbial species (Allan et al., 2013). These records highlight how relatively small regional temperature changes in have altered the physical and biological composition of the High Fens' peat soils (Allan et al., 2013).

2.4.2. History of the study area

The bogs have been significantly altered by human activities. In the temperate High Fens, afforestation is a major land use change affecting peatland ecosystems. The plantation of fast-growing conifers, such as spruce, has historically been promoted for timber production in many upland peatland areas, including here in Belgium (Wastiaux and Schumacker, 2003). While forests are often associated with carbon sequestration, afforestation on peatlands frequently requires drainage and introduces vegetation communities poorly adapted to saturated conditions (Holden et al., 2004). Tree cover also increases evapotranspiration and canopy interception, further reducing soil moisture and enhancing peat drying (Andersen et al., 2011).

When peatlands are drained, the results are often irreversible structural changes. Lowering the water table causes the upper peat to collapse, increasing bulk density and causing subsidence rates that can range from 1 to 2 cm per year following drainage and afforestation (Holden et al., 2004 ; Moore et al., 2026). In the High Fens, historical drainage for spruce forestry and peat extraction has created a discrepancy where past peat thickness likely exceeded modern levels by 1.8 to 3.4 meters (Moore et al., 2026).

Peat extraction constitutes an even more direct form of disturbance. Industrial or historical peat cutting physically removes carbon-rich layers that required millennia to accumulate, irreversibly reducing peat depth and altering local hydrology (Minasny et al., 2024). Even after extraction ceases, restoration remains difficult because the original microtopography, vegetation communities, and hydrological conditions are rarely fully recovered (Gatis et al., 2020).

Because peat accumulation is an extremely slow process, typically occurring over centuries to millennia, anthropogenic disturbances can reverse thousands of years of carbon sequestration within only a few decades (Dargie et al., 2017 ; Moore et al., 2026). Understanding the influence of land use history and human interventions is therefore essential when studying modern spatial variability in Soil Organic Carbon (SOC), especially in landscapes such as the High Fens where drainage, afforestation, and peat extraction have historically modified large portions of the plateau.

3. Methodology

3.1. Overall objectives and rationale of the study

The objective of this study is to bring a different scope to peat soils analysis compared to existing studies. To better grasp and quantify the factors influencing the different topics discussed in this work, an integrated approach was conducted, which is the reason why the concept of critical zone was extensively explained in point 2.3.

Instead of focusing on a relatively long time window within a limited area, the protocol and analysis conducted attempt to identify dynamics in a short time-frame of measurements taken within a single month, from mid-November to mid-December 2025. This temporal aspect does not include evolution over long periods of time. The results might therefore be less precise than usual approaches, but is balanced by studying the area at a bigger spatial scale, extending on a significant part of the plateau. This choice could highlight known dynamics under a different paradigm of research compared to current literature. Figure 1 illustrates the workflow followed throughout the study.

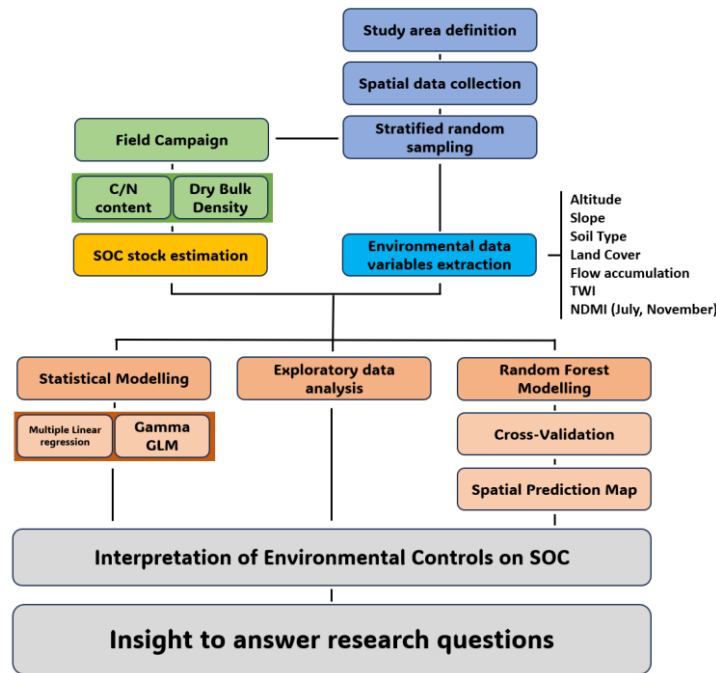


Figure 1: General workflow of the study

To quantify the influence of natural and anthropic factors controlling carbon storage, various methods were explored. On top of satellite data, field observations, soil sampling and laboratory work were conducted on samples collected on the plateau specifically for this study. A total of 36 pits were dug down in heterogenous locations to capture the variety of settings laying on the plateau (figure 2). This approach, combining both large scale satellite data and precise sampling analysis in laboratory is effective to conduct a reliable analysis afterward.

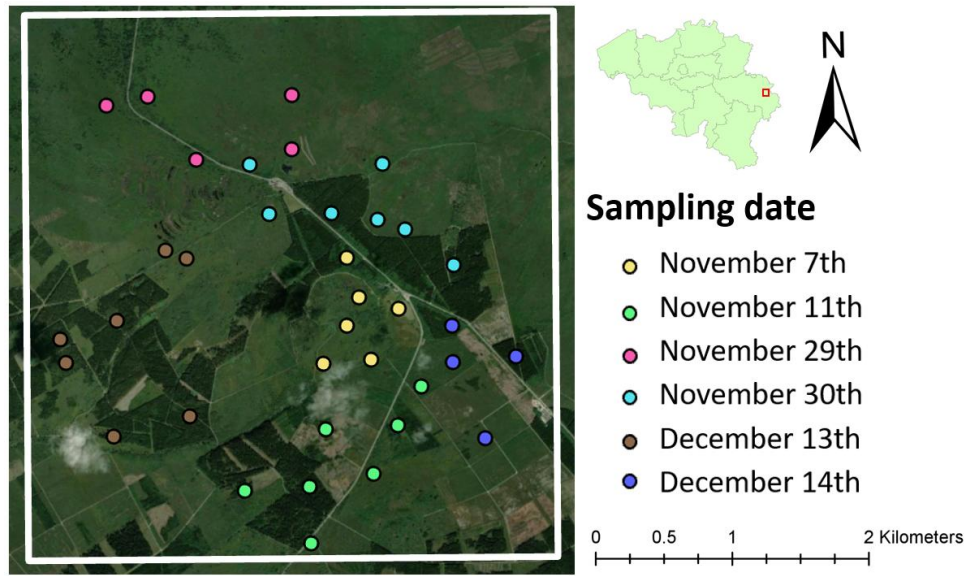


Figure 2: Map of the studied plateau and sampling locations

3.1.1. Main variable of the study

In soil systems, the upper horizon usually retains the highest amount of carbon. A vertical soil profile, divided in different horizons, displays an inverse relationship between depth below the surface and carbon concentration.

After processing the samples, the relationship between carbon sequestration and soil characteristics can be expressed and quantified using Soil Organic Carbon (SOC). SOC is considered a premier indicator for assessing a bog's effectiveness in carbon retention because it directly represents the long-term storage of organic matter derived from living organisms (Gross and Harrison, 2019). Unlike atmospheric or vegetative carbon, which cycle back to the atmosphere relatively quickly, SOC in peatlands can persist for millennia (Gross and Harrison, 2019). This variable is therefore ideal to determine and synthesize how effective a soil is at retaining carbon. It can be estimated using equation 1 :

$$SOC = C \times DBD \times D \quad (1)$$

Where :

- **C** = Proportion of organic carbon contained in the soil
- **DBD** = Dry bulk density (g/cm^3)
- **D** = Thickness of specific horizon of soil (cm)

Once the SOC for every layer of soil is determined for each layer, they are added to estimate the total OC contained at a specific location, which is therefore expressed in g/cm^2 according to the formula. However, it has then been converted to tons per hectare using the following relationship : $1 \text{ g}/\text{cm}^2 = 100 \text{ T}/\text{ha}$. This unit is more standardized in the scientific community and will be written as Mg C ha^{-1} throughout the study.

3.1.2. Independent variables of the study

The literature review section highlights the different fields of research involved in peatland studies. Numerous factors act as parameters, giving an environment its characteristics. However, no single metric can accurately depict the dynamics taking place in any system. To quantify as precisely as possible the processes shaping bog environments and SOC, proxy variables are used to represent these various fields of study.

As discussed earlier, previous research narrowed down most dynamics influencing peatlands to these aspects : climate (temperature and precipitations), relief (slope, altitude, topography), hydrology, vegetation and parent material. Furthermore, human influence, whether direct intervention or indirect climate alteration, has an impact on all of these aspects.

Climatic parameters

Considering the short time frame approach of the study, climatic factors are not extensively included in the model. Peat accumulation or loss is, as seen in the literature, influenced by climatic factors such as temperature and precipitation. However, their role on SOC stock variations is highly gradual, spreading on long time intervals. Moreover, considering the modest extent of the plateau (studied area spans over 19.48 km²), it is considered that precipitations, temperatures or wind speed do not have a strong variance throughout the area. For the same reason, latitude, despite being an important metric due to its influence on climate, was not taken into account.

Topography

A digital elevation model of the study area, with a 1 meter resolution, gives insight to landscapes elements. It was obtained from the National Geographic Institute (NGI). In the case of this study, altitude and slope are used as parameters that could explain the variance of SOC over the plateau. As seen in the peer-reviewed studies, altitude influence the environment itself, and slope plays a significant role in water dynamics (horizontal fluxes and DOC). It could be expected to observe thinner horizons of organic matter on steeper slopes.

As discussed in point 2.2.2, altitude and elevation serve as critical regulators of the climatic conditions that drive or limit peat formation. High precipitation and cool temperatures, typical of the location, create a positive water balance. However, while macro-topographical factors such as overall elevation are strong controllers of the long-term accumulation of peat thickness, they are often less predictive of the spatial variability in topsoil SOC stocks.

Hydrology and drainage

Hydrological components play a significant role, as seen in the state of the art. However, similarly to climate parameters, data with a temporal structure are preferred as it allows to include seasonal factors, which is crucial in regards to water dynamics. Despite this limitation, two proxy variables

related to drainage have been integrated in the analyzed elements. Those being flow accumulation and the Topographic Wetness Index (TWI)

Accumulation flow was calculated based from the initial DEM, using the D8 (Deterministic Eight-direction) method, which is a standard algorithm used in GIS to model surface flow (O'Callaghan and Mark, 1984). It operates on a simple but rigid geometric logic to determine how water moves across a digital landscape.

The D8 algorithm assumes that water from a center cell will flow into one and only one of its eight neighbors. To decide which one, it calculates the slope between the center cell and each neighbor using equation 2 :

$$S = \frac{\Delta Elevation}{Distance} \quad (2)$$

The flow is directed toward the neighbor with the steepest downward slope. If the steepest slope is flat or upward, the cell is considered to be a "sink". In equation 2, the distance value is either 1 for direct neighbours, or $\sqrt{2}$ for diagonal neighbours, as the DEM has a 1 meter resolution. In highly anthropogenic landscapes, where water is forced into specific, narrow paths, D8 is highly practical.

Despite being a good indicator, flow accumulation on its own only provides a glimpse of hydrological dynamics ; its major flaw is that most cells have a relatively low value, often being 0. That limits the quality of the output, as cells tend to either have relatively high values, or be measured as 0, mostly dividing them into two extremes. This is because if they aren't the single steepest path for any neighbour, they collect nothing, even if they are technically "lower" than surrounding ground. It is an accurate depiction of drains, as distribution of potential runoff water consistently follows specific paths, but it partially misses the plateau aspect of the High Fens.

To address this problem, and to reinforce the hydrological aspect of the study, a Topographic Wetness Index (TWI) was calculated. In peer-reviewed hydrology, TWI is the preferred metric for identifying areas of potential saturation and surface runoff (Beven & Kirkby, 1979). Its formula is shown in equation 3 :

$$TWI = \ln\left(\frac{\alpha + 1}{\tan(\beta)}\right) \quad (3)$$

Where:

- α is the local upslope contributing area per unit contour length (in m² given the 1 meter resolution of the DEM)
- β is the local slope angle (in radian)

A unit of 1 has been added to α to ensures that the cell add its own area to the calculation, which avoids obtaining $\ln(0)$ (Moore et al., 1991).

Flow accumulation tells how much water arrives at a location, but the inclusion of local slope takes into account how quickly that water leaves. It creates a "steady-state" hydrological picture. A flat area with high accumulation will have a very high TWI (wetland/flood risk), whereas a

steep area with the same accumulation will have a lower TWI (well-drained). The inclusion of a logarithmic element also addresses the problem of D8 flow accumulation, which tends to include either near-zero or really high values. D-Infinity, however, treats flow as a vector. It allows the flow from one cell to be shared between two downslope neighbors based on the steepest descent angle (Tarboton, 1997). This produces a continuous moisture gradient rather than a "stringy" one. For a TWI, which is meant to represent soil saturation potential, D-inf is estimated to be more representative of the divergent aspect of water and how it physically moves through the topsoil (Sørensen et al., 2006). If the steepest direction falls directly toward a neighbor, all flow goes there. However, if the steepest direction falls between two neighbors, the flow is partitioned proportionally between them based on how close the angle is to each.

Even though the first flow accumulation is less relevant than the topographic wetness index, both of these estimates were kept in the study ; based on literature, it is likely that hydrology and drainage play a major role in SOC variation, hence both of their inclusion.

Vegetation

Vegetation indices derived from remote sensing are frequently used as proxies for ecological dynamics. Spectral metrics such as the Normalized Difference Moisture Index (NDMI) provide indirect data about vegetation water content and plant stress, which are themselves strongly related to peatland hydrological conditions (Gao, 1996). In peatland environments, high NDMI values are generally associated with wetter surfaces and healthier moisture-dependent vegetation, while lower values may indicate drier conditions, vegetation stress, or anthropogenic disturbance. The NDMI is calculated using equation 4, with Near Infrared (NIR) and Short Wave Infrared (SWIR) :

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \quad (4)$$

The spectral bands used come from Sentinel-2, with NIR being its 8th band, and SWIR being its 11th. The data was obtained through the Copernicus Data Space Ecosystem and the NDMI index was calculated using ArcGIS Pro, based on the two bands.

Soil Type

Soil type was integrated as a categorical proxy variable that represent the pedological characteristics of the study area. The data was obtained from the Public Service of Wallonia (SPW). The soils of the area were divided into two major classes : peaty soils and silty-stony soils. This distinction reflects the strong contrast between organic peat-dominated environments and more mineral substrates observed across the High Fens plateau.

As discussed in section 2.2.4., soil characteristics influence hydrological behavior, porosity, oxygen diffusion, and the capacity of soils to retain organic matter. Peaty soils are characterized by high organic matter content, low dry bulk density, and persistent water saturation, conditions that strongly favor long-term carbon accumulation. In contrast, silty-stony soils generally display

higher mineral content, lower water retention capacity, and greater aeration, which can enhance decomposition processes and limit SOC storage.

Land cover

A land cover classification has been manually done to divide the plateau in the 2 major types of land coverage ; forest areas and wetlands. This was based on satellites images, with information starting in 1971. The creation of this simplified land cover map is detailed in point 3.2.1.

Land cover was included as an explanatory variable because vegetation structure and ecosystem type strongly influence peatland hydrology, litter inputs, evapotranspiration, and long-term carbon accumulation. As discussed in section 2.2.3, wetlands dominated by peat-forming vegetation generally maintain saturated conditions favorable to SOC preservation, whereas forested areas, especially those associated with drainage or afforestation, often promote drier conditions and enhanced organic matter decomposition.

To ensure that the variable reflected long-term environmental conditions rather than recent disturbances, only areas whose land cover remained unchanged since 1971 were retained in the analysis. This precaution was considered important because SOC accumulation and depletion occur over long temporal scales, and recently modified environments may not accurately reflect stable carbon storage dynamics. However, the exclusion of a non-negligible part of the total area could be considered as a liability, as a significant part of recently human influenced soils is removed from the sampling framework.

Discussed variables are summarized in table 1 and visualized in figure 3. Figure 3 do not include flow accumulation because it appears noisy, and the NDMI illustrated is from July.

Table 1: Main parameters included in the study

Variable	Unit / Value	Main Aspect addressed	Source of data
Altitude	Meter (m)	Topography	NGI
Slope	Degree (°)	Topography	DEM-derived
Land cover	Wetlands or forests	Environmental dynamics	Satellite imagery
Soil type	Peaty soil or Silty-stony soil	Pedology	SPW
NDMI (moisture index)	Dimensionless (Water stress)	Vegetation	Copernicus
Flow accumulation	Number of cells draining into one (unique value)	Drainage	DEM-derived
TWI (Topographic wetness index)	Dimensionless (Potential for water accumulation and soil saturation)	Drainage	DEM-derived

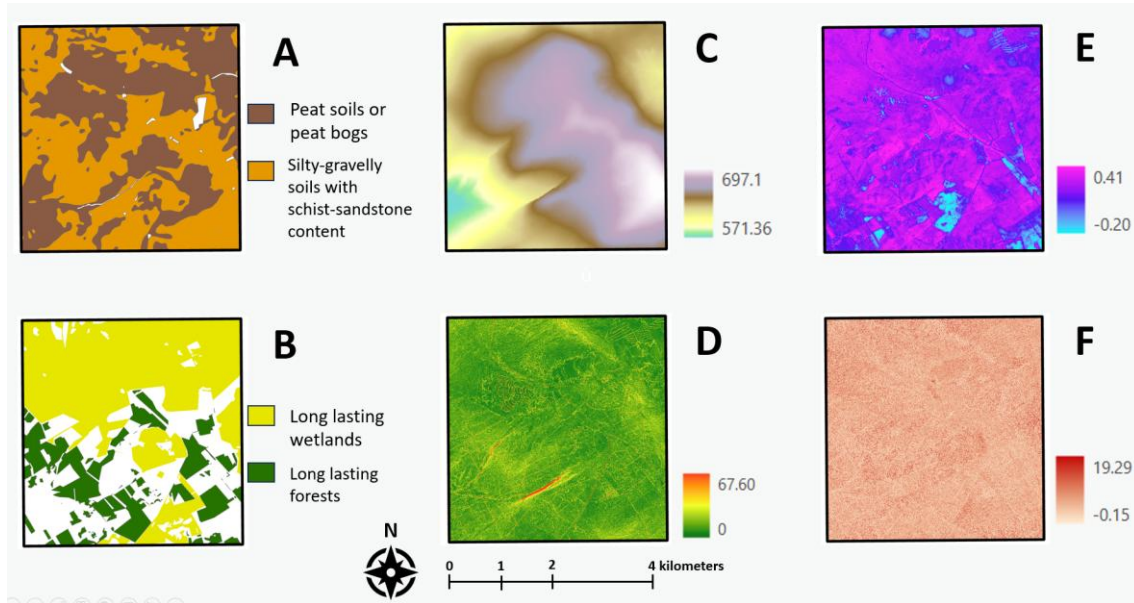


Figure 3: Maps of independent variables (A : Soil Type | B : Long lasting land cover | C : Digital Elevation Model | D : Slope | E : NDMI in July | F : Topographic Wetness Index)

3.2. Methodology followed to establish the sampling points

3.2.1. First assessment of the characteristics of the area

Aerial images were retrieved to assess the evolution of land cover over recent decades. To evaluate this evolution, four different years were analyzed : 1971, 1990, 2010 and 2023. For each of these aerial photos, the land was manually digitalized, dividing it into two main land cover categories, forests and wetlands. Manual digitalization was preferred over supervised classification to avoid different methods being carried out due to the important differences of images resolution and other technical characteristics associated with sensors, as they were strongly revamped over recent decades.

The evolution of soil coverage was then determined, giving a precise overview of how the land was modified over the last 50 years. To study the influence of land cover on SOC, it was decided to only include areas that have not changed since 1971, as carbon accumulation is a long process, and a location that has sustained major changes is not indicative of long-term trends. It is known that soil on deforested areas contains significantly less carbon than before the removal of tree coverage.

3.2.2. Deciding where to conduct sampling

Once this evolution was established over the studied vicinity, the sampling points were determined using a stratified random strategy. To have a statistically significant sampling size, 36 points were placed, meaning that every combination of soil type and land coverage is represented

with eight samples. Despite being randomly generated, multiple iterations were conducted to find a configuration that has points somewhat evenly distributed between the plateau and slopes, and that are not too far from major roads, to facilitate sampling.

It is important to note that two points were later redistributed after reviewing unauthorized areas locations with a forest ranger. However, their class characteristics were unchanged and they were replaced in the same vicinity as it was originally intended. The expeditions to gather soil samples were carried out at the end of 2025, between early November and mid-December. A total of six days were necessary to visit and sample the 36 points, with dates visible in figure 2. The methodology followed on the field to avoid sample contamination is detailed in the annexes (A.1).

3.3. Laboratory methodology

3.3.1. Sample processing

All of the laboratory related processing was conducted at the laboratory of physical geography, UCLouvain. After pre-processing of the soil samples (detailed in A.2), two groups of samples were created (figure A.4), one that was heated to 40°C, and the other to 105°C. Following the heat treatment, the halves subjected to 105°C were used to determine the dry bulk density (DBD) of the material. Since the initial volume of each sub-sample is known, the dry mass obtained after furnace drying provided the final variable needed for DBD estimation, used to determine SOC (equation 5).

$$DBD = \frac{M_{dry}}{V_{total}} \quad (5)$$

Dry bulk density is a physical property defined as the mass of the dry solids divided by the total volume occupied by those solids (g/cm³), including the pore spaces. It serves as a primary indicator of structural integrity, compaction, and porosity of the soil. As discussed in the literature review, peaty soils tend to have relatively low DBD compared to more mineral soils due to hydrological dynamics. The selection of 105°C is the international standard for defining "oven-dry" weight, used to assess DBD in the protocol. This specific temperature is high enough to break the hydrogen bonds of hygroscopic water (water molecules physically bound to particle surfaces) and evaporate it, but at the same time it remains low enough to prevent the combustion or significant loss of organic matter and the structural breakdown of most mineral components. Using a lower temperature might leave residual moisture, leading to an overestimation of density, while higher temperatures could lead to the chemical decomposition of the sample itself (Gardner, 1986).

3.3.2. Description of instruments used

The second batch of samples, heated to 40°C, was analyzed using two instruments in order to determine the amount of total carbon and nitrogen contained in the soil. Compared to the samples used to estimate the dry bulk density, those ones were only treated to remove excess water found in the soil, while preventing mass major chemical bounds to break down, allowing to preserve

important characteristics related to each soil sample. The mass of the samples is also less altered than the 105°C ones.

To determine the amount of total organic carbon and nitrogen contained in the different soil samples, a Macro-Elemental Analyzer was used. The process begins with preparation, where the soil is weighed into a reusable ceramic boat. This boat is pushed into a horizontal combustion tube heated to roughly 900–1350°C (1100° in this study). The sample in the boat undergoes a high-temperature oxidation in a continuous stream of pure oxygen. As the soil burns, the carbon is converted into carbon dioxide (CO₂) and the nitrogen into nitrogen oxides (NO_x). These gases are swept by a carrier gas through a series of scrubbers and reagents to remove moisture and convert the NO_x into pure nitrogen gas (N₂). The gas then passes through a non-dispersive infrared (NDIR) cell, which measures the CO₂ by detecting how much infrared light it absorbs. Finally, the machine's software compares the resulting electrical signal against a calibration curve generated from known standards, providing a precise measurement of the total organic carbon and nitrogen percentage in the sample.

The carbon related results provided by the Macro-Elemental Analyzer are expressed as Total Carbon (TC). The instrument does not make a difference between Organic Carbon (OC) and Inorganic Carbon (IC). Usually, IC would be subtracted from TC to obtain OC. However, OC is assumed to be equal to TC in this study. In ombrotrophic peat bogs, with high acidity, OC accounts for more than 95% of TC (De Vleeschouwer et al., 2010 ; Keller and Bridgman, 2007). As this assumption is less robust for forest environments, it is discussed in the limitations and improvements section.

In parallel, a second instrument was used to determine soil reflective characteristics, called a Mid-Infrared (MIR) Spectrometer, which utilizes FTIR (Fourier Transform Infrared) spectroscopy to analyze soil properties through light rather than combustion. The process begins by placing finely ground soil samples into small wells alongside a gold-plated reference cap used to calibrate the system's background reflection. During the analysis, the machine directs a beam of infrared light at the sample, and an internal mirror oscillates rapidly to perform 128 scans per sample; these multiple measurements are averaged into a single, high-quality signal to eliminate electronic noise and ensure precision. As the infrared light interacts with the soil, specific chemical bonds, found in organic or mineral composites, absorb energy at distinct frequencies, causing them to vibrate. The light that is not absorbed is reflected back to a detector, which generates a spectrum, that can then be used to highlight characteristics of said soil depending on values at certain wavelengths.

3.4. SOC stock estimation methods

As demonstrated with equation 1, SOC stock is determined by dry bulk density, carbon percentage and soil depth. However, given the nature of the samples that were analyzed in the Macro-Elemental Analyzer, the variability of dry bulk density and carbon proportion is not continuously known. This is illustrated in figure 4, depicting the carbon percentage associated with each sample. As measurements have been simplified to discrete 8-centimeters thick samples, intervals of around 20 centimeters on average remain unknown between these measured segments. This has implications on SOC estimation, as gaps in the continuous profile have to be interpolated.

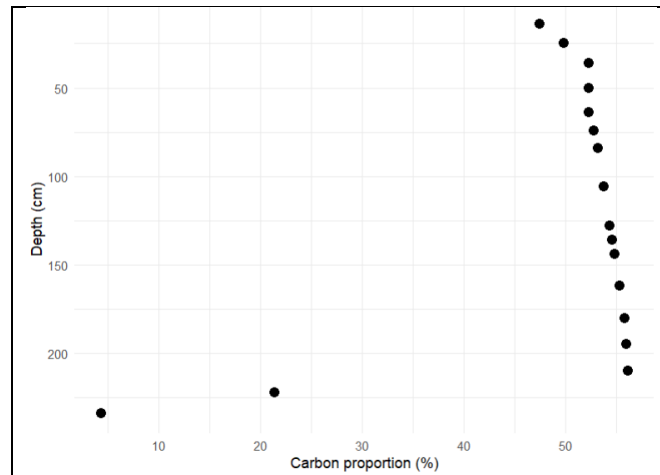


Figure 4: Carbon percentage evolution across vertical profile (pit 5)

Three distinct methods have been carried out to estimate continuous SOC stock values associated with the sampling points. Figure 5 highlights their differences to visually support explanations, the conceptual profile used to visualize these different methods is based on the profile of pit 5, which is representative of bog structures, with relatively constant carbon proportion until an abrupt transition between organic and mostly inorganic horizons.

It was arbitrarily chosen to use carbon percentage as the x-axis in this visualization, but the same transformations are applied to DBD (DBD and carbon percentage follow similar trends visible in figure A.6). In both cases, the objective is to divide the vertical profile in segments and use these virtual carbon percentage and DBD, combined with their thickness, to calculate the final SOC stock value by adding them, from surface to parent material.

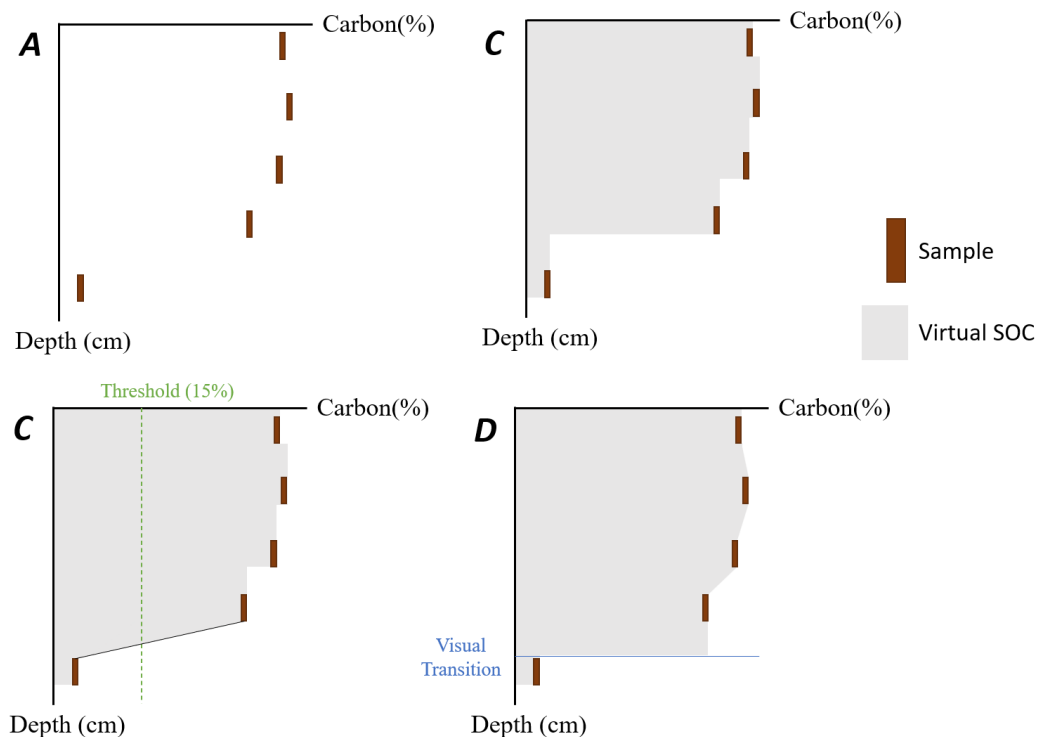


Figure 5: Possible methods used to estimate SOC stock

To obtain a single value of SOC for each pit, three methods were calculated to illustrate and justify the final methodology followed. The first plot, graph A, depicts the objective situation before interpolation. Graph B of figure 5 consists of a simple interpolation, in which unmeasured segments are considered to be similar to the one below them. This rather simplistic interpolation gives a relatively good glimpse of SOC distributions between different pits, but this method consistently underestimate SOC in peat environments in cases where the last sample before the mineral layer is noticeably above the organic-mineral transition, as the mineral value is used just below it.

The second method, visible as situation C in figure 5, comes from the study of Tadiello et al., 2022. This method is highly similar to the previous one, but includes a threshold element. Once the proportion of organic carbon in the soil goes under 15%, a linear interpolation is used to link the samples from two significantly different horizons, to smooth out the overall carbon estimation. This modification is especially important in forest environments, where 15% is at low depth, correcting a systematic underestimation observed with the first method.

Finally, the method depicted in graph D takes both upper and lower sample values to estimate intermediate horizons, and uses the abrupt organic-inorganic transition to visually set a breakpoint threshold in peat. The layer of soil located above said threshold is then given the value of the higher measured sample, while the soil below is set to the lower sample. This method avoids both underestimations in bog and forest environments.

Once carbon percentage and DBD were estimated for the entire profiles, SOC stock could be calculated by adding the SOC values of every sampled and predicted vertical segments.

3.5. Statistical analysis

To investigate the influence of environmental proxies on Soil Organic Carbon (SOC) stocks, a statistical workflow combining exploratory analysis, classical linear modelling, and generalized linear modelling was implemented in RStudio.

SOC stock was used as the response variable. Based on the conceptual framework established from the literature review and the environmental proxies described in Section 3.1.2, the following explanatory variables were initially considered: slope, altitude, NDMI derived from July and November imagery, flow accumulation, Topographic Wetness Index (TWI), land cover, and soil type.

An exploratory data analysis was first conducted using histograms, boxplots, and pairwise scatterplots. This preliminary step was used to examine the distribution of SOC stock values, identify potential outliers, and visually assess relationships between predictors and SOC. The exploratory analysis indicated that SOC values were possibly skewed, with particularly high values observed in wetland and peaty environments compared to forests and silty-soil areas, which influenced the methodological choices.

Following this qualitative analysis, a multiple linear regression was selected as an initial modelling framework because it allows simultaneous assessment of the independent contribution of several predictors to SOC variability.

Prior to model interpretation, the assumptions of ordinary least squares regression were systematically evaluated. Residual normality was assessed using the Shapiro–Wilk test, multicollinearity was quantified using Variance Inflation Factors (VIF), and heteroscedasticity was tested using the Non-Constant Variance Score Test.

The full linear model revealed significant deviations from normality and homoscedasticity, indicating that assumptions required for classical linear regression were not fully satisfied. However, multicollinearity remained within acceptable limits, with all VIF values below 6, suggesting no severe redundancy among predictors.

Because the full linear model violated the assumptions of normality and homoscedasticity, a simplified modelling strategy was adopted prior to fitting the Gamma GLM. Predictors showing weak explanatory contribution, high uncertainty, and non-significant relationships with SOC in the exploratory analyses and full model were progressively excluded to avoid overparameterization given the small sample size of 36 pits. Land cover and soil type were retained because they represented the strongest conceptual and statistical controls on SOC variability in the study area, and because both variables describe broader environmental conditions, already integrating parts of hydrological and ecological processes discussed in the literature review.

As SOC values were strictly positive, right-skewed, and showed increasing variance with higher fitted values (figure 6), a Generalized Linear Model (GLM) with a Gamma error distribution was applied. This type of models are well suited for ecological data that are continuous, positive, and heteroscedastic. This approach models the mean SOC stock as a multiplicative function of the environmental predictors, while making sure that predicted values remain positive and appropriately account the relationship between the mean and variance in the data.

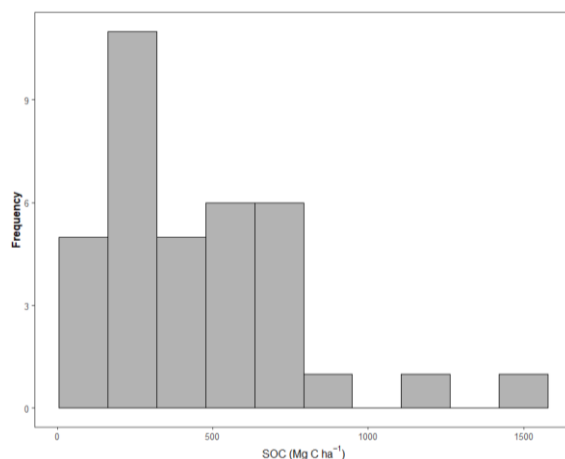


Figure 6: Distribution of estimated SOC stock across pits

Because the full linear model violated the assumptions of normality and homoscedasticity, a simplified modelling strategy was adopted prior to fitting the Gamma GLM. Predictors showing weak explanatory contribution, high uncertainty, and non-significant relationships with SOC in the exploratory analyses and full model were progressively excluded to avoid

overparameterization given the small sample size of 36 pits. Land cover and soil type were retained because they represented the strongest conceptual and statistical controls on SOC variability in the study area, and because both variables describe broader environmental conditions, already integrating parts of hydrological and ecological processes discussed in the literature review.

Model performance was compared between the full linear model and Gamma GLM using Akaike Information Criterion (AIC). Model explanatory performance for the final GLM was additionally quantified using pseudo- R^2 , calculated from explained deviance. Pseudo- R^2 is a set of measures used to how well models like GLMs are fitted, where the traditional R^2 cannot be applied. It indicates how much better the model fits the data compared to a null model, but its values depend on the specific definition used and are not directly comparable to the R^2 of linear regression.

3.6. Predictive modelling of SOC spatial distribution using Random Forest

3.6.1. Preparation of predictor variables and comparison framework

Following the calculation of Soil Organic Carbon (SOC) stocks at the 36 sampling locations and the extraction of explanatory variables, a predictive modelling approach was implemented to estimate the spatial distribution of SOC over the entire study area. The objective of this step is to upscale point-based observations to a continuous surface, allowing the identification of spatial patterns in carbon storage beyond the sampled locations, and provide a better grasp at the overall quantity of carbon contained in the area.

Because SOC variability in peatland systems is influenced by multiple interacting environmental controls, including topography, hydrology, vegetation, soil characteristics, and land cover, modelling approaches capable of integrating several predictors simultaneously are considered optimal for this kind of analysis. The selected explanatory variables were derived from both field observations and independent variable datasets (in raster form), corresponding to the proxies described previously in section 3.1.2. These variables include altitude, slope, flow accumulation, Topographic Wetness Index (TWI), Normalized Difference Moisture Index (NDMI) for July and November, soil type, and land cover. Land cover used a different digitalization, changing from evolution (1971-2023) to 2025 soil occupation. This was done to avoid having N.A values within the dataset, as the original land cover excluded parcels that have had changes, as explained in the methodology.

Prior to model implementation, all raster layers were spatially standardized to ensure their compatibility. The Digital Elevation Model (DEM) with 1-meter resolution served as the reference raster. All predictor rasters were aligned to this common spatial framework by harmonizing their coordinate reference systems, spatial extent, and pixel resolution. Continuous variables were resampled using bilinear interpolation, while categorical layers such as soil type and land cover were resampled using nearest-neighbour interpolation to preserve class integrity.

Two predictive approaches were tested to evaluate the relationship between SOC and environmental predictors: a multiple linear regression model and a Random Forest model. The linear regression model serves as a baseline statistical method, assuming linear and additive

relationships between SOC and predictor variables. Its inclusion allows the assessment of whether relatively simple relationships are sufficient to explain SOC variability in the study area.

Although a Gamma Generalized Linear Model (GLM) was retained as the final inferential model in the statistical analysis section, it was not included in the predictive comparison with the Random Forest model because it was specifically designed for inference and only retained the selected explanatory variables identified as statistically significant (land cover and soil type). The predictive modelling framework aimed to evaluate how well models could use all environmental variables together to predict SOC distribution and account for possible complex relationships between them. For this reason, predictive performance was compared between the Random Forest model and the full multiple linear regression model, since both included the complete set of predictors.

3.6.2. Random Forest implementation and validation

Based on the literature review and the conceptual framework developed throughout this study, SOC storage in peatland environments is expected to respond to complex, non-linear interactions between environmental variables. For example, the influence of hydrology may depend simultaneously on topography, vegetation cover, and soil type, while anthropogenic disturbances can modify several components at once. To better account for these interactions, a Random Forest regression model was selected as the primary machine-learning approach.

Random Forest is an “ensemble” learning method that constructs a large number of decision trees using bootstrap sampling and random subsets of predictor variables (Breiman, 2001). Final predictions are generated by averaging the outputs of all trees, reducing overfitting and improving generalization performance compared to single-tree methods. This approach is well suited to ecological and environmental studies because it can model non-linear relationships, deal with mixed continuous and categorical variables, and remain relatively robust to multicollinearity among predictors.

The Random Forest model was implemented using 500 trees, a value selected to ensure that the model is stable while maintaining reasonable computational efficiency. The number of variables randomly tested at each split (*mtry*) was optimized automatically during model training.

Given the limited sample size of 36, particular attention has been put on model validation. To maximize the use of available observations while maintaining rigorous performance assessment, Leave-One-Out Cross-Validation (LOOCV) was selected as the primary cross-validation strategy. Under this method, the model is iteratively trained on 35 observations and tested on the remaining one until all samples have been used as validation points. This approach is particularly appropriate for small datasets because it minimizes information loss during training.

To evaluate the robustness of model performance under alternative partitioning strategies, a second validation procedure based on repeated k-fold cross-validation was also implemented. In this case, the dataset was randomly divided into five folds, repeated multiple times to reduce dependence on a single random iteration. The objective behind this complementary validation

strategy is to assess whether instability are present or not, potentially linked to sample partitioning in small datasets.

Once trained, the selected model was applied to the full stack of aligned raster predictors to generate a continuous SOC prediction surface across the study area. Predictions were calculated for each raster cell individually, using the corresponding environmental variable values as model inputs. The resulting SOC raster was subsequently clipped to the exact boundaries of the study area to remove predictions outside the relevant zone.

In addition to spatial prediction, variable importance metrics were extracted from the Random Forest model to quantify the relative contribution of each environmental predictor to SOC estimation. This provides a complementary perspective on the relative influence of environmental factors, which is discussed in the Results and Discussion sections.

4. Results

4.1. Primary results analysis

4.1.1. Qualitative field observations

Soil depth variations are remarkable, with organic horizons displaying major differences in depth from one pit to another, ranging from a few centimeters to several meters.

On the field, three pits have had land cover changes since 2023; previous forests that were recently cut down. Together with the only pit located in a sward, they have the lowest estimated SOC stock values among the 36 pits.

Despite being divided into four categories according to land cover and soil type, two duos of parameters seem to be commonly intertwined. Those are peaty soils in wetlands and silty-stony soils in forests. These combinations were already indirectly addressed in the state of the art, with some variables strongly entangled due to influences between themselves.

The soil associated with these two main systems are as follows (figure 7, pictures A and B). Wetlands have relatively high water table, sometimes completely saturated with water up to the surface. Soil itself has a high percentage of organic carbon and peat horizons can range from dozens of centimeters to several meters. The presence of organic matter in the profile ends abruptly, often only transitioning over few centimeters from organic to mineral horizons that contain grey and reduced plastic clays (figure 7, picture C). In contrast, forests have a dry, shallow soil. Horizons are much more pronounced, and only range from 3 to 30 centimeters on average. The soil is more silty than plastic, and turns to lighter colours once organic matter becomes scarce in deeper horizons. Elements such as boulders and tree roots make said soil visually heterogeneous and sometimes inexistant, with bedrock being exposed (figure 7, picture D).



Figure 7: Pictures taken on field. A : Wetlands | B : Forest | C : Saturated peat core | D : Dry silty soil

4.1.2. Instruments outputs

After comparing the variability of repeated measurements obtained from both instruments on identical soil samples, it was decided to retain the values generated by the Macro-Elemental Analyzer for SOC estimation. Although the MIR spectrometer showed relatively stable results overall, small variations between replicates and acquisition days were still observed, with relative variations ranging from 0.5 to 5%. Graphs displaying this error variability are displayed in the annexes (figure A.2). In contrast, the Macro-Elemental Analyzer produced more consistent and precise measurements, having a direct quantification of carbon and nitrogen through combustion and gas analysis. The precision of the Macro-Elemental Analyzer was assessed using repeated measurements of reference standards. The obtained values showed very limited variability, ranging with measurements varying by only 0.006% of relative carbon. Consequently, the Macro-Elemental Analyzer was considered more reliable for estimating SOC stocks. The distribution of carbon percentage given by the Macro-Elemental Analyzer are synthesized in figure A.7.

The use of the Macro-Elemental Analyzer also made it possible to investigate the relationship between carbon and nitrogen concentrations within the collected soil samples. Figure 8 illustrates the relationship between carbon (%) and nitrogen (%) measured across all analyzed samples. Overall, the data display a strong positive relationship, with nitrogen concentrations increasing proportionally with carbon content. This trend appears approximately linear for carbon concentrations up to around 50%. However, beyond this threshold, the relationship changes noticeably, with nitrogen values no longer increasing proportionally and showing a marked decline relative to carbon concentration. This pattern is likely related to the ombrotrophic nature of the High Fens peatlands. As discussed in the literature review, ombrotrophic bogs are exclusively supplied by atmospheric precipitation and therefore receive very limited mineral and nutrient inputs from groundwater or surrounding soils. These environments are typically nutrient-poor and strongly acidic, conditions that restrict nitrogen retention.

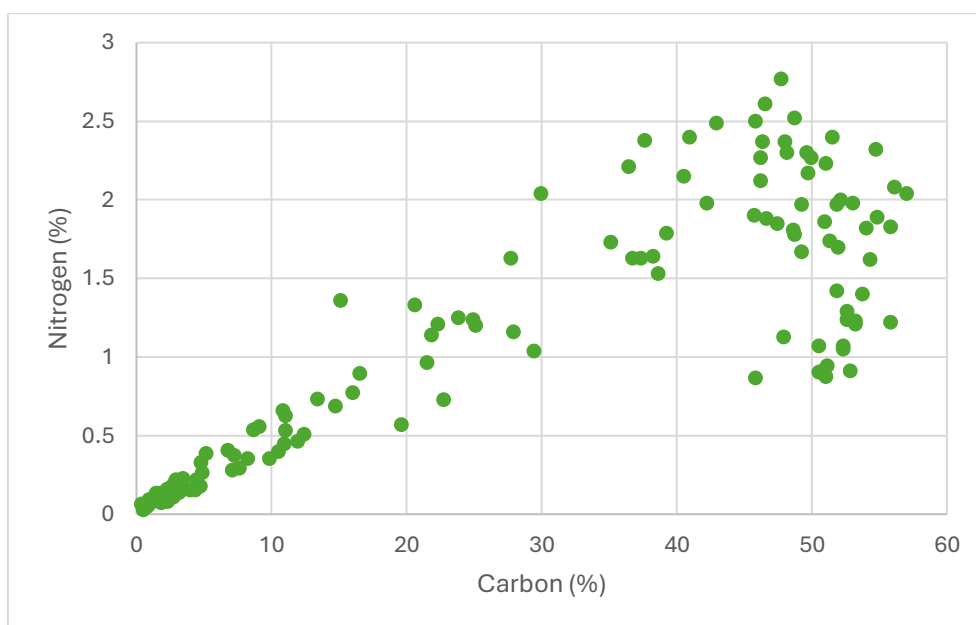


Figure 8: Relationship between carbon and nitrogen in sampled horizons

4.1.3 SOC stock estimation results

Figure 9 represents the different distribution of estimated SOC stock according to the different methods used to calculate it. The one that was used in the calculation, based on visual transition, tends to have significantly higher values compared to the two other methods. As discussed in section 3.4, this method is more robust as it avoids SOC underestimations, both in peaty and silty soils.

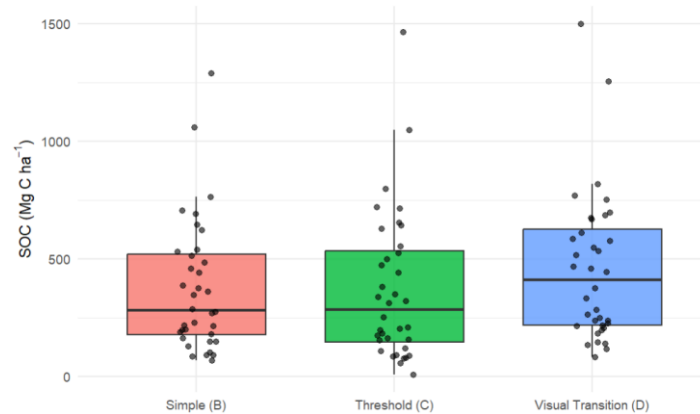


Figure 9: Estimated SOC for each pit depending on carbon interpolation method

Calculated SOC values displayed substantial spatial variability across the 36 sampling locations. Values ranged from 83.58 T/ha to 1499.96 T/ha, with a mean SOC of 455.96 T/ha and a median of 410.65 T/ha. The difference between mean and median suggests a moderately right-skewed distribution, reflecting the presence of several locations with particularly high carbon stocks.

The distribution of SOC stock values was previously identified as strongly skewed in section 3.6. The complete SOC estimates for each sampled pit are presented in figure 10. Overall, SOC stocks display important spatial variability across the study area, with neighboring sampling points sometimes having major differences in estimated carbon accumulation. For instance, points 5 and 6, located only approximately 200 meters apart, show a difference of more than seven times in estimated SOC stock. This strong local variability suggests that SOC accumulation in the High Fens is controlled by highly heterogeneous environmental conditions. Figure 10 also highlight the spatially heterogeneous behaviour of SOC stocks, with land cover as the map background.

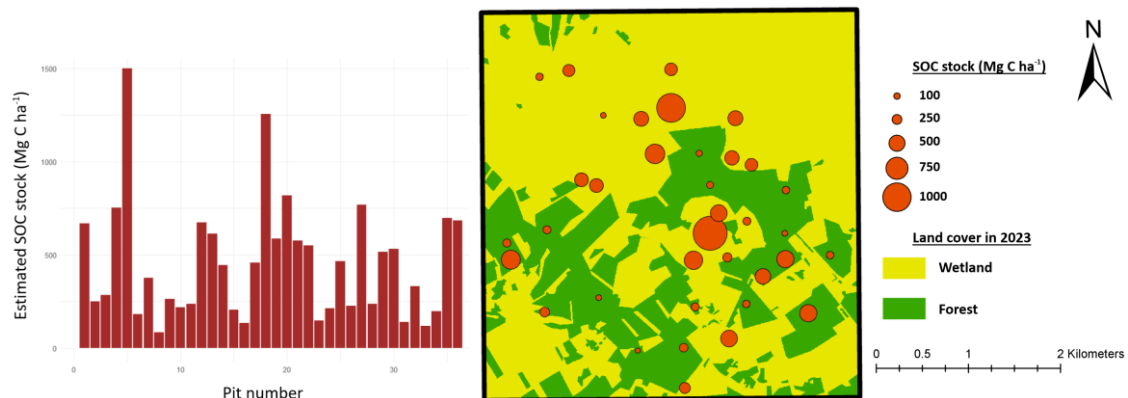


Figure 10: SOC stock estimation and distribution of sampled pits

Figure 11 depicts SOC accumulation over soil deepness. Peaty soils are characterized by substantially deeper organic horizons, commonly reaching depths of 80 to 90 centimeters, while silty-stony soils generally remain shallower and rarely exceed 50 centimeters within the sampled profiles. Moreover, peat soil outliers can reach up to several meters in certain locations of the plateau, with thickness appearing to be the main control of SOC stock accumulation.

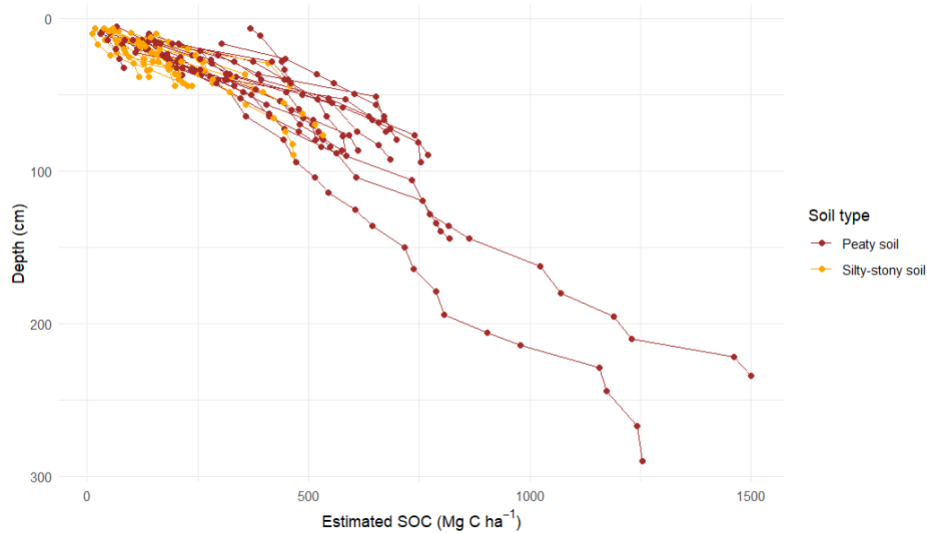


Figure 11: SOC stock accumulation according to depth

4.2. Statistical analysis

4.2.1. First Assessment

As part of the statistical analysis, continuous environmental variables were first individually compared to SOC stock values in order to provide an initial overview of potential relationships (figure 12). Most variables do not display any clear or consistent trend with SOC accumulation, suggesting either weak direct influence or non-linear interactions that cannot easily be identified through simple visual inspection. Among the tested predictors, only the NDMI derived from November imagery showed a significant correlation with SOC (Pearson's $r = -0.523$, $p = 0.001$), indicating that SOC decreases as NDMI increases. This preliminary observation is consistent with the expected influence of soil moisture on peat preservation and organic matter accumulation in wetland environments.

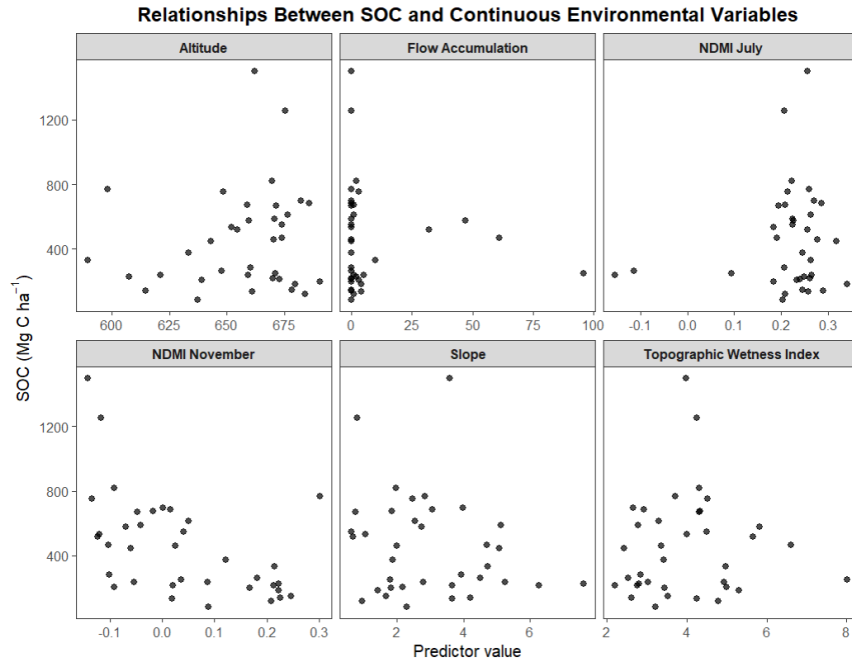


Figure 12: Scatterplots of continuous variables over SOC stock

The categorical variables display clear differences in SOC stock between groups (figure 13). In both cases, wetlands and peaty soils are associated with substantially higher SOC stocks compared to forests and silty-stony soils. In addition to higher median values, these groups also exhibit a wider range of SOC variability, reflecting the heterogeneous nature of peat accumulation across the plateau. Conversely, forest and silty-stony soil sites consistently show lower SOC stocks and a narrower distribution of values. These first visual observations already suggest that land cover and soil type may represent major controls on SOC accumulation within the study area. One-way ANOVA showed that SOC differed significantly among land-use classes ($F(1,34) = 7.64$, $p = 0.009$), explaining 18.3% of the total variance. Soil type also had a significant effect on SOC ($F(1,34) = 18.46$, $p < 0.001$), explaining 35.2% of the variance. Soil type exhibited a stronger influence on SOC than land cover. However, this exploratory analysis only compares the variables independently, and only serves as a first overview.

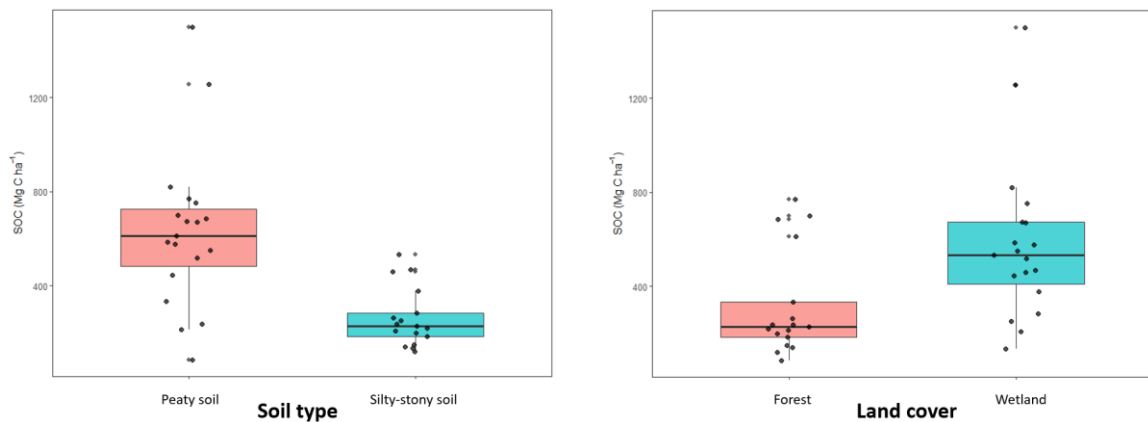


Figure 13: Boxplots of discrete parameters over SOC stock

4.2.2. Linear regression and Gamma GLM

The initial full multiple linear regression model, including all environmental predictors, explained a moderate proportion of SOC variability ($R^2 = 0.53$; adjusted $R^2 = 0.39$; $p = 0.004$).

Among all predictors, only soil type was statistically significant within the full model. Specifically, silty-stony soils were associated with significantly lower SOC stocks compared to organic peaty soils ($\beta = -298.48$, $p = 0.003$). Slope, altitude, NDMI indices, flow accumulation, TWI, and land cover were not independently significant (table 2).

Table 2: Multiple linear regression results

Predictor	Estimate	Std. Error	t value	p value
Intercept	255.21	1523.57	0.17	0.868
Slope	-7.08	37.92	-0.19	0.853
Altitude	0.37	2.03	0.18	0.858
NDMI (November)	-553.23	551.94	-1.00	0.325
NDMI (July)	346.27	457.90	0.76	0.456
Flow accumulation	-1.81	4.22	-0.43	0.672
TWI	3.31	74.43	0.04	0.965
Land cover (Wetland)	129.13	141.51	0.91	0.370
Soil type (Silty-stony)	-298.48	89.85	-3.32	0.003

Diagnostic testing indicated that assumptions of ordinary least squares regression were not respected. Residuals significantly deviated from normality (Shapiro–Wilk: $W = 0.918$, $p = 0.011$), and heteroscedasticity was detected (Non-Constant Variance Score Test: $\chi^2 = 8.45$, $p = 0.0036$), confirming non-constant residual variance across fitted values. Additional residual related graphs are visible as figure A.5.

Multicollinearity remained acceptable despite inclusion of all predictors, with VIF values ranging from 1.13 to 5.23. Although TWI and flow accumulation showed moderately elevated VIF values, no severe collinearity was detected. Given these violations, the full Gaussian linear model was considered unsuitable for final inference.

A Gamma GLM was therefore fitted using land cover and soil type as explanatory variables. This model provided substantially improved fit relative to the full linear model, with a lower AIC (477.0) compared to the linear model (508.2), visible in table 3.

Table 3: Comparison of LM and GLM performances

Model	df	AIC
Full linear model	10	508.21
Gamma GLM	4	477.01

The final Gamma GLM explained approximately 56.7% of deviance (pseudo- $R^2 = 0.567$), indicating relatively good explanatory performance.

Within the final model, both retained predictors were highly significant (table 4). Wetland sites were positively associated with SOC accumulation ($\beta = 0.539$, $p < 0.001$), while silty-stony soils were strongly negatively associated with SOC stocks relative to peaty soils ($\beta = -0.832$, $p < 0.001$).

Table 4: Simplified GLM results

Predictor	Estimate	Std. Error	t value	p value
<i>Intercept</i>	<i>6.103</i>	<i>0.129</i>	<i>47.30</i>	<i><0.0001</i>
Landuse (Wetland)	0.539	0.144	3.74	0.0007
Soil type (Silty-stony)	-0.832	0.144	-5.77	<0.0001

Because the model is a Gamma GLM with log link, the raw coefficients in table 4 are on the log scale. By reporting exponentiated coefficients, wetlands have $1.71\times$ higher expected SOC than forests ($e^{0.539}$), while peaty soils have 56% higher expected SOC than silty-stony soils ($1 - e^{-0.832}$). Figure 14 highlights how the Gamma model estimates the distribution of SOC based on soil type and land cover configuration, with a interval of confidence of 95%.

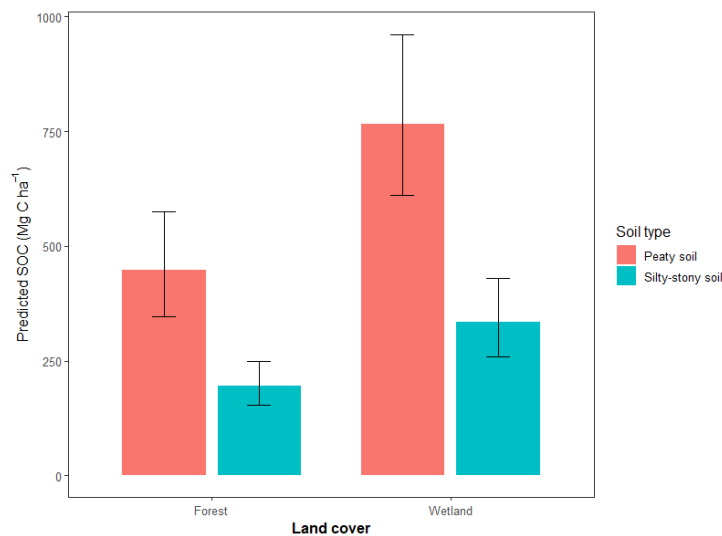


Figure 14: SOC prediction of Gamma GLM combinations

These results indicate that SOC distribution within the study area is primarily structured by categorical environmental characteristics, particularly land cover and soil type, rather than by continuous topographic or remotely sensed variables. Specifically, wetlands and peaty soils were associated with substantially greater SOC storage, supporting the expectation that peat-forming environments with persistent moisture and organic substrate accumulation represent efficient zones of long-term carbon storage.

In contrast, the absence of significant effects for slope, altitude, NDMI, TWI, and flow accumulation suggests comparatively weaker influence on SOC variation within the study area, or that their effects are indirectly captured through broader land use and soil classifications.

Overall, the statistical analysis indicates that SOC variability in the High Fens is predominantly controlled by pedological conditions and land cover, highlighting the dominant role of peatland ecosystems in regional carbon storage. These results will be reviewed further in the discussion.

4.3. RandomForest performance and predictions

4.3.1. Predictive model performance

Two predictive approaches were tested to estimate Soil Organic Carbon (SOC) over the study area: a multiple linear regression model and a Random Forest regression model. Both models were trained using the 36 sampling points and evaluated using Leave-One-Out Cross-Validation (LOOCV), selected as the primary validation strategy due to the limited sample size. This method ensures that each observation is used once as a validation point while maximizing the number of observations available for training at each iteration.

The linear regression model produced relatively limited predictive performances. Under LOOCV, it achieved a Relative Root Mean Square Error (RRMSE) of 63.6% (RMSE = 289.97 T/ha), a coefficient of determination (R^2) of 0.25, and a Mean Absolute Error (MAE) of 208.31 T/ha. These values indicate that linear relationships alone only explain a relatively modest fraction of the observed SOC variability. An RRMSE of 63.6% is high, meaning prediction error is roughly two-thirds of the mean SOC stock value.

The Random Forest model provided an improvement in predictive accuracy. After parameter tuning, the optimal configuration retained 500 trees and a value of $mtry = 5$, corresponding to the number of variables randomly tested at each split. Under LOOCV, this model achieved an RMSE of 252.14 T/ha, which is a RRMSE of 55.3%, an R^2 of 0.34, and an MAE of 184.29 T/ha. Compared with the linear regression, the Random Forest reduced both RMSE and MAE while increasing the proportion of explained variance. This clearly makes the LM an overall weaker predictive model than the Random Forest one, which aligns with the violated normality assumptions. Despite this improvement, both models still display high errors and imprecision. This aspect is further reviewed in the discussion.

Figure 15 highlights the differences of prediction between the two models.

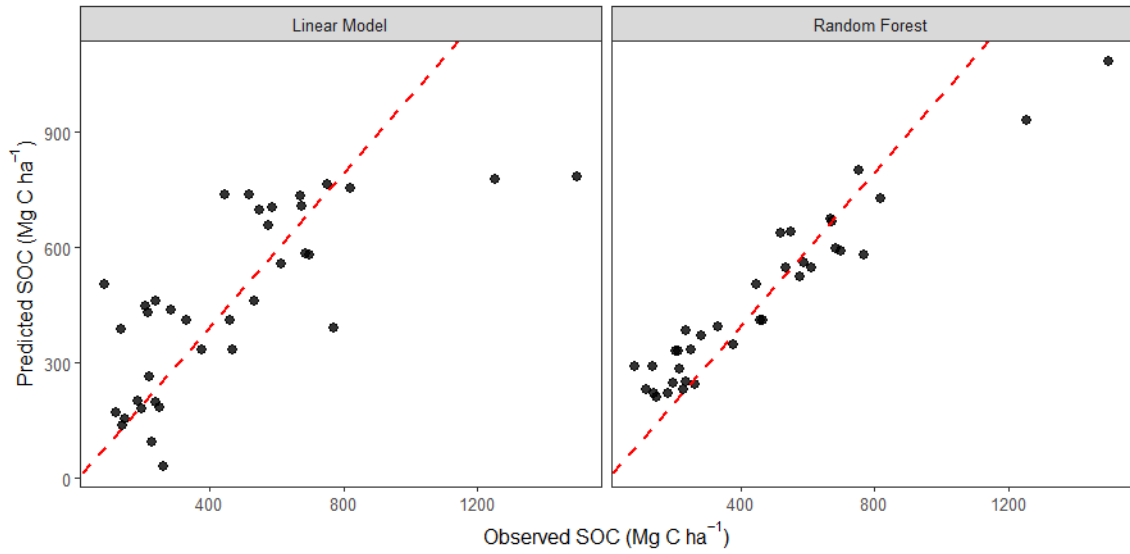


Figure 15: Comparison of LM and RF predictive performances

A second validation procedure based on repeated 5-fold cross-validation was also implemented to assess model robustness under a different partitioning strategy. Under this framework, the Random Forest achieved an RMSE of 234.43 T/ha, an R^2 of 0.50, and an MAE of 178.26 T/ha. Although these values suggest stronger predictive performances, the variability between folds remained relatively high, with a standard deviation of 0.24 for R^2 . This indicates that model performance is somewhat sensitive to the composition of training and validation subsets (figure 16).

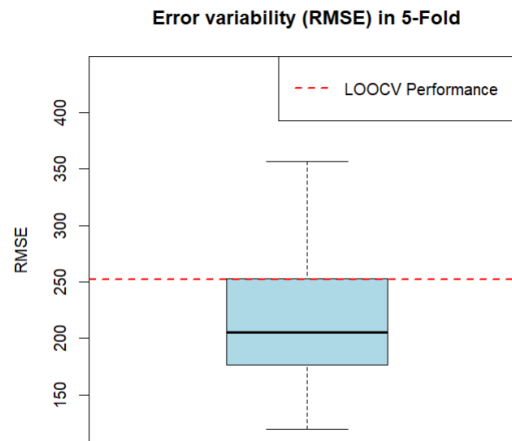


Figure 16: Comparison of LOOCV and 5-fold RMSE

Because LOOCV is generally more conservative and particularly suited to small datasets, it was retained as the primary reference for model evaluation. Based on these overall performances, the Random Forest model was selected for the spatial prediction of SOC over the entire study area.

4.3.2. Relative importance of environmental predictors

To better understand the relative contribution of each environmental predictor, variable importance was extracted from the final Random Forest model (figure 17). Clear differences were observed between predictors.

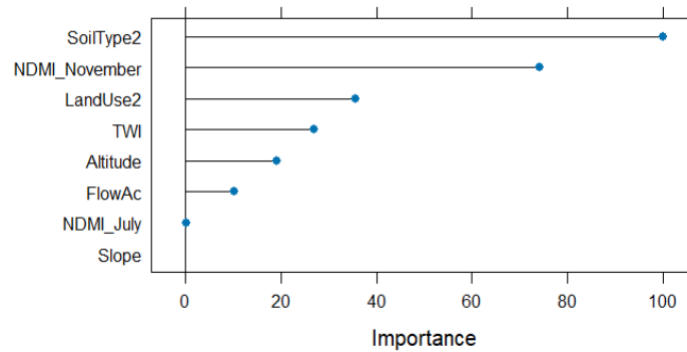


Figure 17: Importance of variables in the RF model

Soil type was identified as the dominant variable influencing SOC predictions, receiving the highest normalized importance score (100.00). This variable was followed by NDMI measured in November (74.07), indicating that late-autumn vegetation moisture conditions were also strongly associated with SOC distribution.

A second group of variables showed intermediate importance. Land cover ranked third (35.67), followed by Topographic Wetness Index (TWI) (26.90) and altitude (19.18). These variables therefore contributed to the model, although to a lesser extent than soil type and November NDMI.

Other predictors had a more limited influence. Flow accumulation showed a lower importance score (10.33), while NDMI measured in July contributed only marginally (0.32). Finally, slope did not contribute measurably to the final model, with an importance score of 0.00.

The complete ranking of predictor importance is summarized in Table 5. Overall, the results indicate that the final model relied primarily on categorical variables and moisture-related indicators, while several topographic metrics contributed less strongly to SOC prediction.

Table 5: Importance of variables in the RF model

Variable	Importance
Soil Type	100.00
NDMI November	74.07
Land Cover	35.67
TWI	26.90
Altitude	19.18
Flow Accumulation	10.33
NDMI July	0.32
Slope	0.00

4.3.3. Spatial prediction of SOC distribution

The resulting map (figure 18) highlights strong spatial heterogeneity in predicted SOC stocks, with higher values concentrated in areas corresponding to peatland environments and lower values associated with mineral soils or historically disturbed areas. This pattern is coherent with field observations, where deeper organic horizons and darker soil profiles were predominantly observed in wetland sectors, while forested or mineral-dominated areas displayed thinner organic layers and lower carbon content.

Predicted SOC values generally follow the distribution of major peatland zones, confirming the importance of soil type and moisture conditions identified in the variable importance analysis. Areas characterized by high predicted carbon stocks tend to coincide with flatter, wetter portions of the plateau, whereas peripheral slopes and forested margins exhibit lower predicted values. The Random Forest model estimates that around 905395.7 tons of organic carbon are stored in the soil of the studied area. Reported over the 19.48 km² surface, the average SOC stock ends up at 464.61 Mg C ha⁻¹ according to the prediction model.

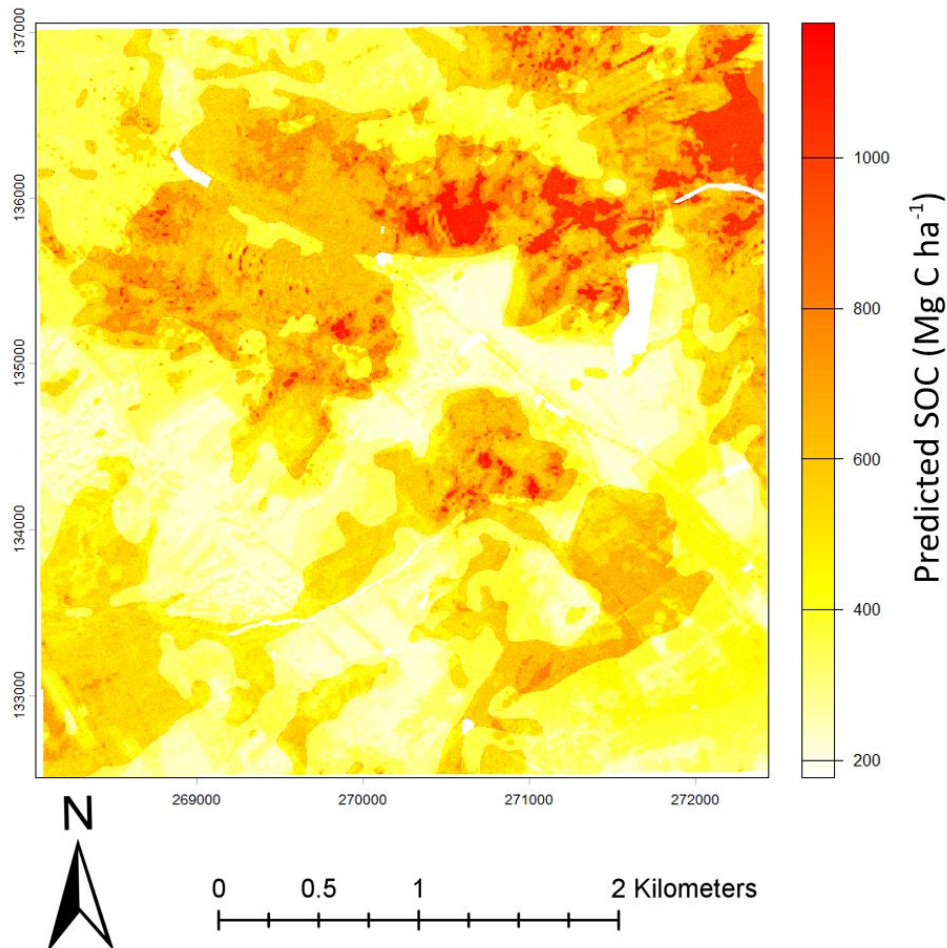


Figure 18: Prediction map of SOC stock across the study area

5. Discussion

The discussion is structured around the three main research questions of the study presented in introduction. First, the dominant environmental controls influencing SOC variability are examined using both field observations and statistical outputs. Second, the relevance and limitations of the broader-scale sampling strategy combined with remote sensing approaches are evaluated. Finally, the predictive capacity of the spatial modelling framework is discussed, alongside its implications for carbon monitoring in the High Fens region.

The second part of the discussion addresses limitations, alternative methodology choices and future research insights.

5.1. Research questions

5.1.1. Environmental controls of SOC variability in the High Fens

The results obtained in this study indicate that SOC stock variability across the High Fens plateau is strongly structured by the interaction between topography, drainage, vegetation characteristics, soil type, and land cover. However, while the general trends observed are globally consistent with the peatland literature, some results partially diverge from expectations concluded in previous studies. In particular, hydrological proxy variables such as flow accumulation and Topographic Wetness Index (TWI) did not emerge as dominant statistical predictors of SOC spatial variation despite hydrology being widely described as one of, if not the principal control of peatland carbon storage (Holden et al., 2004 ; Hasan et al., 2012 ; Andersen et al., 2011). In fact, the Gamma GLM showed more robust results when only taking land cover and soil type into account.

The strongest SOC values were consistently associated with peaty wetland environments, whereas forested areas dominated by silty-stony soils displayed substantially lower carbon stocks. These patterns are coherent with the field observations carried out during sampling campaigns, where wetlands were characterized by thick saturated organic horizons, while forest soils appeared thinner, drier, and more mineralized. This duality is illustrated in figure 19. These contrasts align with the general understanding of peatland functioning established in previous research, where long-term water saturation limits oxygen diffusion, slows microbial decomposition, and allows organic matter accumulation over long temporal periods (Clymo, 1984 ; Dargie et al., 2017 ; Swinnen et al., 2019).

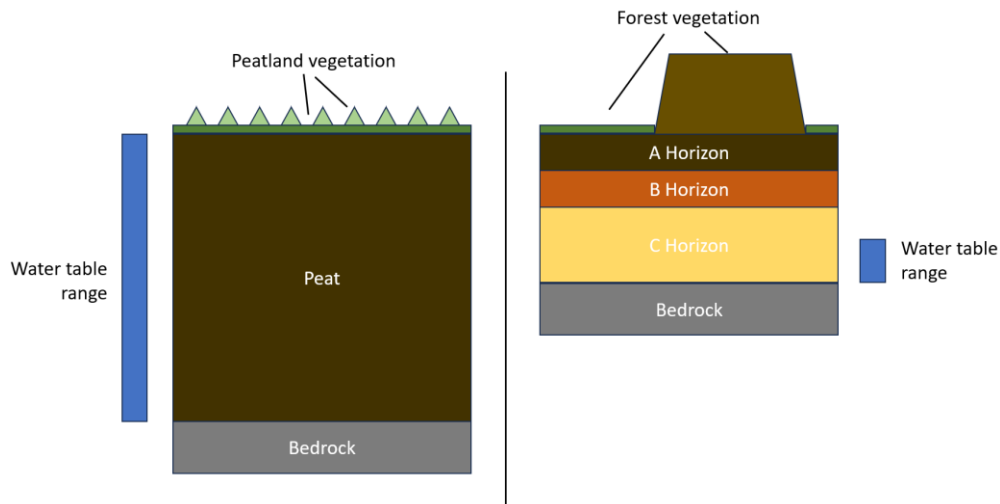


Figure 19: Comparison of the two main observed soil systems

Nonetheless, although hydrology is theoretically central to peat accumulation, its related variables showed weaker explanatory power than other environmental categories such as land cover and soil type. This discrepancy shows the complexity of the dynamics on the plateau and the limitations of representing hydrological dynamics with simplified topographic proxies. Flow accumulation and TWI were expected to strongly correlate with SOC because both variables are commonly used to represent water direction and saturation potential in environmental studies (Beven and Kirkby, 1979 ; Sørensen et al., 2006). Their limited statistical importance in the present analysis is likely related to the following aspects.

First, DEM-derived indices such as TWI and D8 flow accumulation primarily represent simplified surface runoff dynamics and topographic convergence. While these proxies are useful indicators of potential saturation, they may inadequately capture the actual hydrological processes of peatlands, which depends on a much wider range of interacting processes including subsurface flows, peat permeability, drainage structures, seasonal water-table fluctuations, and microtopography (Holden et al., 2004 ; Tarboton, 1997). In particular, the predominantly flat peatlands of the High Fens plateau (surface slopes $< 5^\circ$) are influenced primarily by shallow groundwater processes, reducing the relevance of surface topographic gradients.

Second, part of the hydrological influence may already be indirectly integrated into other variables such as land cover and soil type. Wetlands and peaty soils already reflect long-term saturated conditions favorable to peat accumulation, whereas forests and silty-stony soils generally correspond to drier and more aerated environments. As a result, categorical variables may partly absorb the explanatory contribution of hydrological proxies. This interpretation could explain why land cover and soil type emerged as stronger predictors despite the recognized importance of hydrology in peatland systems.

Slope and altitude also showed relatively limited explanatory capacity compared to expectations coming from previous literature. Studies conducted in mountainous or strongly contrasted peatland systems often report clear relationships between topography, water redistribution, and peat accumulation (Nasrul et al., 2020 ; Brosens et al., 2020). However, the relatively low topographic variability of the High Fens plateau may reduce the influence of these variables at

the scale investigated in this study. Furthermore, several authors emphasize that microtopographic structures such as hummocks, hollows, and localized depressions often have stronger controls on peatland hydrology than the overall topographic gradients (Keiser et al., 2024 ; Li et al., 2024). Because the present analysis relied mainly on DEM-derived proxies with broader spatial representation (1 meter resolution), part of this fine-scale variability may not have been fully captured. The “blanket” aspect of the High Fens peatland, meaning that peat accumulation tends to smooth out the surface relief, might partially explain this weak interaction. With peat thickness increasing, the water table could be less impacted by bedrock interactions. This was already observed in Scottish bog (Swinnen et al., 2019). Macro-topography would therefore be significantly different from bedrock slope, intensifying the weak relationship.

Vegetation (through NDMI) and land cover relationships appears to play a more significant ecological role in SOC variability. Wetland environments characterized by peat-forming vegetation such as *Sphagnum* contribute to maintaining acidic and waterlogged conditions that are favorable to carbon preservation and accumulation (Clymo, 1984 ; Andersen et al., 2011). In contrast, forest environments are usually associated with greater evapotranspiration, more oxygen availability, and stronger decomposition processes (Del Giudice and Lindo, 2017 ; Holden et al., 2004). The strong statistical significance of land cover may therefore reflect the cumulative influence of several interconnected environmental mechanisms simultaneously affecting peat formation and decomposition, although it did not clearly appear as multicollinearity with studied proxy variables.

The relatively limited performance of NDMI also illustrates the difficulty of representing long-term peatland processes through short-term remote sensing indicators. Although NDMI is frequently used as a proxy for vegetation moisture and plant stress (Gao, 1996), its relationship with SOC remained relatively weak in this study. This may come from the temporal aspect of satellite images being mismatched with the long-term dynamics of peat accumulation. In addition, NDMI primarily reflects surface vegetation moisture and maybe not represent deeper hydrological processes directly controlling peat preservation. Surprisingly, the November based imagery turned out to be more useful in the RF prediction compared to its July counterpart. This is most likely related to the differences of water stress responses from both peatland and forest vegetation.

Overall, the results suggest that SOC variability across the High Fens cannot be explained through isolated environmental variables alone. Instead, carbon storage appears to emerge from the interaction between hydrology, vegetation, soil properties, topography, and anthropogenic disturbances having influences on all of these research fields. The lack of direct anthropogenic-related variable in the study might explain why the models seem to miss a non-negligible part of the variance. This interpretation aligns with the Critical Zone perspective developed throughout the literature review, where environmental systems are understood as strongly interconnected and dynamically coupled (Lin, 2010). A missing link in such framework might strongly affect prediction and statistical performances. The relatively limited statistical importance of some expected predictors therefore does not necessarily invalidate their ecological importance, but rather emphasizes the difficulty of representing complex peatland dynamics through simplified environmental proxies and relatively small-scale datasets.

5.1.2. Relevance and limitations of the broader-scale sampling approach

One of the principal objectives of this study was to evaluate whether a broader-scale sampling strategy combined with remote sensing and GIS-derived environmental proxies could effectively characterize the spatial variability of SOC stock across the High Fens plateau. Overall, the results suggest that this approach was successful in identifying major spatial trends and dominant environmental controls despite the relatively limited number of sampling locations. The integration of field observations, laboratory analyses, remote sensing indices, and spatial modelling therefore provided a useful framework for investigating SOC variability at the scale of the plateau.

This spatial diversity of the broad area proved particularly useful for identifying large-scale contrasts in SOC distribution and understanding the relationships between carbon storage, land cover, and soil characteristics. Rather than focusing exclusively on highly localized peatland processes, the methodology adopted in this study aimed to capture broader environmental gradients operating across the landscape. In this regard, the approach appears well adapted for exploratory SOC assessments conducted at regional scales.

The integration of GIS-derived variables and remote sensing products also offered several advantages. DEM-derived topographic variables, vegetation indices, and land-cover classifications provided continuous spatial information across the entire study area, allowing environmental conditions observed at individual pits to be extrapolated at broader scales. Such approaches are increasingly used in digital soil mapping and peatland monitoring studies because they allow relatively large territories to be investigated while limiting the need for extremely dense field sampling campaigns (Minasny et al., 2013 ; Kesik et al., 2022). In the present study, these spatial datasets contributed to identifying general environmental patterns despite the complexity of peatland dynamics.

However, the results also highlight several limitations associated with this broader-scale methodology. Although broad environmental gradients were successfully identified, some local-scale processes influencing SOC variability were likely insufficiently represented. Peatland systems are characterized by strong spatial heterogeneity, often controlled by microtopography, localized hydrological conditions, and small-scale vegetation dynamics (Keiser et al., 2024 ; Li et al., 2024). Because the study relied primarily on environmental proxies derived from broader-resolution spatial datasets, part of this fine-scale variability may not have been fully captured. This limitation likely contributed to the relatively weak statistical performance of certain variables such as TWI or NDMI.

The relatively limited number of sampling pits also constitutes an important source of uncertainty. Although the selected sites covered a broad range of environmental conditions, 36 sampling locations remain modest, considering the complexity and heterogeneity of peatland systems. This is particularly the case for peaty soils as they displayed a really high range of SOC values (going from less than 200 to almost 1500 Mg C ha⁻¹). Some environmental relationships may therefore have been underrepresented or oversimplified within the statistical models. Increasing the density of field observations would likely improve the robustness of future spatial predictions and reduce uncertainties associated with local variability.

Simplified classifications such as land-cover only being two discrete categories can potentially mask transitional or heterogeneous areas. While such simplifications are necessary modelling approaches over the plateau, they still reduce the ecological complexity represented within the analysis.

Despite these limitations, the broader-scale methodology adopted in this study still demonstrates considerable potential for regional SOC stock assessment in peatland environments. The combination of field sampling, laboratory analyses, GIS-derived variables, and statistical modelling allowed the identification of meaningful environmental patterns while remaining within the constraints of a master's thesis. Overall, the results seem to capture the global SOC trends of the plateau, but many crucial aspects end up overlooked, such as micro-topography, micro-vegetation, and hydrological processes. While it appears less precise than small-scale, long-term studies, the use of broad sampling strategies and use of satellite-based imagery could be useful to quickly assess the general “health” of peatland environments and create monitoring plans. In a rapidly changing climate, the presented methodology could provide an aggregated measure of how peatlands evolve at small-time scales (year to year or decade to decade basis).

5.1.3. Predictive performance and spatial modelling of SOC

The predictive modelling conducted in this study demonstrates that SOC spatial distribution across the High Fens plateau can be estimated with moderate success using Random Forest prediction.

The strongest predictions were generally associated with high environmental contrasts, particularly between peaty wetlands and more mineralized forest environments. This suggests that the modelling framework successfully captured the dominant large-scale gradients controlling SOC distribution across the plateau. Variables such as land cover, soil type, and NDMI consistently contributed the most to model performance, reinforcing their importance as integrated indicators of long-term environmental conditions.

The Random Forest model generally produced more realistic spatial outputs than linear approaches, likely because of its ability to account for non-linear relationships and interactions between environmental variables. Peatland systems are inherently complex and rarely follow strictly linear environmental responses, which may explain the weaker performance of simpler statistical models. Nevertheless, even the Random Forest approach remains constrained by the quality and representativeness of the input variables. As discussed previously, some key peatland processes, particularly hydrological dynamics, were only indirectly represented within the modelling framework. It is apparent that the model had more struggle predicting values for wetlands / peaty soils than for forests / silty-stony soils. This is most likely because the low number of samples combined with extremely high variability of SOC in peat soils (sometimes over 1000 Mg C ha⁻¹). With only two pits having SOC stocks valued above 4 digits, the afterward prediction cannot reach a high certainty.

In their study from 2003, Wastiaux and Schumacker measured and estimated peat thickness over parts of the wetlands. Their resulting mapping can be used to make a qualitative comparison with the SOC stock predicted here, in figure 20. While not quantitatively comparable, thickness and

stock are strongly associated with each other, and both maps indicate similar trends in heterogeneity locations. Thickness and SOC stock are effective proxies to see how carbon sequestration varies several fold over short distances in some key areas of the plateau, highlighting its complex distribution in the bog. The uncropped map from their study is available in the annex section (figure A.3).

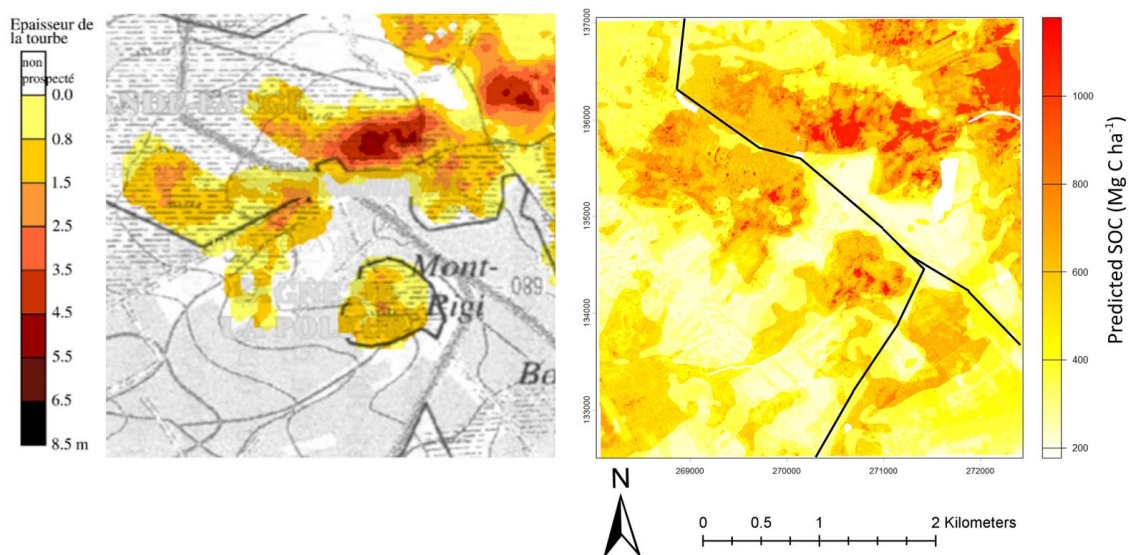


Figure 20: Comparison between measured peat thickness (Wastiaux and Schumacker, 2003) and SOC stock prediction

Despite these limitations, the modelling approach developed here still demonstrates strong potential for regional peatland monitoring. The combination of field sampling, remote sensing, and machine learning techniques provides a relatively accessible framework for identifying carbon-rich areas and monitoring broad environmental changes across the High Fens plateau. In the context of climate change and increasing pressure on peatland ecosystems, such approaches could contribute to future conservation planning and carbon management strategies by helping identify areas potentially vulnerable to degradation or hydrological disturbance.

5.2. Implications, limitations, and future perspectives

Overall, this study demonstrates that spatial variation in SOC stocks across the High Fens plateau is controlled by the interaction of multiple environmental processes operating simultaneously across different spatial scales. Hydrology, vegetation, soil properties, topography, and anthropogenic disturbances all appear to contribute to peatland carbon dynamics, although their statistical representation within the modelling framework varied considerably. The results therefore support the Critical Zone perspective developed throughout the literature review, where environmental systems are viewed as interconnected rather than controlled by isolated variables (Lin, 2010).

The methodology developed in this study also highlights the potential of combining field sampling, GIS-derived environmental variables, remote sensing products, and statistical modelling for regional SOC assessments. While the predictive performances remain moderate,

the approach proved capable of identifying major environmental gradients and broad SOC distribution patterns across the plateau. In this regard, broader-scale methodologies may represent useful tools for preliminary peatland monitoring and carbon assessment, particularly when long-term ecological monitoring remains unavailable or difficult to implement.

However, several limitations remain important when interpreting the results. The relatively limited number of sampling pits, strong heterogeneity of peatland environments, and lack of seasonal, drainage, and anthropogenic data introduced uncertainties within both the statistical analyses and the spatial predictions. Furthermore, several environmental variables only indirectly represented the ecological processes controlling peat accumulation and preservation. Hydrological dynamics, in particular, remain difficult to characterize using simplified DEM-derived proxies alone. The absence of direct water-table measurements, seasonal monitoring, and finer-scale microtopographic data likely reduced the ability of the models to fully capture local SOC variability. Moreover, SOC calculation method or laboratory methodology, and assumptions that organic carbon is equal to total carbon also introduced error margins.

Future research could therefore improve the present framework by integrating higher-resolution environmental datasets, seasonal hydrological measurements, and denser sampling strategies. The use of LiDAR-derived microtopography, continuous groundwater monitoring, or multi-temporal satellite imagery may notably strengthen the representation of peatland functioning. Similarly, extending the temporal dimension of the study would help better evaluate how peatland carbon dynamics respond to climate variability and anthropogenic disturbances over time. UAVs could bring a new paradigm shift in bog data collection considering their high-precision mapping capabilities.

An innovative approach was developed by Swinnen et al. in 2019, where unaltered peat thickness was predicted over a Scottish peatland, allowing to determine the extent of human influence over the bog. It is known that some areas on the plateau were historically covered by a several additional meters of peat that were excavated in relatively recent centuries. This could be a crucial variable to implement in a model to enhance its accuracy and explained variance, but it could not be replicated in this study.

While the soil aspects were extensively explored, parent material influence was not explicitly included in the study. Parent material may partly explain why soil type emerged as one of the strongest predictors of SOC variability. A plausible hypothesis is that the observed soil differences are closely linked to variations in the underlying bedrock. Areas characterized by fine-grained shale formations might develop weathered horizons rich in reduced and plastic clays, which can restrict water percolation, promote subsurface water stagnation, and facilitate the formation of a shallow water table above the bedrock (Keiser et al., 2024 ; Su et al., 2022). Such conditions are favorable to peat accumulation and long-term organic matter preservation. In contrast, coarser sandstone-dominated substrates generally produce less clay-rich weathering material and allow greater water infiltration and drainage (Keller and Bridgham, 2007). These sites are therefore expected to develop thinner soils with lower organic matter accumulation. Integrating parent material or geological maps into future studies could help explain these relationships and improve the understanding of SOC spatial variability across the High Fens.

Despite its limitations, this study contributes to improving the understanding of SOC spatial variability within the High Fens region and highlights the importance of peatland conservation in the context of climate change. While imprecise for detailed measurements, the overall characteristics of the plateau have been steadily highlighted, allowing for time-efficient estimates of the whole environment status. As major terrestrial carbon reservoirs, peatlands play a critical role in long-term carbon storage, but remain highly vulnerable to hydrological disturbances, drainage, and warming conditions. Improving the monitoring and spatial assessment of these environments therefore represents an important step toward more effective peatland management and conservation strategies in Belgium and beyond.

6. Conclusion

This study investigated the environmental controls influencing Soil Organic Carbon (SOC) stocks across the High Fens plateau and evaluated the capacity of spatial modelling approaches to predict their distribution using limited field observations combined with environmental proxy variables.

The results demonstrate that SOC variability in the High Fens is primarily controlled by broad eco-hydrological conditions represented by land cover and soil type. Wetland environments associated with peaty soils consistently displayed the highest SOC stocks, while forested areas developed on silty-stony soils contained significantly lower carbon reserves. These findings confirm the fundamental importance of long-term water saturation and organic matter accumulation in maintaining peatland carbon storage capacity.

Although topographic and hydrological variables such as slope, flow accumulation, and Topographic Wetness Index (TWI) contributed to the interpretation of environmental dynamics, their direct statistical influence on SOC variability remained secondary compared to the broader environmental conditions represented by soil type and land cover. This suggests that, at the spatial scale investigated, peatland functioning emerges from the combined interaction of multiple factors rather than from isolated environmental gradients.

The statistical analyses further highlighted the limitations of classical linear approaches for modelling peatland SOC distributions. Because SOC values were highly skewed and heteroscedastic, the Gamma Generalized Linear Model provided a more appropriate inferential framework than ordinary least squares regression. In parallel, the Random Forest predictive approach successfully captured non-linear interactions between environmental predictors and generated a spatial representation of SOC distribution estimated across the plateau. These results illustrate the relevance of machine-learning approaches for modelling complex Critical Zone environments where hydrology, vegetation, topography, and human disturbance interact simultaneously.

Beyond methodological considerations, this work also emphasizes the significant importance of the High Fens as a long-term carbon reservoir. The presence of thick organic horizons and highly saturated peat deposits confirms the major role of these ecosystems in regional carbon sequestration. However, field observations and historical context equally highlight their vulnerability to anthropogenic disturbances such as drainage, afforestation, and peat extraction. Even localized alterations of hydrological conditions may accelerate peat degradation and transform these ecosystems from carbon sinks into carbon sources.

Several limitations should still be acknowledged. The relatively small sampling size, the short duration nature of field measurements, and the absence of direct temporal hydrological monitoring constrain the interpretation of seasonal and long-term processes. In addition, assumptions regarding inorganic carbon content and the simplification of land cover classes introduce uncertainties that could be refined in future studies.

Future research could improve this framework by integrating larger sampling campaigns, continuous hydrological measurements, higher-resolution vegetation mapping, and temporal monitoring of greenhouse gas fluxes. Finding better proxies to characterize anthropogenic

influence could also be a great addition in similar studies. Combining field observations with LiDAR-derived microtopography and long-term climate datasets could also help better quantify the role of micro-relief and seasonal hydrological variability in controlling SOC dynamics. Overall, this study demonstrates that combining field sampling, remote sensing, statistical modelling, and machine-learning approaches provides an effective framework to understand and predict carbon storage dynamics in peatland environments.

Through a multidisciplinary Critical Zone perspective, the thesis highlights how interconnected environmental processes shape SOC distribution in the High Fens and reinforces the importance of protecting these fragile ecosystems under ongoing climatic and anthropogenic pressures.

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Annexes

A.1. Field expedition protocol

A uniform protocol was followed for every point to gather soil samples, using an undisturbed soil corer, which allows its user to collect soil without modifying its density (figure A.1). The steps of the procedure were as follow :

- Reach the location and updates its coordinates to take into account small changes in position
- Remove excessive vegetation from the soil to avoid surface plants
- Place the auger on a lower portion of the soil (microtopography is heavily influenced by *Molinia caerulea* presence)
- Position the auger as vertical as possible, push it into the soil, and strike it with a mallet to bury it deeper if necessary
- Once the auger reaches 50 centimeters deep, twist the auger by 180 degrees to close the lid of the Russian corer device
- Bring the auger back to the surface, open it, and carefully transfer the soil core in a rigid PVC pipe of 50 centimeters, half open along its length
- Remove excessive material from the pipe as to keep the volume of sampled soil similar to the volume of the half open PVC tube, in order to only keep soil that fits in the half pipe and wrap it up using plastic foil to avoid drying
- Clean the auger to avoid contamination on the next sample
- Repeat the process with the next 50 centimeters interval, adding extensions to the auger if necessary to reach the new depth, collecting a new sampling core every time.
- Once the soil shifts from a dark color to a light color with a plastic texture, stop 10 to 15 centimeters after reaching this non-organic layer.
- Carry on to the next point

Performing this protocol on all samples ensures that a uniform method is followed, regardless of soil characteristics. Following this procedure, it takes around an hour and a half to navigate to a point and conduct the steps described above.



Figure A.1: Russian undisturbed soil corer (image from GroundGrocer)

A.2. Laboratory protocol

After every expedition, the samples were unwrapped and divided in a specific way. On every 50 centimeter core, two or three parts of 8 centimeters were cut and isolated from the rest of the core. Their limits were chosen arbitrarily, depending on the aspect of the soil profile ; the objective was to have homogenous patches of 8 centimeters to conduct measurements on those small samples. Three sections were made, except with homogeneous bog profiles, in which case only 2 were enough to accurately represent the whole core. The deepest part of the 36 samples were systematically taken, meaning that there is always a value for part of the soil where organic matter is scarce.

Once these sub-samples were made, they were again divided into two parts of equal mass by cutting along the length of the sample, to ensure that they both have the same depth range. For every sub-sample, one half went 48 hours in a 40°C furnace, and the other half was heated to 105°C for 24 hours.

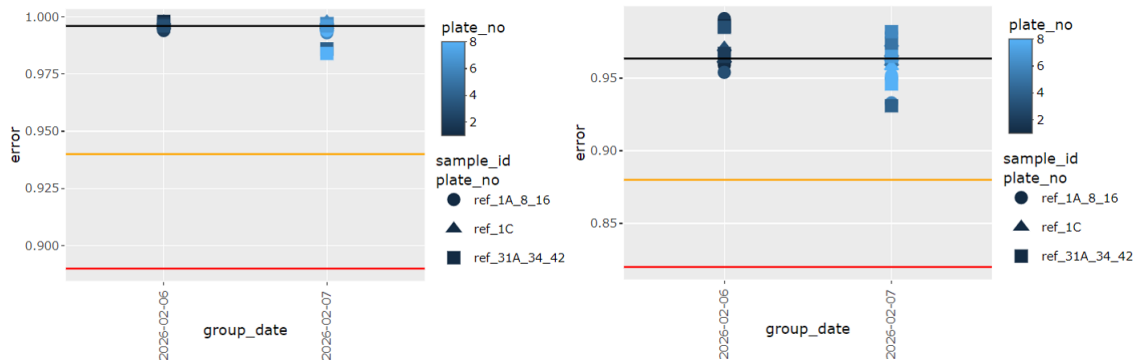


Figure A.2: Error estimates related to MIR measurements

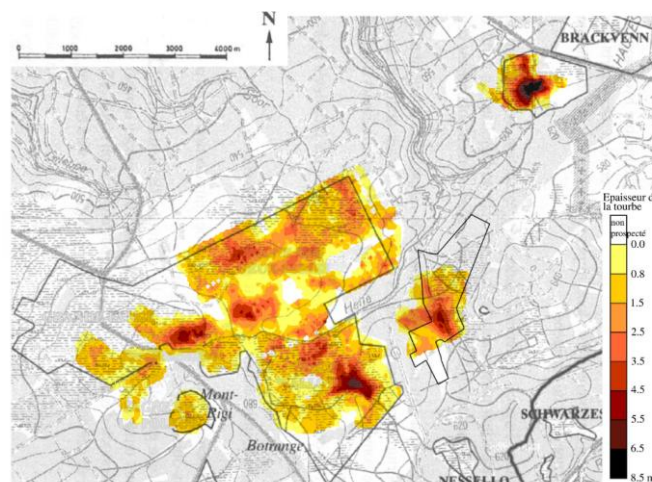


Figure A.3: Complete map from Wastiaux and Schumacker, 2003



Figure A.4: Samples before heating process

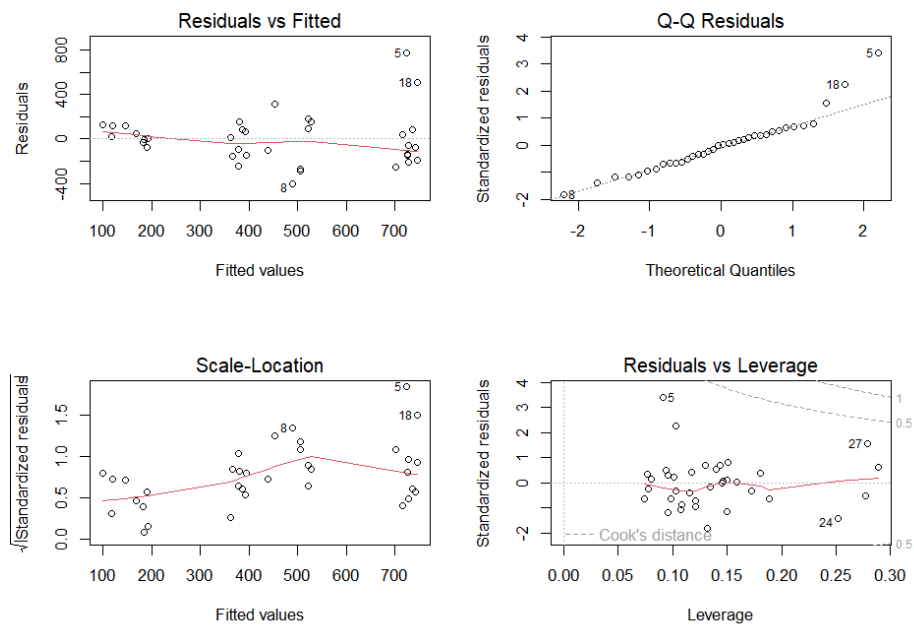


Figure A.5: Residuals of multiple linear regression

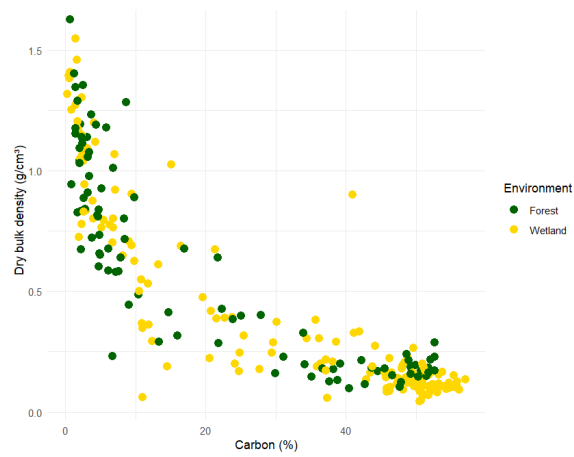


Figure A.6: Relationship between DBD and carbon percentage

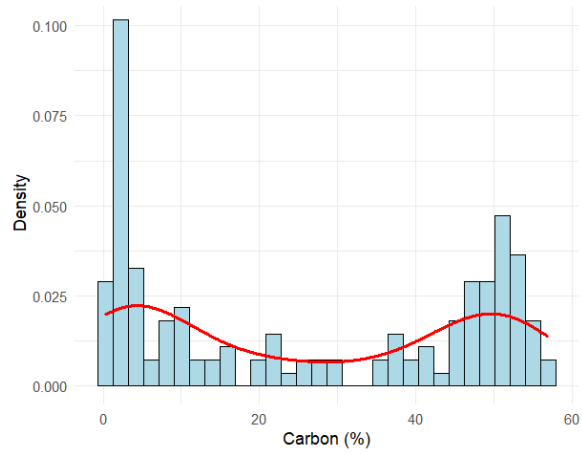


Figure A.7: Carbon percentage of samples after Macro-Elemental Analyzer analysis

Data availability and use of AI

The data produced and used in this study is freely available online :

- <https://doi.org/10.5281/zenodo.19897702>

Generative AI was partially used to improve the English phrasing of the project. No methodological steps, results, figures or hypothesis were made using generative intelligence.

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