

Joint Master in EU Trade and Climate Diplomacy

Assessing the Impact of the EU CAP-FTA Framework on Topsoil Organic Carbon Storage in Partner Countries

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THESIS PITCH

A short elevator pitch providing a brief overview of the thesis can be found via this link:

https://youtu.be/Zg_yCr0v2PI

STATUTORY DECLARATION

I hereby declare that I have composed the present thesis autonomously and without use of any other than the cited sources or means. I have indicated parts that were taken out of published or unpublished work correctly and in a verifiable manner through a quotation. I further assure that I have not presented this thesis to any other institute or university for evaluation and that it has not been published before.

2026.06.21 *Holtkamp, Rens*

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And I also thank anyone who reads this thesis, for I am grateful for your interest and attention. I hope you finish reading knowing a little more about the interface between the environment, trade and agriculture and that, one day, we have tackled the problems related to this interface as that is vital in sustaining our wonderful and vibrant planet – our home.

2026.06.21 *Holtkamp, Rens*

ABSTRACT

This thesis investigates the environmental externalities of the EU's trade-agriculture framework, specifically focusing on the impact of Free Trade Agreements (FTAs) on Soil Organic Carbon (SOC) storage in partner countries. As global EU liberalisation intensifies, concerns regarding the externalisation of environmental costs have become central to climate diplomacy. This research addresses the research question: "To what extent does the implementation of EU FTAs affect SOC storage in partner countries?" Employing a staggered Synthetic and a pairwise Difference-in-Differences analysis, the study examines longitudinal datasets across multiple cohorts of FTA-adopting countries, comparing their SOC trajectories against a selected synthetic control group. The analysis reveals a complex, predominantly negative relationship between trade engagement and soil health. The results yield a final aggregated average treatment effect of -9.92 t/ha, indicating a trend of SOC depletion following FTA implementation. While heterogeneity exists – ranging from SOC increase observed in Morocco to the severe SOC loss in the Ivory Coast and Ukraine – the findings suggest that the current institutional framework fails to internalise ecological costs of agricultural production. This thesis argues that existing EU trade policies jeopardise long-term pedological stability. Consequently, the study concludes with policy recommendations aimed at embedding ecological safeguards, such as mirror clauses and enhanced certification schemes, into future EU trade and agricultural policy to ensure soil restoration and carbon stability.

Key words: Topsoil, Soil Organic Carbon (SOC), Soil Health, European Union (EU), Free Trade Agreement (FTA), Agriculture, Common Agricultural Policy (CAP) Synthetic Difference-in-Difference (SynthDiD)

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1 INTRODUCTION

1.1 CONTEXT AND BACKGROUND

The EU plays a central, if declining, role in global agricultural trade. Thus, changes in the EU's agricultural policy can be expected to have impacts on partner countries. This impact materialised through price changes and the EU's import demand for agricultural commodities and currently results in supply chain effects and reduced domestic greenhouse gas emissions ([Matthews, 2018](#)).

The EU's Common Agricultural Policy (CAP) is a central pillar of European integration, aiming for a productive agricultural community with fair standards of living via direct payments to farmers ([Meester, 2004](#)). The core objective of the CAP is to smoothen internal differences in agricultural competitiveness between regions and Member States, in order to prevent less competitive agricultural communities – predominantly in Southern and Eastern Member States – from being pushed out of the market ([Moreddu et al., 2011](#)). While successive reforms in 2003, 2013, and 2023 have increasingly integrated environmental 'greening' rules to promote climate action within the EU ([Kornher & Von Braun, 2020](#); [Matthews, 2018](#); [Moreddu et al., 2011](#)), these domestic improvements can unconsciously create – or at least fail to reduce – external pressures. As the EU de-intensifies its own agricultural land to meet internal sustainable development and climate goals, it often maintains or increases its reliance on imports for animal feed and bulk commodities, facilitated by Free Trade Agreements ([Matthews, 2018](#)).

This dynamic creates a 'trade-environment nexus,' where EU trade policy acts as a transmission channel for environmental costs in partner countries ([Kornher & Von Braun, 2020](#)). Partner countries, such as the Ivory Coast, Morocco, and Ukraine, are incentivised to specialise and intensify production in specific commodities – like vegetable oils, cereals, or fruits – or to apply a larger agricultural area to meet EU market demand; extensification ([Kornher & Von Braun, 2020](#)). Soil health, and specifically Soil Organic Carbon (SOC) storage, can thereby be degraded by such trade-driven agricultural intensification and extensification. SOC is herein specified as the mass fraction of carbon in the fine earth material (<2 mm) as determined by combustion at 900 °C ([Leenaars et al., 2014](#)).

To minimise the externalisation of environmental costs, strengthening environmental protection in partner countries is the best solution ([Matthews, 2018](#)). However, this requires significant bureaucratic, administrative capacity and results in a trade-off between planet and

profit in partner countries. Several certification schemes are already in place for specific commodities to encourage sustainable imports, although with mixed success. Bans on unsustainable imports via trade policy could similarly be a useful instrument but may not enjoy popular support and need to take into account WTO rules and jurisprudence (Matthews, 2018). In any case, before the EU takes any action combating externalisation of environmental costs, the existence of such costs must be established.

1.2 PROBLEM STATEMENT

There are multiple factors that deteriorate due to agricultural intensification such as acidity, level of bioturbation and biological activity, balance in nutrient ratios, and topsoil organic carbon. SOC is one of the main indicators of soil quality, largely determines crop productivity, and its depletion via acidification of carbon is a source of greenhouse gasses. (Simfukwe et al., 2021) It is this combined impact that determined the focus of this study to be specifically soil organic carbon.

Significant research and knowledge exist on the effects of the CAP and the EU's FTAs on global food prices and external value chain effects leading to external environmental pressure – particularly deforestation – and internal environmental pressures regarding a comprehensive set of environmental aspects, under which SOC. Still a significant gap remains regarding the external effect on SOC in partner countries.

This research will, thus, combat this knowledge gap by investigating the causal relationship between the EU's CAP, as amplified through FTAs, and the resulting change in topsoil organic carbon within partner countries. It will do so via a synthetic Difference-in-Difference method, addressing the potential 'environmental externalisation' due to EU trade agreements.

1.3 OVERVIEW OF THESIS STRUCTURE

This research begins by establishing the background of the CAP-FTA nexus in the Literature Review, identifying the transmission mechanisms through which trade-driven economic incentives pressure partner-country agricultural systems toward intensification and land-use change. Here, this thesis is placed within the context of the research problem and existing literature, highlighting a distinct gap in retrospective, causal evaluations of soil health outcomes. Subsequently, the Research Question and hypothesis are identified, addressing the potential externalisation of environmental costs from the EU to its trade partners.

The [Methodology](#) section sets out a quasi-experimental approach based on the [Synthetic Difference-in-Differences](#) (SynthDiD) method. It argues that this approach combines the strengths of the Synthetic Control Method and the Difference-in-Difference method, while elaborating on the necessary data harmonisation and analyses and highlighting potential [Limitations](#).

The next chapters describe how the different treatment groups of FTA and non-FTA partner countries are selected, on what basis, and what the effects of their agricultural policy frameworks are on this thesis in [Case Selection and Qualitative Analysis](#), and how the data input is collected and managed in the section [Data Harmonisation](#). Next, the qualitative analysis will be presented and visualised in [Results: Quantitative Analysis](#), where the most important outcomes of the synthetic Difference-in-Difference method will be highlighted.

In the [Discussion](#), the research question will be answered. This section will go one step further than the previous chapter by analysing the results and subsequently coming to conclusions and their implications, as well as providing [Policy Recommendations](#) to minimise externalisation of environmental costs within the EU's trade-agriculture framework.

Lastly, the [Conclusion](#) summarises [Key Findings](#), then argues for the political and ecological [Significance](#) of identifying these impacts for the future of EU climate and trade diplomacy and closes with [Recommendations for Further Research](#).

2 LITERATURE REVIEW

The primary channel through which EU agricultural and trade policy impacts global food production is its historical destabilising effect on rural development and depressing world market prices (Borrell & Hubbard, 2000; Matthews, 2018). This area has been subject to extensive research focusing on how market distortions – driven by high price supports and export subsidies – traditionally encouraged overproduction and ‘dumping’ in partner-country markets (Blanco, 2018; Kornher & Von Braun, 2020; Matthews, 2015; Meester, 2004; Moreddu et al., 2011). However, successive CAP reforms since 1992 have significantly reduced protectionist and overproduction pressures, effectively narrowing the gap between domestic and global price indicators (Blanco, 2018; Matthews, 2015; Rudloff & Brüntrup, 2018). Thus, reducing the Normal Rate of protectionism from 70% in 1986-88 to 5% in 2015-17 by, among other measures, shifting support from market prices to decoupling direct payment for farmer production and eliminating export subsidies (Matthews, 2018; Moreddu et al., 2011; Rudloff & Brüntrup, 2018).

A second transmission channel involves supply chain effects, where EU demand for agricultural imports pressures partner-country farmers to prioritise export volume and efficiency over sustainable land management (Moreddu et al., 2011). The CAP, via a growing demand for food, feed, and bioenergy, is linked to land use change, biodiversity loss, and environmental damage in partner countries (Blanco, 2018). This broader trade-environment nexus outside of the EU is well-documented (Barthel et al., 2018; Blanco, 2018; Kornher & Von Braun, 2020; Prins et al., 2011). However, there has been a particular focus on protein-rich livestock feed, leading to deforestation and environmental degradation in South American ecosystems like the Amazon (Barthel et al., 2018; Blanco, 2018; Kornher & Von Braun, 2020). EU demand for animal feed, imported beef, and imported palm oil – for diesel production and cosmetic manufacture as well as food – has been directly linked to tropical deforestation (Barthel et al., 2018; Prins et al., 2011; Schulmeister, 2015).

Within Europe, the environmental impact of this policy-trade nexus is also well-established, with documented impacts regarding reductions in nitrogen and greenhouse gas emissions, reduced grazing pressure, and soil erosion (Blanco, 2018; Gocht et al., 2017; Hart & Baldock, 2011; Matthews, 2018; Moreddu et al., 2011). Regarding soil organic carbon specifically, different studies mention the EU-wide impact of the CAP. Several reports highlight the domestic reduction of soil-related emissions, thus an increase in SOC, due to carbon sequestration, increased soil cover, crop diversification, carbon-rich soil protection

schemes, and set-aside supply control measures (Boellstorff & Benito, 2005; Cantore, 2012; Matthews, 2018; Moreddu et al., 2011). Further reports highlight the negative effect on SOC due to the use of organic soils or conversion of grassland to arable land (Borrelli & Panagos, 2020; Gocht et al., 2017).

However, existing studies exhibit a significant gap regarding the ex-post causal assessment of soil health in partner countries. Some reports use predictive Computable General Equilibrium (CGE) models to simulate future trade or agricultural impacts, which often fail to capture the diversity of local adjustments in land use intensity and technology (Calzadilla et al., 2011). Other research focuses on metamodels that are used to predict soil degradation impacts of land management responses to different policies (Lakshminarayan et al., 1996).

Furthermore, there is vast biophysical literature on how specific land management practices like no-till or cover cropping affect soil erosion and SOC in and outside the EU (Kornher & Von Braun, 2020; López-Vicente et al., 2013; Schuler & Sattler, 2008; Souchère et al., 2003). Yet these biophysical findings are on no occasion integrated with longitudinal trade policy data to establish a causal link to trade mechanisms in non-EU countries.

Supplementary studies acknowledge that the CAP, and specifically the 'greening'-rules within the CAP, could increase the import of agricultural goods from developing countries, while explicitly stating not to take into account the negative effects that could then arise, such as an increase in land use change and intensive food production (Cantore, 2012).

The field has evolved from simple trend analyses to more complex bio-economic modelling, yet a gap remains in evidence-based, retrospective evaluations of actual soil outcomes following FTA implementation in partner countries. By applying a quasi-experimental design, this research fills this methodological gap, moving beyond associational evidence to identify the specific policy shocks that lead to measurable changes in the drivers of soil health.

2.1 RESEARCH QUESTION

The problem this thesis addresses is the potential 'environmental leakage' or 'carbon externalisation' inherent in EU trade agreements. While the EU projects a green image domestically, its trade agreements may be causally linked to soil degradation and the loss of carbon storage capacity in the global south and other third countries, particularly topsoil, as that is more easily affected by changes in land management. This study asks:

What is the causal impact of the EU's Common Agricultural Policy, as amplified through Free Trade Agreements, on the topsoil organic carbon storage capacity of partner countries?

3 METHODOLOGY

The transition from identifying theoretical gaps to empirical evaluation requires a robust framework capable of isolating policy-driven environmental outcomes. While the existing literature establishes a clear trade-environment nexus, it lacks retrospective, causal assessments regarding the externalisation of soil health costs in partner countries. This methodology addresses this knowledge gap by shifting from predictive modelling to a quasi-experimental evaluation of actual soil organic carbon changes following trade liberalisation.

3.1 RESEARCH POSITION AND PARADIGM

3.1.1 Ontological and Epistemological Position

This research is situated within a post-positivist research paradigm. Ontologically, it adopts a critical realist stance, asserting that an objective physical reality – specifically SOC and its response to land management – exists independently of human observation. However, it acknowledges that this reality can only be understood imperfectly and probabilistically due to the inherent complexity of biophysical and social systems.

Epistemologically, this study pursues objectivity through quantitative causal assessments. By using the Synthetic Difference-in-Differences method, the research seeks to move beyond ‘associational evidence’ to identifying policy shocks that lead to measurable environmental changes. The use of a quasi-experimental design reflects a belief that while absolute ‘truth’ in social-ecological systems is difficult to capture, it can be approximated.

3.1.2 Research Paradigm: Pragmatic Functionalism

While the core methodology is quantitative, the paradigm is also informed by pragmatism. The research is driven by a functional need to solve the ‘problem’ of carbon externalisation due to the EU CAP-FTA nexus. By bridging biophysical soil science with longitudinal trade policy data, the study rejects a narrow disciplinary silo in favour of a methodology that produces actionable evidence for policymakers. This approach recognises that knowledge is most valuable when it assists the EU in aligning its trade framework with global climate commitments.

3.2 DISCUSSION OF THE METHOD: SYNTHDID

To isolate the causal impact of the CAP as amplified by FTAs on SOC, this research employs a quasi-experimental design based on the Synthetic Difference-in-Differences

method. A quasi-experimental design is needed here because trade agreements are non-random policy interventions. Since random assignment is impossible, this method treats the FTA entry as a natural experiment to compare outcomes before and after implementation.

This relatively novel approach was initially used in a preliminary form of matched Difference-in-Difference by the OECD, where the isolated impact of the EU Emissions Trading System (ETS) on carbon emissions and economic performance was assessed ([Dechezleprêtre et al., 2018](#)). The OECD economic department used matched treatment groups of energy plants that were covered by the ETS policy (treatment group) and those that were not (control group). This research will mimic this method, as both cases resemble non-random policy interventions on a continental scale, affecting carbon fluxes and the economic reality of their relative sectors.

The SynthDiD method constructs a counterfactual for the treated group by reweighting control units to match the pre-treatment trajectories of treated units as closely as possible. Here, the treatment is the adoption of an FTA. Then, the treatment effect is projected by comparing the outcomes of the treated unit and the synthetic control group. This approach combines the strengths of the Synthetic Control Method (SCM) and the Difference-in-Difference (DiD) method ([Arkhangelsky et al., 2021](#)).

- SynthDiD is more sufficient than the traditional DiD because it relaxes the strict 'Parallel Trends Assumption' ([Arkhangelsky et al., 2021](#); [Porreca, 2022](#)). In trade and agriculture, it is difficult to argue that countries like Ukraine and non-FTA partners would have followed parallel trends without the EU agreement. SynthDiD 'creates' a parallel trend by weighting the control group to minimise the variation between the treated and control groups in the pre-treatment stage.
- SynthDiD is uniquely suited for this study as it provides a 'double robust' estimation that manages the staggered adoption of FTAs, where different partners, such as Morocco (2000), Colombia (2013), and Ukraine (2016), signed and adopted an FTA at various times ([Porreca, 2022](#)).
- Additionally, unlike the SCM, which requires a long pre-treatment period and large data samples to be valid, SynthDiD remains effective even if pre-treatment data turns out to be limited in years or samples. Furthermore, SCM is designed for a few treated units, whereas SynthDiD is designed to use multiple units ([Arkhangelsky et al., 2021](#)).

The analysis will be executed using the SynthDiD package in R, which facilitates the construction of a custom counterfactual for each treated unit from a control pool of non-FTA countries.

3.3 RESEARCH DESIGN

As mentioned, this study employs a quasi-experimental research design centred on the Synthetic Difference-in-Differences method. A quasi-experimental approach is necessary because FTA entries are non-random policy interventions where traditional random assignment is impossible. The research follows a six-stage methodological framework:

1. *Case selection*: identifying treatment and control groups.
2. *Qualitative screening*: evaluating national policy disruptions to isolate FTA effect.
3. *Data harmonisation*: processing secondary longitudinal Soil Organic Carbon datasets.
4. *SynthDiD modelling*: executing the staggered treatment model in R.
5. *Pairwise DiD control*: executing the Pairwise Difference-in-Difference method in R.
6. *Quantitative evaluation*: analysing model output to derive policy implications.

3.3.1 Case Selection

The research cases for the treatment group will be selected to represent diverse agricultural products (e.g., Ukrainian cereals, Moroccan tomatoes, and Ivory Coast cocoa beans), from a diverse selection of regions and soil types, which are influenced by EU market demand and based on the availability of data. The synthetic control group will consist of regional competitors that do not have an active FTA with the EU but share similar climatic zones, export profiles, and soil types.

However, it is not possible to create two similar or even equal groups. The purpose of the selection of specific partner countries and the subsequent analysis of their agricultural policy frameworks is to minimise uneven circumstances regarding climate, exports, or soil type and to bring disturbing factors like an agricultural policy reform to the light. Therefore, this study uses comparative pairing to minimise variance in climate, export profiles, and soil types.

3.3.2 Qualitative Analysis

To ensure that the treatment effects are not influenced by domestic factors, the quantitative model is supplemented by a qualitative policy review of national agricultural reforms. This involves identifying 'disturbances' (e.g. Ukraine's Land Reform or Morocco's Green Plan) to rule out domestic shocks occurring alongside FTA implementation affecting the causal claim.

3.3.3 Data Collection and Harmonisation

Evidence for this study is drawn from secondary longitudinal datasets that provide snapshots of SOC content over time. Primary soil data will be sourced from the [ISRIC Data Hub](#), which provides global maps of historic SOC stocks. This will be supplemented by [FAO's Global Soil Information System \(GLOSIS\)](#) which holds more recent data.

A crucial technical step in this methodology is the harmonisation of data units. SOC data often vary between concentration (g/kg) and stock (ton/ha). These units will be converted by incorporating density estimates and standardised soil depths – typically the top 0-30 cm layer, where carbon is most susceptible to management-induced change.

3.3.4 SynthDiD model in R

The harmonised data is processed using the SynthDiD package in R, which is uniquely suited for this study as it manages staggered treatment timing. Unlike the traditional Synthetic Control Method, SynthDiD is effective with multiple treated units and limited pre-treatment data. The model constructs a counterfactual by reweighting control units to match the pre-treatment trajectories of the FTA partners, providing a "double robust" estimation of the treatment effect.

3.3.5 Pairwise DiD as Control

The Pairwise Difference-in-Difference method operates along the same basic principles as the SynthDiD. However, as it takes the selected pair as the sole control variable, there is no option to describe different weights to different units, years or countries to match the pre-treatment period. Thus, without an exact match in pre-treatment period, the significance and certainty of its results decrease heavily. Therefore, this method is not taken as the primary analysis, but as a substitute and control for cases where pre-treatment shows strong resemblance.

3.3.6 Quantitative Analysis of the Results

The final stage involves visualising the treatment effect – the divergence between the treated unit and its synthetic counterfactual following FTA adoption. Results are presented through tables and graphs to highlight significant outcomes of the model. These findings are then used to answer the research question and formulate policy recommendations for the EU's trade-agriculture framework.

3.4 ETHICAL CONSIDERATIONS

This research adheres to the foundational ethical principles of academic integrity, transparency, and non-maleficence. Given the quasi-experimental nature of the study, several specific ethical and practical dimensions are addressed below.

3.4.1 Methodological Ethics and Integrity

The primary ethical obligation in this study involves the autonomous composition of the thesis and the accurate representation of data. To ensure transparency and repeatability, all data harmonisation steps – such as converting SOC concentration (g/kg) to stocks (ton/ha) – are explicitly documented to prevent the manipulation of results. Furthermore, the use of the SynthDiD method provides a ‘double robust’ estimation, minimising the risk of cherry-picking control groups to achieve statistical significance.

3.4.2 Data Access and Sensitivity

This study relies exclusively on secondary longitudinal datasets from public repositories, including the ISRIC Data Hub and the FAO Soil Portal. Consequently, there are no risks associated with human subject participation, informed consent, or the handling of personally identifiable information. The data is biophysical and macroeconomic in nature, posing no threat to the safety or privacy of individuals in partner countries.

3.4.3 Researcher Bias

To mitigate researcher bias, the thesis incorporates a qualitative policy analysis to screen for domestic shocks which might independently explain SOC changes and an extra control step by way of Pairwise DiD analysis. These serve as neutralising steps to ensure the causal claim is not unfairly biased against EU trade policy.

3.4.4 Impact and Responsibility

In line with the principle of ‘doing no harm,’ the findings are intended to support sustainable trade. By identifying potential carbon externalisation, the research seeks to provide evidence for better green conditionalities, aiming to protect the long-term food security and soil capital of partner countries rather than criticising their development.

3.5 LIMITATIONS

3.5.1 Methodological Constrains

The proposed methodology rests on assumptions that introduce limitations. One challenge is the ‘purity’ of the counterfactual. The SynthDiD model assumes that in the absence of an FTA, the CAP would exert no influence on the soil health of partner countries. In reality, the CAP’s influence is partially indirect; it shapes the broader European agricultural system, which subsequently transmits price signals, import and export incentives, and standards to world markets regardless of trade status (Matthews, 2018; Moreddu et al., 2011). This suggests that the control and pre-treatment groups may already be ‘contaminated’ by indirect

CAP spillovers. Consequently, if the control group is already responding to CAP-driven shifts, the research may underestimate the causal impact of the policy.

Furthermore, the implementation of an FTA serves as a 'bundled treatment'. While the CAP defines the EU's internal agricultural landscape, an FTA exposes a partner country to the entire EU socio-economic system, including its high-income consumer base, culturally western dietary preferences, and specific climate-driven demand patterns (Moreddu et al., 2011). Distinguishing the effect of the CAP as a policy instrument from the general effect of increased EU market demand – and from specific tariff-free commodities – is difficult. This complexity may lead to an overestimation of the CAP's specific role if environmental degradation is driven more by the scale of EU consumption than by the structure of agricultural subsidies and regulations.

Thirdly, biophysical SOC dynamics are sensitive to non-trade variables, such as local climate variability and national policy reforms. While the methodology includes qualitative screening of national policies, unobserved or underestimated internal shifts – such as changes in land tenure or national irrigation schemes – may coincide with FTA implementation, reducing the accuracy of the findings.

Finally, transposition of the location of measurement from the ISRIC Data Hub to FAO's GLOSIS maps and from FAO's GLOSIS maps to the FOA/UNESCO Soil Map of the World was done on a manual basis and thus susceptible to human error. This is a limitation in the precision and, thus, certainty of the results of this thesis.

3.5.2 Time and Resource Constraints

This research is conducted within the inherent temporal and resource boundaries of a solitary researcher at Master's level. Recognising these practical constraints is essential, as no single study can cover every population or method. The limited time horizon (a few months) restricts the depth of the qualitative policy analysis that can be applied to the extensive donor pool of control countries. This constraint inevitably limits the generalisability of findings across all global biomes.

Additionally, a smaller sample of countries and measurements per country increases the risk that unique domestic policy shifts or localised environmental anomalies may influence the results and – as all smaller sample sizes do – increases the standard deviation of the analysis results. To mitigate this, the study prioritises depth over breadth by focusing on high-impact partner countries, using the SynthDiD approach to maximise the reliability of the construction of the counterfactual within the available time frame.

A fundamental challenge for this study is the scarcity and unevenness of longitudinal SOC data. Currently, no single high-resolution dataset covers the global land surface over a long-term period (>10 years) in a spatially continuous format. This necessitates the synthesis of data from disparate sources, which presents technical hurdles like unit inconsistency, depth dependency, and spatial heterogeneity. While the next two chapters on [Case Selection and Comparative Framework](#) and [Data Management](#) describe how each technical hurdle is handled, the increase in complexity and number of steps may inadvertently impact the results and their certainty or significance in unexpected ways.

4 CASE SELECTION AND COMPARATIVE FRAMEWORK

Given the non-random nature of trade agreements, this research relies on a quasi-experimental approach that pairs ‘treated’ partner countries with ‘synthetic’ control countries with similar characteristics but lack such an agreement. The transition from theory to empirical evaluation of SOC dynamics requires careful selection of partner countries, moving beyond geographic proximity.

The objective of the selection process is to minimise discrepancies in variables, like climatic zones, soil types, and export profiles, thereby ensuring that observed SOC divergence can be more confidently attributed to the policy shock of trade liberalisation. This chapter:

- *outlines* the rationale behind the multi-dimensional selection criteria for treatment and control groups used to isolate the causal impact of the CAP, as amplified via FTAs,
- *justifies* the inclusion of specific high-impact partner countries representing diverse agricultural commodities, and
- *establishes* the comparative pairings that form the basis of the SynthDiD model.

4.1 SELECTION CRITERIA AND RATIONALE

4.1.1 Biophysical and Climatic Similarity

Soil Organic Carbon is one of the main indicators of soil quality, which governs the rates of sequestration and decomposition. Additionally, its depletion leads to significant reductions in crop productivity ([Simfukwe et al., 2021](#)). The stability of SOC is governed by vertical depth gradients and is highly sensitive to abiotic factors such as topography and climate, specifically precipitation and temperature patterns ([Paltineanu et al., 2025](#)). As elaborated in [Box 1](#), soil types and abiotic factors strongly influence the response of SOC to differing modifications. Thus, soil types – characterised by their fraction of carbon and fine earth material – must be similar across paired countries to ensure that their response to agricultural change is comparable.

Consequently, pairings are made within the same regional and soil-type cluster to maintain climatic and pedological consistency, respectively. The selection prioritises countries where the annual precipitation and mean temperatures are aligned, as these factors dictate the carbon sequestration potential ([Paltineanu et al., 2025](#)). By matching a ‘treated’ country like Ukraine with a control like Kazakhstan, the model accounts for the continental climate and Mollisols that both countries face – see [Box 1](#). This focuses the analysis on the divergence caused by the EU trade framework.

BOX 1 - SOIL TYPE CHARACTERISTICS & INFLUENCE OF AGRICULTURE

Efficiency of carbon stabilisation varies significantly between soil types (Simfukwe et al., 2021), necessitating a comprehensive understanding of their chemical and physical properties. The selection of treatment and control pairings is, thus, grounded in the way soil types and therefore SOC responds to human intervention.

Mollisols; Chernozems and Kastanozems

Chernozems, found in the continental steppe regions of Eurasia, are the most fertile soils globally, extending over 230 million hectares. They are characterised by a deep and dark chernic horizon (humus) rich in organic matter (>1% SOC) and have a high capacity to absorb and sequester atmospheric carbon (Zharlygassov et al., 2024). However, these soils are prone to compaction, degradation, and erosion under intensive farming and mechanical tillage (Labaz et al., 2024; Xu et al., 2020).

In the 'Black Earth Belt,' located in Russia and Ukraine, the highest reductions in SOC have been detected in the top 10 cm of soil, where losses can range from 38% to 43% under continuously cropped fields (Mikhailova et al., 2000). Mollisols, in general, have lost about 50% of their carbon stock worldwide (Xu et al., 2020).

Kastanozems – Chernozems and Kastanozems are both found in Kazakhstan (Zharlygassov et al., 2024) – are similar but often occur in drier regions. They have a high capacity for mineral association, but their SOC is more sensitive to aridity and temperature effecting microbial activity (Fujii et al., 2020).

Tropical Soils; Ferralsols, Lixisols, and Acrisols

Deep chemical weathering in the humid, hot temperature tropics give rise to Ferralsols, Lixisols, and Acrisols, which are rich in iron, aluminium, and rapid microbial activity. These soils have a near absence of weatherable minerals and low cation exchange capacity (CEC), making the role of SOC even more critical for maintaining fertility (Nachtergaele et al., 2024; Silatsa et al., 2024).

When these soils are converted from forest to annual crops or plantations – as seen in the Ivory Coast and Colombia – reduced litter input leads to a loss of carbon stocks (FOA & JRC, 2023; Sari et al., 2025). In that case, stimulation of root respiration and microbial activity in these tropical soils turns them into net carbon emitters (Valenzuela-Balcázar et al., 2021).

Arid Soils; Regosols, Calcisols, and Cambisols

Regosols, Calcisols, and Cambisols, found in arid regions such as in Tunisia and Morocco, are typically sandy and slightly or moderately weathered. These soils have low water-holding capacity and are vulnerable to desertification, erosion, salinization, and seawater intrusion in coastal areas (Balghiti et al., 2024; Moussadek et al., 2015). In these environments, SOC is often concentrated in the very thin topsoil layer, which is easily lost through sheet erosion (Balghiti et al., 2024). The trade-driven expansion of agriculture into these zones forces intensification in areas where the biophysical tipping point for carbon sequestration is low.

EU Agricultural Import Profiles

In 2024, the EU's share of agricultural products in total exports was 9,1%, while imports reached 8,0%, reaching a value of €195 billion. Cacao imports reached €16 billion, dominating the foodstuffs (processed food) import sector. The largest sector of fruits and vegetable products, valued at 38% of EU imports, mainly consists of fruits and nuts (€23 billion), coffee and tea (€16 billion), oils and seeds (€14,5 billion), and cereals (€9,5 billion) (Eurostat, 2026a). Partner countries are often incentivised to specialise and intensify production in these tariff-free commodities to meet this demand, leading to land-use change and the adoption of intensive management practices.

The trade-environment nexus is driven by EU demand for specific commodities, such as vegetable oils, cereals, and fruits. For the treatment group to be representative, it must reflect a diversity of agricultural products influenced by the CAP's internal subsidies and the EU's import profile. Additionally, the export sectors of selected countries must be significantly oriented towards the EU market. The selection, therefore, includes countries representing different sectors of the EU import, such as cereals (Ukraine), edible fruits and nuts (Morocco, Peru), and cocoa (Ivory Coast).

Socio-Economic Comparability

While the SynthDiD method relaxes some requirements of traditional models, it still benefits from comparing units with similar development trajectories (Arkhangelsky et al., 2021). Factors such as the degree of agricultural mechanisation, agricultural technology, land tenure systems, average farm size, and the relative importance of agriculture to the national GDP must, thus, be considered (Daum, 2022; Gáfaró et al., 2023; Güler & Kandemir, 2025).

By matching countries with similar socio-economic foundations – such as the bimodal agrarian structures of Ukraine and Kazakhstan (Wengle et al., 2024; Yessymkhanova et al., 2021) or the tropical export-led mixed agribusiness sectors of Colombia and Brazil (FAO, n.d.) – the model ensures that the economic incentives provided by an FTA act upon similar structural foundations.

4.2 TREATMENT GROUP: SELECTED FTA PARTNERS

The treatment group consists of countries that had FTAs with the EU in place by 2016 or earlier. This cutoff is motivated by data availability and timing considerations. The Global Soil Information System (GLOSIS) provides the most comprehensive and detailed SOC data, specifically the [Global Soil Organic Carbon Map v1.5](#), which reflects conditions around 2019. Because both the implementation of FTAs and their effects on soil systems unfold gradually over time, only agreements that were already well established by 2016 are suitable for analysis. In addition, as outlined in the previous section, the selected countries were chosen to capture a broad range of the EU's externalised agricultural footprint, spanning diverse biomes and commodity groups.

4.2.1 Ukraine: A Mismanaged Continental Cereal Hub

The Ukrainian soil is dominated by Chernozems, covering 25,3 million hectares, equalling two-thirds of the country (Baliuk et al., 2017). These soils are among the most fertile and carbon-rich in the world but have suffered from accelerated degradation and erosion due to the use of increasingly powerful machinery and intensive tillage; losing between 15 and 40% of SOC and becoming a global greenhouse gas emitter (Baliuk et al., 2017; Xu et al., 2020).

Ukraine represents a critical case due to its role as a "breadbasket" for Europe and the world (Wengle et al., 2024). Its bimodal agricultural sector is a central pillar of the economy; its share of GDP reached 10,3% in 2019 (NationMaster, 2020). Additionally, the implementation of the Deep and Comprehensive Free Trade Area (DCFTA) in 2016 deepened Ukraine's integration into the EU agricultural market. In 2021, Ukraine provided a significant share of EU imports for vegetable oils, oilseeds, and fats (24,4%) and cereals (28,8%) (DG AGRI, 2025I). In 2024, despite the ongoing war, Ukraine's exports to the EU remained significant, with the EU accounting for 60% of all exports, valued at \$24,8 billion (Matuszak, 2025).

This combination of the high trade volume toward the EU, the importance of its agricultural sector, and the mismanaged Chernozem soils makes Ukraine an ideal case for assessing how market-driven demand impacts the long-term storage of carbon in deep humus horizons.

4.2.2 Morocco: Horticulture under Climate Stress

The agricultural sector in Morocco contributes to 12% of GDP and employs more than a quarter of the labour force. However, this productivity is threatened by extreme climate vulnerability, with temperatures rising by more than 1°C since 1901 and droughts becoming more frequent ([Achli et al., 2024](#); [Razzouki et al., 2025](#)). The expansion of citrus and vegetable production – often involving deep ploughing, extensive fertilisation, pesticide control, and intensive irrigation – and more grazing pressure pose significant risks of water depletion, biodiversity loss, nutrient pollution, desertification, soil erosion, and SOC reduction in Morocco's arid soil regions ([Benabdelkader et al., 2021](#)).

For now, Moroccan fruit and vegetable exports have shown sustained growth, with the EU absorbing around 64% of Morocco's total export volume in this sector ([Arhzaf & Eljai, 2026](#)). As a Mediterranean partner with a long-standing FTA (the 1996 Association Agreement), Morocco provides a perspective on how EU market demand for horticultural products drives changes in SOC in arid regions, under stress from climate change.

4.2.3 Ivory Coast: West Africa's Cacao Producer

The Ivory Coast is characterised by tree and root crop farming systems ([FAO, n.d.](#)) and is the world's leading producer of cocoa beans ([Lefort, 2025](#)). The export of cacao is worth nearly \$5 billion in 2019 and supports more than 2 million farmers ([Mekonnen, 2025](#)). Facilitated by the Economic Partnership Agreement (EPA) between West Africa and the EU and the EPA between the EU and the Ivory Coast that has been applied provisionally since 2008, the EU receives two-thirds of the exports of the Ivory Coast ([Delegation of the EU to the Republic of Côte d'Ivoire, 2024](#)).

This trade-driven demand has been a major driver of deforestation, with approximately 2,4 million hectares of forest cleared between 2000 and 2019 to grow cocoa beans ([Lefort, 2025](#)). Cocoa farmers, in 70% of the cases illegally, clear new land rather than reusing existing plots, which has led to a loss of 45% in tropical forests ([Mekonnen, 2025](#)). This extensification strategy – fuelled by climate change making existing plantations unsuitable for production ([Asante et al., 2025](#)) – has devastating consequences for SOC storage, as tropical forest soils lose their primary carbon inputs once the forest canopy is removed ([FOA & JRC, 2023](#); [Sari et al., 2025](#)).

The 2024 EU Regulation on Deforestation-Free Products adds a policy layer to this case, aiming to stimulate the transition toward sustainable agroforestry while maintaining the Ivory Coast's exports to the EU ([Lefort, 2025](#)). This makes a compelling case for the Ivory Coast.

4.2.4 Colombia: Diverse Tropical and Highland Systems

Following the application of its FTA in 2013, Colombia has consolidated its position as a primary supplier of high-value agricultural commodities, particularly coffee, bananas, and cut flowers ([DG AGRI, 2025d](#)).

Colombia represents South American tropical highland and lowland contexts. Therefore, its agricultural landscape is pedologically diverse, featuring fertile volcanic Andosols and Phaeozems in coffee-growing highlands, alongside deeply weathered Ferralsols in lowland banana plantations ([IUSS, n.d.](#)). The intensification of these sectors – driven by tariff-free access to the EU's consumer base – could present a significant risk to SOC. Intensive coffee cultivation, often involving high nutrient inputs and land clearing on steep slopes, is particularly prone to topsoil erosion and carbon depletion ([Leceta et al., 2024](#); [FAO, n.d.](#)).

Due to sustainable land management practices and minimal tillage, Colombia's extensive mixed systems currently allow for the prevention of soil degradation and the conservation of SOC ([FAO, n.d.](#)). This case evaluates how trade-induced impacts affect long-term carbon sequestration potential in extensive and sustainable agricultural systems.

4.2.5 Peru: Andean Diversification

Peru represents a South American partner where trade-driven economic incentives have led to a steeper growth in the agro-export sector than the regional average, namely 15,4% compared to 4%. Following the 2013 FTA with the EU, Peru has emerged as a leader in products like blueberries, grapes, avocados, lima beans, and quinoa. Fresh fruit and vegetable exports reached over \$8,2 billion in 2024, with the EU being a main recipient ([DG AGRI, 2025b](#); [Directorate for Promotion of Exports, 2025](#)).

The Peruvian agricultural landscape is uniquely diverse, ranging from coastal desert plains to high Andean mountain systems, overwhelmingly managed by indigenous communities. While traditional high-altitude mixed terrace systems on carbon-rich Anthrosols have historically been predominant, modern export-oriented intensification often targets different soil groups, such as Phaeozems and Andosols near the coast ([FAO, n.d.](#); [Leceta et al., 2024](#)).

Thus, Peru provides for an interesting case, with two very distinct agricultural systems. One is the historically sustainable but low-yielding high-altitude terrace systems, which face risks of soil erosion due to steep slopes, and the other is the expansion of irrigated farming systems along the coast and inland valleys. The latter allows for high intensification but relies on non-renewable water resources and may lead to topsoil and nutrient loss ([FAO, n.d.](#)).

4.3 CONTROL GROUP: SELECTED NON-FTA PARTNERS

For each treated country, a synthetic control partner has been identified. These countries share the biophysical and socio-economic characteristics and trade profiles of the treated units but operate without the specific policy ‘treatment’ of a comprehensive EU FTA.

4.3.1 Ukraine vs. Kazakhstan: Continental Cereal Belts

Ukraine and Kazakhstan both possess vast, fertile steppe used for large-scale cereal production ([Zharlygassov et al., 2024](#)). Both are dominated by Mollisols; Chernozems in Ukraine and a combination of Chernozems and Kastanozems in Kazakhstan ([IUSS, n.d.](#)). These soils have a uniquely high carbon sequestration capacity but have lost significant SOC stocks due to Soviet-era land conversion and modern tillage technology ([Xu et al., 2020](#)).

Regarding trade profiles, both Ukraine and Kazakhstan have agricultural sectors employing approximately 13% of the population on 30 million hectares of arable land ([DG AGRI, 2025e](#); [DG AGRI, 2025i](#)). Although the total share of EU imports from Kazakhstan is significantly smaller than that of Ukraine – €322 million compared to €13.094 million in 2024 – the import profile is similar. The EU imports mainly cereals (35%), oils (34%), and oilseeds (15%) from Kazakhstan ([DG AGRI, 2025e](#)).

Considering socio-economic characteristics, both countries exhibit bimodal agrarian structures ([Wengle et al., 2024](#); [Yessymkhanova et al., 2021](#)). While Ukraine redirected its exports toward EU markets via the DCFTA, Kazakhstan lacks a comparable comprehensive trade agreement, allowing the model to isolate the effect of FTA-driven intensification.

4.3.2 Morocco vs. Tunisia: Mediterranean Arid Zones

Morocco and Tunisia share the Mediterranean climatic zone, characterised by extreme aridity and high vulnerability to climate change. Both rely on shallow, sandy soils like Xerosols and Yermosols that are inherently low in SOC ([Balghiti et al., 2024](#)). Additionally, both countries and their agricultural sectors face increasing pressure from increasing temperatures and prolonged droughts due to climate change ([Razzouki et al., 2025](#)).

Both Morocco’s and Tunisia’s agricultural sectors are characterised by Sparse and Highland Mixed farming systems ([FAO, n.d.](#)). However, where these countries do differ is in their trading profiles. While Morocco exports mainly vegetables (49%) and fruits and nuts (34%), olives and olive oil come third with 5% of exports to the EU; Tunisia exports mainly olives and olive oil (72%), with vegetables and fruits and nuts coming second and third place ([DG AGRI, 2025h](#); [DG AGRI, 2025k](#)).

While this is not an ideal comparison, no other country in the Middle East and North African region provides a better alternative. Algeria exports a large share of fruits and nuts to the EU, but a negligible amount of vegetables and olive products, while its total share of EU exports only reaches €89 million (compared to billions for Morocco and Tunisia), minimising the EU's overall effect on its agricultural system and soil quality (DG AGRI, 2025a). Moreover, Libya's exports to the EU only reach €2 million, excluding Libya as a high-impact partner (DG AGRI, 2025f). Lastly, moving further to the East, soil profiles and farming systems no longer resemble those of Morocco (FAO, n.d.).

Pairing Morocco and Tunisia, while not perfect, allows isolation of the effect of trade-driven agricultural specialisation in fragile arid horticulture against a background of climatic stress.

4.3.3 Ivory Coast vs. Nigeria: West African Tropical Exporters

The Ivory Coast and Nigeria are major West African economies situated in the humid tropical rainforest and savanna zones. They share similar soil profiles dominated by Ferralsols, Lixisols, and Acrisols, which are deeply weathered and sensitive to the loss of perennial vegetation (IUSS, n.d.). Additionally, both countries are characterised by tree and root crop farming systems, producing mainly cacao, tea, and coffee (FAO, n.d.).

From a socio-macroeconomic perspective, both the Ivory Coast and Nigeria have a rural population of about 46%, where agriculture is an important sector of the economy and daily life. In Nigeria, the share of added value due to agriculture is 22,7% of total GDP, and 34,3% of the population is employed in agriculture. The numbers for the Ivory Coast are 14,7% and 45,2% respectively. The export profile of both countries to the EU consists of almost 90% of cacao, tea, coffee, and spices (DG AGRI, 2025g; DG AGRI, 2025i).

By comparing the two, research can evaluate whether FTA-driven incentives lead to more intensive and carbon-depleting land-use patterns among the mentioned export groups than those in a non-FTA neighbour, specifically for sensitive tropical soil systems.

4.3.4 Peru vs. Bolivia: South American Highland

The main similarity between Peru and Bolivia is that both their agricultural systems are dominated by over 40% of high-altitude mixed farming systems, with some forest-based farming systems more land-inward (FAO, n.d.). Agro-ecologically, this area of South America has great diversity, with a wide variety of soil types accompanied by striking changes in altitude, temperature, humidity, and rainfall. However, the soils mostly found in both countries are Andosols, Cambisols, Leptosols and Regosols – with low fertility as a common denominator (FAO, n.d.; IUSS, n.d.)

Socio-economically, both countries are known for their prominent levels of indigenous and rural communities (FAO, n.d.), characterised by poverty and a lack of infrastructure, education, and health. Additionally, in both countries, roughly 24% of the total population is employed in agriculture. Lastly, Export by Peru as well as Bolivia to the EU are led by the fruits and nuts sector and supplemented by the cacao, coffee and tea sector (DG AGRI, 2025b; DG AGRI, 2025j). With many similarities, Bolivia is a suitable case to be compared with Peru in a SynthDiD analysis.

4.3.5 Colombia vs. Brazil: Tropical Commodity Competitors

Colombia and Brazil possess vast areas of Ferralsols and Acrisols in their lowland agricultural zones (IUSS, n.d.), characterised by deep chemical weathering and a high dependency on SOC for fertility maintenance (Nachtergaele et al., 2024; Silatsa et al., 2024). In their coffee-growing regions, both countries share Arenosols, Cambisols, Gleysols, and Leptosols, which are highly susceptible to topsoil erosion and carbon depletion under intensive cultivation (IUSS, n.d.; FAO, n.d.), and conversion of these soils from forest or agroforestry to annual crops, as documented in Box 1.

Regarding trade profiles, both countries export similar high-value tropical commodities to the EU, particularly coffee and fresh fruit. Brazil, like Colombia, exports coffee and fruits to the EU, with Brazil being the EU's top importing market for coffee and agricultural imports in general. Unlike Colombia, Brazil also exports many other high volumes of goods, mainly soy, but also beef and cereals (DG AGRI, 2025c).

Socio-economically, both Colombia and Brazil are characterised by tropical export-led mixed agribusiness sectors in their lowlands and by smallholder-dominated farming systems in their highland zones (FAO, n.d.). Both exhibit bimodal agrarian structures in which large-scale mechanised farming coexists with family farms, although Brazil's agricultural system is more differentiated (FAO, n.d.; Gáfaró et al., 2023).

Crucially, no EU-Brazil FTA was in force during the analytical window of this study: the EU-Mercosur interim Trade and Partnership Agreements were only signed and provisionally applied in 2026 (DG Trade, 2026). By comparing Colombia and Brazil, this research evaluates whether the 2013 FTA accelerated SOC depletion in Colombia relative to the structurally and biophysically comparable Brazil that exported under standard trade terms.

4.4 POLICY DISRUPTIONS

The quasi-experimental nature of this research necessitates a ‘purity’ check of the counterfactual to isolate the CAP-FTA effect from internal shocks. Starting with Ukraine, the primary ‘disturbing factor’ is its 2020 Land Reform, which ended a long-standing moratorium on the sale of agricultural land ([Wengle et al., 2024](#)). While such a gradual shift could impact SOC through changes in land management, this major reform happened after the timeframe of this study.

In Morocco, several years after the implementation of the FTA in 1996, a major policy shock occurred with the adoption of the Plan Maroc Vert in 2008. This policy was a sector-wide modernisation strategy to increase the size and production of the agricultural sector, while reducing poverty ([Inter-Networks Rural Development, 2016](#)). Critics might argue that the intensification of fruit and vegetable production in Morocco is a result of this plan rather than the FTA, although years later. However, sub-projects within the Green Morocco Plan – such as the Council for Higher Water and Climate and the National Irrigation Program for Water Conservation – were explicitly designed to integrate climate change mitigation and irrigation efficiency ([Benabdelkader et al., 2021](#)). This counters parts of the effects on SOC.

In the Ivory Coast, disturbing factors are the creation of the Coffee-Cocoa Management Committee (CGFCC) in 2008 and the re-establishment of a fixed-price mechanism for farmers in 2011 ([Katayama et al., 2017](#)). While these domestic regulatory shifts aimed to stabilise the sector, they occurred alongside the provisional application of the EPA in 2008 and its implementation. However, these domestic governance and financial reforms enabled the sector to supply the volume and quality demands of external markets, rather than creating demand ([Katayama et al., 2017](#)).

The principal disturbing factor for Colombia is the rural transformation following the 2016 Peace Agreement, which opened previously inaccessible highland and Amazon areas to legal settlement ([The University of Edinburgh, 2016](#)). However, the timing of this agreement occurs well after the initial 2013 FTA implementation.

In the case of Peru, the most significant agricultural reforms happened in 1970 with its collectivist land reform on national agricultural productivity and in the late 1980s and early 1990s with new macroeconomic policies ([Espinoza & Escobal, 2025](#); [Trivelli et al., 2003](#)). After liberalisation in the 2000s, Peru signed an FTA with the USA in 2009 and with China in 2010. Closer to the implementation of Peru’s FTA with the EU in 2013, there have been fewer significant agricultural reforms.

Still, worth mentioning is the Rural Land Titling and Registration Project started in 2006 and ongoing during the implementation of Peru's EU FTA, where individuals receive formal land property rights which they had previously informally occupied (IISD & IFPRI, 2017). However, most forest cover was cleared, and thus most SOC was lost, before receiving a title (Gunderson et al., 2026).

4.5 SUMMARY OF THE SELECTION FRAMEWORK

The established framework ensures that the research represents a diverse and globally significant sample of the EU's global trade-environment nexus. By using comparative pairing, the research minimises the risk of attributing SOC changes to regional environmental differences or national policy changes. Instead, the model focuses on the divergence between these pairs following the specific 'policy shock' of FTA implementation, providing the causal evidence necessary to address externalisation of SOC-pressure.

This systematic selection process accounts for the biophysical sensitivity of SOC, the economic transmission mechanisms of EU market demand, and the socio-economic factors that define agricultural production in partner countries. Ultimately, this framework provides the foundational structure for the quantitative analysis required to answer whether the 'greening' of the CAP domestically has been offset by soil degradation in the EU's global trade partners.

5 DATA MANAGEMENT

This section outlines the data management pipeline required to implement the Synthetic Difference-in-Differences method in RStudio. To ensure methodological transparency and replicability, the workflow is presented in three stages: first, data collection (distinguishing between the sources used and the data extracted); second, data harmonisation and formatting; and finally, the set-up and execution of the model in RStudio.

5.1 DATA COLLECTION

5.1.1 Used sources

WoSIS's latest Organic Carbon Map (ISRIC Data Hub)

The empirical evidence for this study is drawn from secondary longitudinal datasets providing periodic snapshots of SOC content. Data spanning 1973 to 2009 were sourced from the [ISRIC Data Hub](#), which provides global maps of SOC stocks at 250 m and 100 m resolutions. Although the Data Hub archives records from 1918 to 2013, observations before 1973 were excluded, as these years predate the implementation of the first relevant FTA – the 1996 EU-Morocco agreement – by more than 25 years; extending the timeframe further would reduce temporal relevance. Conversely, data post-2009 were omitted due to unavailability for the specific countries under analysis.

The [WoSIS latest Organic Carbon Map](#) depicts the gravimetric SOC in the fine earth fraction in g/kg. As a "dynamic dataset," it continuously integrates the recent, quality-assessed, and standardised soil data managed by the ISRIC World Soil Information Service (WoSIS), updating automatically as new data are acquired ([De Sousa et al., 2020](#)).

The map aggregates thousands of primary, spatially distributed data points. Each spatial measurement provides structured attributes, including: soil profile ID, layer ID, dataset ID, soil profile code, layer name, upper and lower measurement depths, presence of an organic surface, positional uncertainty, average SOC value for the specified depth parameters, measurement method, country, continent, and measurement date.

[Figure 1](#) shows a snapshot of the [WoSIS Latest Organic Carbon map](#) for one data point in Tunisia. For the scope of this research, the extracted variables are restricted to 1) the upper and lower depths of the measurement, 2) the average SOC value within those depth parameters, and 3) the year the measurement was conducted.



Figure 1: snapshot of the WoSIS Latest Organic Carbon map for a data point in Tunisia.

Topsoil Organic Carbon and Bulk Density Maps (FAO's GLOSIS)

More recent observations for the years 2012 and 2019 were extracted from [FAO's Global Soil Information System \(GLOSIS\)](#). GLOSIS is an online platform managed by the FAO that allows the public to overlay and analyse soil maps. For baseline consistency, the platform's default 'UN country boundaries of the World' and linked 'place names' layers were used.

Three additional layers were integrated for this analysis:

- The Global Soil Organic Carbon Map v1.5 (GSOC)
- The Topsoil organic carbon from HWSD v.1.2 (Global)
- The Topsoil reference bulk density from HWSD v.1.2 (Global)

The [Global Soil Organic Carbon Map v1.5](#) is the first global SOC map produced through a participatory, consultative process under the guidance of the Intergovernmental Technical Panel on Soils. Participating countries standardised their methodologies and applied modern soil mapping tools to develop national maps, which the Global Soil Partnership subsequently combined into a harmonised global product ([Global Soil Partnership Secretariat et al., 2019](#)). Published in 2019 with a supplementary [report](#) and revised in 2026, this map provides a detailed spatial distribution of topsoil SOC worldwide in tonnes per hectare, defining topsoil as the upper 30 cm of the soil profile ([Global Soil Partnership Secretariat et al., 2019](#)).

Figure 2 shows a snapshot of the [Global Soil Organic Carbon Map](#) for a Tunisian data point.

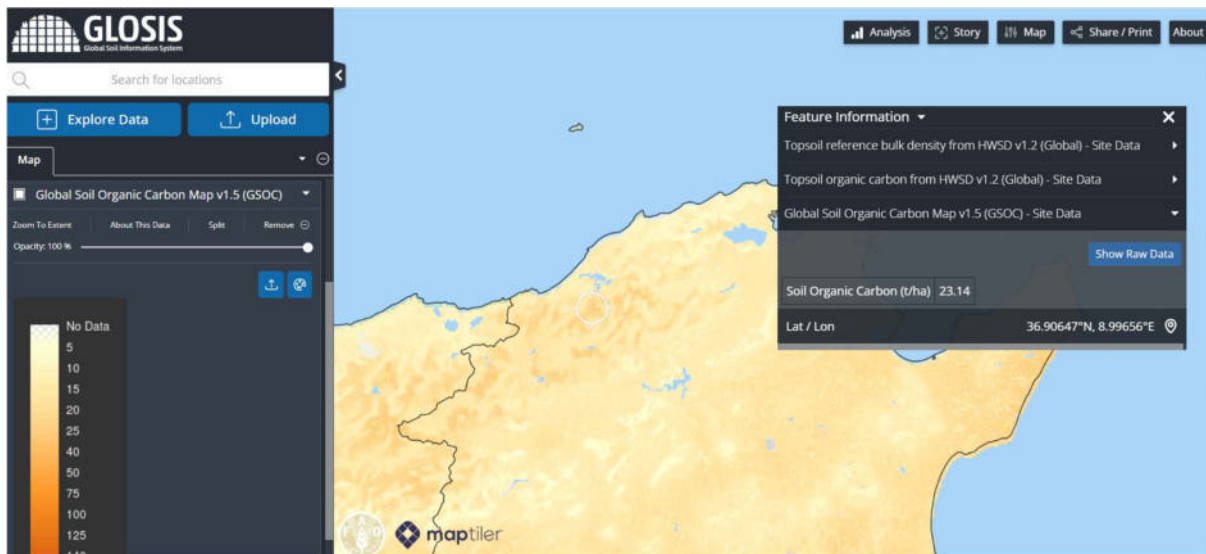


Figure 2: Snapshot of the Global Soil Organic Carbon Map v1.5 for one data point in Tunisia.

The 'Topsoil organic carbon' and 'Topsoil reference bulk density' layers are derived from the [Harmonised World Soil Database \(HWSD\)](#) version 1.2. The HWSD is a raster database based on a 2012 FAO report. It integrates over 16.000 harmonised soil property units by combining regional and national soil inventories with the FAO-UNESCO World Soil Map ([FAO, 2012a](#)). The Topsoil Organic Carbon from HWSD v1.2 (Global) Map provides topsoil organic carbon as a percentage of weight ([FAO, 2012b](#)). The Topsoil reference bulk density from HWSD v1.2 (Global) map depicts bulk density, defined as the mass of solid soil particles divided by the total volume they occupy, including pore space ([FAO, 2012c](#)).

Figure 3 shows a snapshot of the [Harmonised World Soil Database \(HWSD\)](#) in FOA's [Global Soil Information System \(GLOSIS\)](#) for a Tunisian data point on topsoil SOC and bulk density.

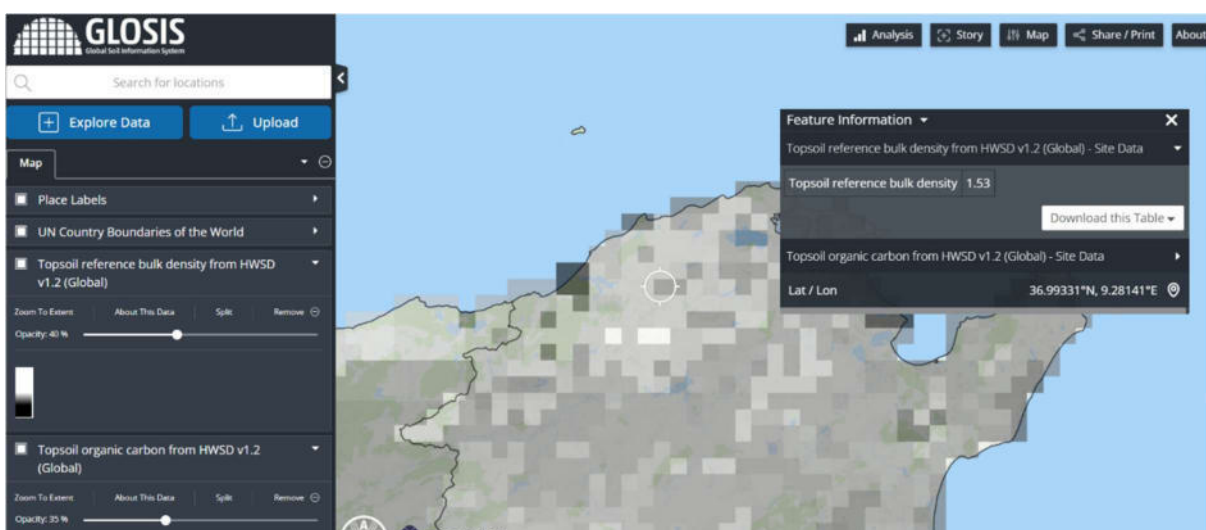


Figure 3: Snapshot of the HWSD in GLOSIS for one data point in Tunisia for topsoil SOC and bulk density.

Soil Map of the World (FAO/UNESCO)

To control for soil type classifications across the data points, the FAO/UNESCO Soil Map of the World was used (FAO & UNESCO, 1974). Based on the geographic distribution of the selected case studies, the specific map sheets extracted were: 'IV – South America', 'V – Europe', 'VI – Africa', and 'VIII – North and Central Asia'.

5.1.2 Data extraction

WoSIS's latest Organic Carbon Map (ISRIC Data Hub)

To maximise data density within the constraints of this thesis, all available topsoil measurements and their corresponding data points were extracted, subject to the following exclusion criteria:

- *Upper depth > 0 cm*: Profiles where the initial measurement depth starts below the surface (e.g., 5 cm instead of 0 cm) were excluded. Neglecting the uppermost, typically most carbon-dense soil layer, leads to an underestimate of total topsoil SOC.
- *Lower depth < 30 cm*: Profiles with maximum depths shallower than 30 cm (e.g., 20 cm) were excluded to avoid underestimating topsoil SOC. (Kazakhstan serves as an exception due to a total lack of alternative data between 25 and 30 cm depth before 2012).
- *Overbroad depth ranges (0 to > 30 cm)*: Profiles where a single measurement spans from the surface to a depth exceeding 30 cm (e.g., 0–50 cm) were excluded. Averaging the high-density surface carbon with lower-density subsoil layers artificially dilutes and underestimates the topsoil SOC value.
- *Temporal limits (≤ 1972)*: Measurements taken in 1972 or earlier were excluded, as data relevance decays with excessive lead time before FTA implementation.
- *Temporal limits (> 2012)*: Measurements taken after 2012 were excluded, as the FAO GLOSIS maps serve as the primary data source for this later timeframe.
- *Urban profiles*: Data points located within cities were excluded, as urban soils do not accurately reflect the shifts in SOC driven by agricultural practices.
- *Statistical outliers*: Measurements were flagged as outliers and omitted if their SOC was more than double that of the second, third or fourth highest value – depending on the number of outliers.

Where high data density made extracting every single point unfeasible within the timeframe of this thesis, a subset of data points was selected based on the following prioritised criteria:

- *Soil type overlap*: Maximising matching soil classifications between pairs to control for baseline soil properties.
- *Spatial proximity*: Selecting data points based on geographic proximity to the respective country pair to isolate treatment effects.
- *Random selection*: If the dataset remained overly abundant after applying the steps above, a random sampling approach was used to determine the final data points (applied exclusively to Brazil).

Topsoil Organic Carbon and Bulk Density Maps (FAO's GLOSIS)

For every historical measurement coordinate extracted from the WoSIS map, the corresponding 2012 and 2019 topsoil organic carbon values, reference bulk density, and geographic coordinates were extracted from the FAO GLOSIS layers. This matching process was conducted manually. Because manual spatial transposition is inherently subject to human error, this represents an acknowledged limitation in the precision and certainty of the results.

Soil Map of the World (FAO/UNESCO)

Similarly, the corresponding soil type classification was manually extracted for each coordinate identified in the WoSIS and GLOSIS datasets. This manual cross-referencing introduces an additional potential source of human error, bounding the precision and certainty of the data points.

5.2 DATA HARMONISATION

5.2.1 Calculation of the SOC Content per Coordinate

Integrating the datasets yields a multi-parameter profile for each geographic coordinate:

- Reference bulk density in kilograms per cubic decimetre [kg/dm^3] or grams per cubic centimetre [g/cm^3] for the topsoil (0–30 cm).
- 2019 topsoil (0–30 cm) SOC in tonnes per hectare [t/ha].
- 2012 topsoil (0–30 cm) SOC as a weight percentage [%w].
- Historical SOC in grams per kilogram [g/kg] for discrete soil layers for a given year.

Following the standard methodologies of the International Soil Reference and Information Centre (Batjes, 1996) used in international benchmarks such as the Soil Atlas of Africa (Arwyn et al., 2012), these parameters were harmonised into a uniform target metric: tonnes of SOC per hectare [t/ha] for the 0–30 cm topsoil layer per year per coordinate.

For observations in 2012 and prior, the first step requires calculating the SOC content in kilograms per cubic meter of soil [kg/m^3]. Because the source units differ between 2012 [%w] and historical years [g/kg], two separate formulas are used, demonstrated below using Tunisia as a case example (Table 1).

$$\text{Historic years: } SOC [\text{g}/\text{kg}] * \rho [\text{kg}/\text{dm}^3] = SOC [\text{g}/\text{dm}^3] = SOC [\text{kg}/\text{m}^3]$$

$$\text{Example: } 13,6 [\text{g}/\text{kg}] * 1,43 [\text{kg}/\text{dm}^3] = 19,45 [\text{g}/\text{dm}^3] = 19,45 [\text{kg}/\text{m}^3]$$

$$\text{For the year 2012: } (SOC [\%w] / 100) * \rho [\text{kg}/\text{dm}^3] * 1.000 = SOC [\text{kg}/\text{m}^3]$$

$$\text{Example: } (0,22 [\%w] / 100) * 1,43 [\text{kg}/\text{dm}^3] * 1.000 = 3,15 [\text{kg}/\text{m}^3]$$

Both primary calculations express SOC density scaled to a depth of 1 meter. To adjust for the actual thickness of the sampled soil layer, the value is multiplied by the layer thickness:

$$(D_{\text{Lower}} [\text{m}] - D_{\text{Upper}} [\text{m}]) * SOC [\text{kg}/\text{m}^3] = SOC [\text{kg}/\text{m}^2]$$

$$\text{Example: } (0,3 [\text{m}] - 0,0 [\text{m}]) * 3,15 [\text{kg}/\text{m}^3] = 0,9438 [\text{kg}/\text{m}^2]$$

To go from the SOC content in kilograms per square meter of soil layer, the original values are squared times 10.000 to go from square meters to hectares and divided by 1.000 to go from kilograms to tonnes:

$$SOC [\text{kg}/\text{m}^2] * 10.000 / 1.000 = SOC [\text{t}/\text{ha}]$$

$$\text{Example: } 0,9438 [\text{kg}/\text{m}^2] * 10.000 / 1.000 = 9,438 [\text{t}/\text{ha}]$$

The last step is to take the cumulative value of all layers to get the value for the entire topsoil:

$$Layer_1 [\text{t}/\text{ha}] + Layer_2 [\text{t}/\text{ha}] + \dots Layer_N [\text{t}/\text{ha}] = \text{Total SOC} [\text{t}/\text{ha}]$$

$$\text{Example: } 13,614 [\text{t}/\text{ha}] + 36,894 [\text{t}/\text{ha}] + 4,876 [\text{t}/\text{ha}] = 55,38 [\text{t}/\text{ha}]$$

Table 1 provides a snapshot of Annex 1 ‘Soil data’ to illustrate this harmonisation process, which was systematically repeated for every coordinate across all study countries.

5.2.2 Soil Layers Deeper than 30 Centimetres

Soil layers with an upper depth starting below 30 cm (e.g., 40 cm) were excluded since they fall entirely within the subsoil. However, several historical measurements feature hybrid layers that cross the topsoil-subsoil boundary, starting above 30 cm and ending below it (e.g., 27–49 cm).

Table 1: Snapshot of *Annex 1 'Soil data'*, Sheet 'Morocco vs Tunisia'. Green cells depict the input parameters extracted from the secondary sources mentioned in section 5.1.1 'Used sources', blue cells depict intermediate steps, orange cells depict the final values used in the analysis, and purple cells depict the input parameters directly used in the analysis.

Tunisia		36.51605°N, 8.68689°E			Cambisol		
	Depth [m]	SOC [g/kg]	ρ [kg/dm ³]	SOC [kg/m ³]	SOC [kg/m ²]	SOC [t/ha]	
1986	0	0,07	13,6	1,43	19,45	1,361	13,614
	0,07	0,27	12,9	1,43	18,45	3,689	36,894
	0,49	0,27	0,3	11,4	1,43	16,25	0,488
Total SOC							55,38
2012		SOC [%w]					
	0	0,3	0,22	1,43	3,15	0,9438	9,438
Total SOC							9,438
2019							
Total SOC							18,2

Applying the average SOC of the entire 27–49 cm layer directly to the 27–30 cm topsoil segment would lead to an underestimation because SOC concentrations typically decline with depth. To correct for this, a linear slope was calculated between the SOC value at the midpoint of the adjacent upper layer and the SOC value at the midpoint of the boundary-spanning layer. This slope was then used to estimate the specific SOC value at the midpoint of the topsoil segment (27–30 cm).

Using the Tunisian data from [Table 1](#) as an example:

- Average SOC in the boundary layer (27–49 cm; midpoint = 38 cm): 12,9 [g/kg]
- Average SOC in the adjacent upper layer (7–27 cm; midpoint = 17 cm): 10,1 [g/kg]
- The linear slope between these midpoints is calculated as:

$$\frac{10,1 \text{ [g/kg]} - 12,9 \text{ [g/kg]}}{\frac{0,49 \text{ [m]} + 27 \text{ [m]}}{2} - \frac{0,27 \text{ [m]} + 0,07 \text{ [m]}}{2}} = -13,33 \text{ [g/kg/m]}$$

- The estimated SOC at the midpoint of the topsoil segment (28.5 cm) is projected from the upper layer baseline:

$$12,9 \text{ [g/kg]} - 13,33 \text{ [g/kg/m]} * \left(\frac{0,27 - 0,07 \text{ [m]}}{2} + \frac{0,3 - 0,27 \text{ [m]}}{2} \right) = 11,4 \text{ [g/kg]}$$

5.2.3 Conglomeration of Data Points

When multiple measurement profiles were clustered within close spatial proximity, they were aggregated into a single spatial unit by averaging individual soil layers rather than keeping them as independent observations. This aggregation prevents a sharp localised shift in SOC within a tiny geographic area from disproportionately skewing national trends, while simultaneously increasing the statistical reliability of the coordinate's yearly average by maximising the underlying sample size.

In the example below, in [Figure 4](#) on the Ivory Coast, the seemingly one measurement within the red box contains three distinct profile records. Each profile consists of approximately ten individual soil layers, yielding 31 raw data points.

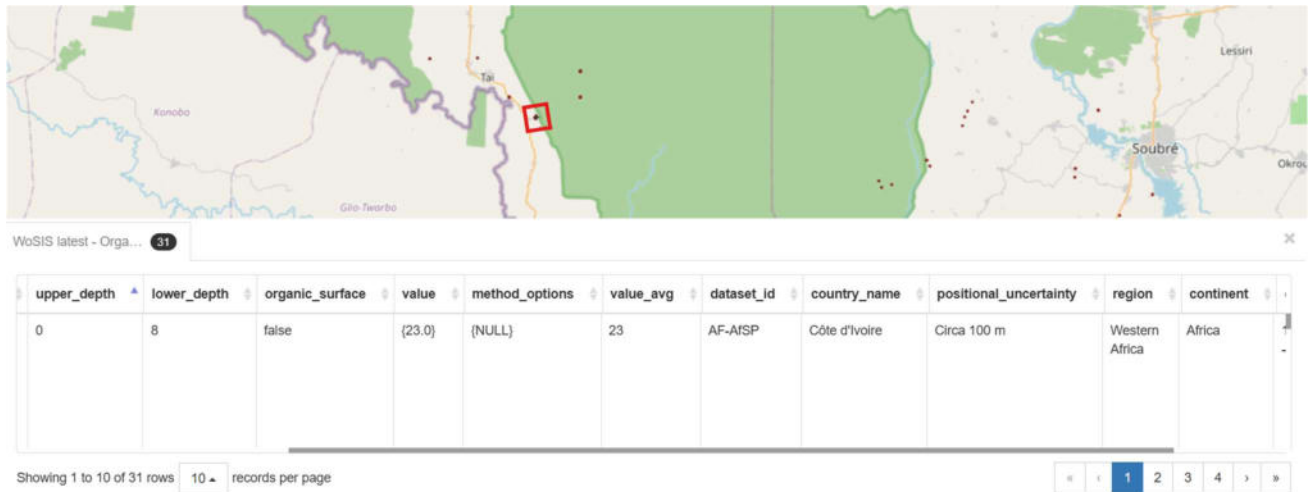


Figure 4: Snapshot of the WoSIS Latest Organic Carbon map for a data point in Tunisia.

If the boundaries of the soil layers match across all profiles in a cluster, the layer averages are calculated directly. If the layer depths are mismatched – for example, if Profile A records a top layer of 0–8 cm while Profile B records 0–10 cm – the depth parameters are harmonised by calculating their mean depth boundaries prior to averaging the SOC values.

[Table 2](#) shows the aggregated result of the cluster depicted in [Figure 4](#). In this instance, the adjusted upper topsoil layer unified six values, and the lower layer united seven values.

$$D_{average\ upper\ topsoil\ layer} = (0,08 + 0,07 + 0,05 + 0,06 + 0,1 + 0,05)/6 = 0,07 [m]$$

$$D_{average\ lower\ topsoil\ layer} = (0,35 + 0,36 + 0,25 + 0,25 + 0,4 + 0,4 + 0,35 + 0,3)/7 = 0,38 [m]$$

$$SOC_{average\ upper\ topsoil\ layer} = (23 + 14 + 14 + 15 + 19 + 61)/6 = 24,3 [g/kg]$$

$$SOC_{average\ lower\ topsoil\ layer} = (7 + 10 + 11 + 9 + 9 + 21 + 8)/7 = 10,71 [g/kg]$$

Note: The baseline value of 10,71 [g/kg] does not match the final 13,7 [g/kg] reported in [Table 2](#). The 10,71 [g/kg] figure represents the unadjusted average for the raw 7–38 cm layer, whereas the 13,7 [g/kg] value represents the depth-corrected estimate optimised for the strict 7–30 cm topsoil boundary via the methodology detailed in [Section 5.2.2](#).

Ivory Coast		5.77857°N, 7.35524°W				Ferrasol	
1990	Depth [m]	SOC [g/kg]	ρ [kg/dm ³]	SOC [kg/m ³]	SOC [kg/m ²]	SOC [t/ha]	
	0	0,07	24,3	1,58	38,45	2,63	26,27
	0,38	0,07	0,30	13,6	1,58	21,46	4,97
Total SOC							75,98

Table 2: Aggregated results for the spatial cluster shown in [Figure 4](#).

5.2.4 Yearly averages

If a country contained multiple spatial coordinates for a given year, the national representative value for that time step was calculated as the simple mean of all available coordinates.

5.2.5 Filling in the gaps

The SynthDiD package in RStudio requires a balanced panel dataset with continuous, unbroken annual observations for every unit. Because the [ISRIC Data Hub](#) does not provide data for every single calendar year, missing values had to be estimated.

To bridge these temporal gaps, missing annual entries were calculated via linear interpolation between the nearest available historical years using the FORECAST linear function in Excel. Additionally, if a country's earliest historical record post-dated the 1973 baseline (e.g., beginning in 1976 instead of 1973), the missing initial years (1973–1975) were backfilled using a constant value equal to the first available observed year. [Table 3](#) illustrates this backfilling and interpolation approach using data from the Ivory Coast.

Table 3: Interlocking annual data and interpolation matrix for the Ivory Coast.

Ivory Coast	1973	68,68	0	2008
Ivory Coast	1974	68,68	0	2008
Ivory Coast	1975	68,68	0	2008
Ivory Coast	1976	68,68	0	2008
Ivory Coast	1977	69,83	0	2008
Ivory Coast	1978	70,98	0	2008
Ivory Coast	1979	72,12	0	2008

5.3 SET-UP AND USE OF RSTUDIO

The data analysis for this thesis was executed using RStudio version 3.6.1. Because the synthdid package is not currently hosted on R's Comprehensive R Archive Network (CRAN) repository, executing a standard `install.packages("synthdid")` command would result in an error. Therefore, to download and use the SynthDiD-package within RStudio, version 2.5.0 of the remotes package was installed first (see [Box 2](#)).

In [Box 2](#), as well as in subsequent boxes, the prompts entered into RStudio are displayed in blue, while the direct software outputs are shown in black. For clarity, red text displayed by RStudio, such as warnings, errors, or intermediate outputs, has been omitted from these boxes.

BOX 2 – INSTALLING GITHUB INSTALLER: REMOTES

```
> install.packages("remotes")  
  
* installing *source* package 'remotes' ...  
...  
* DONE (remotes)
```

Following this, version 0.0.9 of the synthdid package was downloaded via the remotes package and loaded into the active RStudio library, as illustrated in [Box 3](#).

BOX 3 – INSTALLING THE 'SYNTHDID'-PACKAGE

```
> remotes::install_github("synth-inference/synthdid")  
These packages have more recent versions available.  
It is recommended to update all of them.  
Which would you like to update?  
  
1: All  
2: CRAN packages only  
3: None  
4: mvtnorm (1.0-11 -> 1.3-7) [CRAN]  
  
Enter one or more numbers, or an empty line to skip updates: 1  
mvtnorm (1.0-11 -> 1.3-7) [CRAN]  
* DONE (synthdid)  
  
> library(synthdid)  
> library(ggplot2)  
> library(readr)  
> library(dplyr)
```

The subsequent step involves importing the soil data into RStudio. Before doing so, however, the active working directory must be established in RStudio via the menu pathway: ‘Session’ → ‘Set Working Directory’ → ‘Choose Directory....’ This defines the file path from which RStudio will extract the necessary datasets. Furthermore, before importing data into RStudio, it is recommended to convert the source files into a Comma-Separated Values (CSV) format. This file type is readily readable by standard R packages.

If the CSV file uses semicolons (;) as delimiters instead of commas (,), a standard `read_csv` command will interpret the entire row as a single text string (e.g., country;year;SOC...), mistakenly treating the dataset as having only one column. Using the `read_csv2` command resolves this issue.

Once the data is imported, the accuracy of the import process is verified using the `head(dt)` function. [Box 4](#) details the execution of both the importation and verification steps.

BOX 4 – IMPORTING AND VERIFYING DATA

```
> dt <- read_csv2("Data RStudio.csv")
> head(dt)
# A tibble: 6 x 9
  country year SOC treat treatment_cohort Notes X7
  <chr>   <dbl> <dbl> <dbl>          <dbl> <lgl>   <lgl>
1 Ukraine 1973 125.    0         2016 NA      NA
2 Ukraine 1974 125.    0         2016 NA      NA
3 Ukraine 1975 125.    0         2016 NA      NA
4 Ukraine 1976 125.    0         2016 NA      NA
5 Ukraine 1977 125.    0         2016 NA      NA
6 Ukraine 1978 82.0    0         2016 NA      NA
```

Following successful data import and verification, the columns required for the analysis must be selected, thereby omitting empty or otherwise irrelevant columns. Additionally, their data types must be verified as numeric to ensure they are not misread as character strings (text). Finally, the structural result is controlled for correctness, as shown in [Box 5](#).

BOX 5 – COLUMN SELECTION AND NUMERIC FORMATTING

```
> dt <- dt[, c("country", "year", "SOC", "treat", "treatment_cohort")]

> dt$treat <- as.numeric(dt$treat)
> dt$SOC <- as.numeric(dt$SOC)

> str(dt)
Classes 'tbl_df', 'tbl' and 'data.frame':    470 obs. of  5 variables:
 $ country      : chr  "Ukraine" "Ukraine" "Ukraine" "Ukraine" ...
 $ year         : num  1973 1974 1975 1976 1977 ...
 $ SOC          : num  125 125 125 125 125 ...
 $ treat        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ treatment_cohort: num  2016 2016 2016 2016 2016 ...
```

At this stage, the environment is fully prepared to initiate the staggered SynthDiD analysis using the synthdid package. This analysis consists of six primary steps, shown in [Box 6](#) :

- *Clean the data frame*: Ensure that all column data types are explicitly correct and that the treatment indicator column (treat) is uniformly formatted as a numeric binary variable in the dataset before looping over individual cohorts. While this step is technically redundant, it pre-emptively eliminates data-type errors before they can disrupt the estimation process.
- *Create treatment implementation cohorts*: Because partner countries implemented their respective FTAs in different years, RStudio must isolate distinct cohorts based on treatment implementation dates. In this step, the never-treated non-FTA control group is excluded from the cohort creation itself, resulting in a list of four distinct treatment cohorts (g):
 1. Morocco (1996)
 2. Ivory Coast (2008)
 3. Colombia and Peru (2013)
 4. Ukraine (2016)
- *Initialise an estimation list*: Create a list structure to store the individual cohort estimates, which allows them to be used collectively in a single staggered estimation.
- *Loop over each cohort*: Execute the analytical sequence sequentially for one group at a time by comparing each specific treatment cohort (g) against the baseline non-FTA control cohort (designated as 9999).
- *Configure the estimation matrix*: Set up the underlying data matrix required for the staggered SynthDiD analysis by assigning country as the unit variable, year as the

time variable, SOC as the outcome variable, and treat (being the presence of an FTA) as the treatment variable.

- *Estimate synthetic treatment effects*: Compute the synthetic treatment effect for each of the identified cohorts.

Upon completing these steps, the individual treatment effects for each country cohort can be observed. These results are generated by printing the summary output of the estimation.

Additionally, a manual aggregation of the individual cohort results can be performed. In this aggregation, the cohort containing Colombia and Peru is assigned twice the mathematical weight of the other cohorts, given that it comprises two distinct countries. Using these individual cohort estimates, the weighted mean is calculated and extracted.

The corresponding black software outputs from RStudio are omitted from [Box 6](#), as these findings belong properly within the Results section of this thesis.

BOX 6 – STAGGERED SYNTHETIC DIFFERENCE-IN-DIFFERENCE MODEL

```
> dt$country <- as.factor(dt$country)
> dt$year <- as.numeric(dt$year)
> dt$SOC <- as.numeric(dt$SOC)
> dt$treat <- as.numeric(as.character(dt$treat))

> cohorts <- unique(dt$treatment_cohort[dt$treatment_cohort != 9999])

> staggered_estimates <- list()

> for (g in cohorts) {
+   subset_dt <- dt %>% filter(treatment_cohort == g | treatment_cohort == 9999) %>% as.data.frame()

+   setup <- panel.matrices(subset_dt, unit = 'country', time = 'year', outcome = 'SOC', treatment = 'treat')

+   staggered_estimates[[as.character(g)]] <- synthdid_estimate(setup$Y, setup$N0, setup$T0)
+ }

> for (g in cohorts) {
+   cat("\n--- FTA Adoption Cohort:", g, "---\n")
+   print(summary(staggered_estimates[[as.character(g)]]))
+ }

> weights <- c(1, 1, 1, 2)
> all_estimates <- c(-5.47, 4.99, -21.78, -14.38)
> overall_att <- weighted.mean(all_estimates, weights)
> print(overall_att)
```

Subsequently, graphical plots for each cohort can be generated, following the example provided in [Box 7](#).

BOX 7 – PLOT CREATION

```
> plot(staggered_estimates[['1996']])  
> plot(staggered_estimates[['2016']])  
> plot(staggered_estimates[['2008']])
```

Finally, as outlined in the methodology chapter, the Pairwise Difference-in-Differences (Pairwise-DiD) method is applied to verify and validate the empirical results obtained from the staggered SynthDiD approach. The sequential process for the Pairwise-DiD method, illustrated in [Box 8](#), is structured as follows:

- *Establish analytical pairs:* Pair each treated country directly with the corresponding control (non-FTA) countries.
- *Configure variables:* Define the model parameters as either factor variables or numeric variables, mirroring the data preparation steps executed for the Synth-DiD method.
- *Run the regression model:* Execute the Difference-in-Differences regression analysis using a model specification that incorporates interaction terms (country, year, and treatment status) alongside fixed effects to capture variations in SOC.
- *Calculate and extract effects:* Compute the specific Pairwise-DiD effect for each treated country relative to its non-treated counterfactual baseline and print the resulting coefficients within a standardised treatment summary table

BOX 8 – PAIRWISE DIFFERENCE-IN-DIFFERENCE

```
> for (treated_unit in names(pairs)) {  
+   control_unit <- pairs[[treated_unit]]  
+   sub_dt <- dt[dt$country %in% c(treated_unit, control_unit),  
+ ]  
+   sub_dt$SOC <- as.numeric(sub_dt$SOC)  
+   sub_dt$treat <- as.numeric(sub_dt$treat)  
+   sub_dt$country <- as.factor(sub_dt$country)  
+   sub_dt$year <- as.factor(sub_dt$year)  
+   model <- lm(SOC ~ treat + country + year, data = sub_dt)  
  
+   cat("\n--- Pairwise DiD Effect:", treated_unit, "vs",  
+ control_unit, "---\n")  
+   print(summary(model)$coefficients["treat", ])}  

```

6 RESULTS: QUANTITATIVE ANALYSIS

In this section, the results of the quantitative data analysis are presented through tables and corresponding graphical visualisations. The accompanying text elaborates on the trends observable within these figures and tables, highlighting the most significant empirical outcomes derived from the Synthetic Difference-in-Differences method. The presentation of these outcomes is divided into two distinct sections: the first focuses on the primary extracted data, and the second details the secondary analysed data.

6.1 PRIMARY EXTRACTED DATA

Figures 5 through 9 provide visual representations of the extracted annual data for SOC content, measured in tonnes per hectare within the topsoil layer for each country. In these graphs, orange dashed lines and square markers represent treatment countries – those with which the EU has implemented an FTA. Conversely, blue dotted lines and circular markers denote control countries – those without an active EU trade agreement. Furthermore, the square and circular markers reflect directly calculated annual averages, whereas the dashed and dotted lines indicate the indirectly interpolated values for annual SOC content.

Figure 5 depicts the comparative trends for Ukraine and Kazakhstan. While Ukraine's slightly increasing trendline pre-dating its FTA implementation in 2016, afterwards, declines to a slightly downward trajectory in SOC content, Kazakhstan's steeply rising SOC content shifts to a more moderate upward trend. Furthermore, considering a longer timeframe prior to FTA implementation, Ukraine's SOC path appeared less predictable and more volatile than that of Kazakhstan.

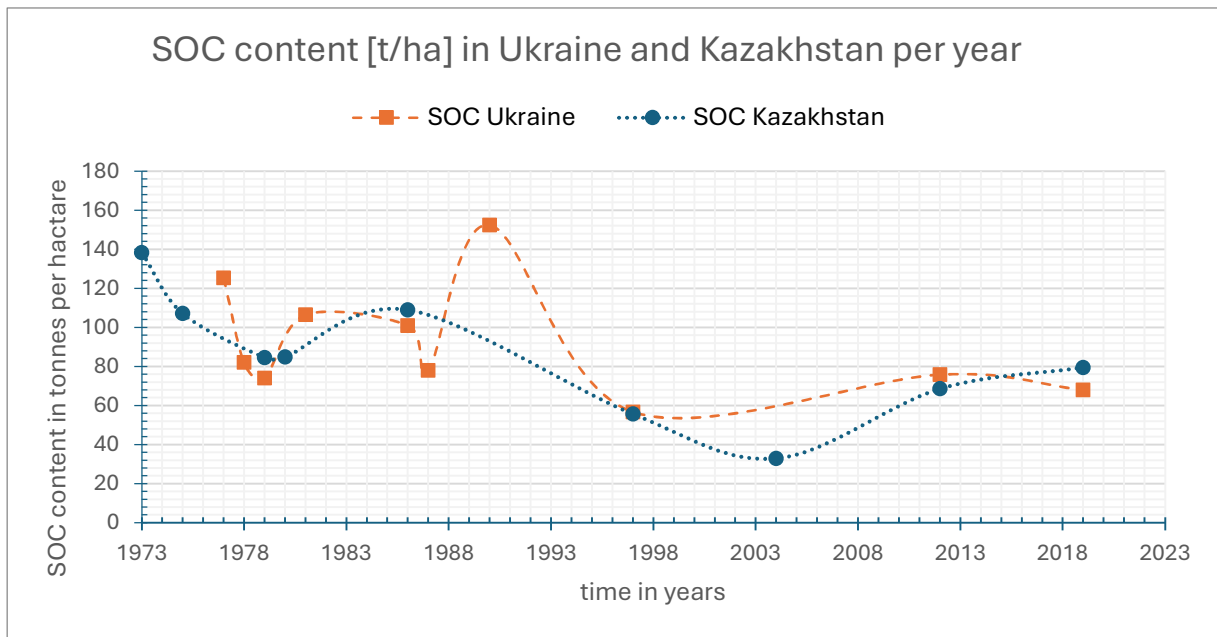


Figure 5: SOC content in tonnes per hectare in Ukraine and Kazakhstan per year.

Figure 6 illustrates the trends for Morocco and Tunisia. While Morocco's slightly declining trendline pre-dating its FTA implementation in 1996 shows no significant shift in its slightly downward trend in SOC content, Tunisia's decreasing SOC content shifted toward a steep increase after 1996. Furthermore, taking a longer timeframe after FTA implementation, Morocco is observed to preserve its downward path in SOC content, while Tunisia's upward trend reversed, reverting to a decline.

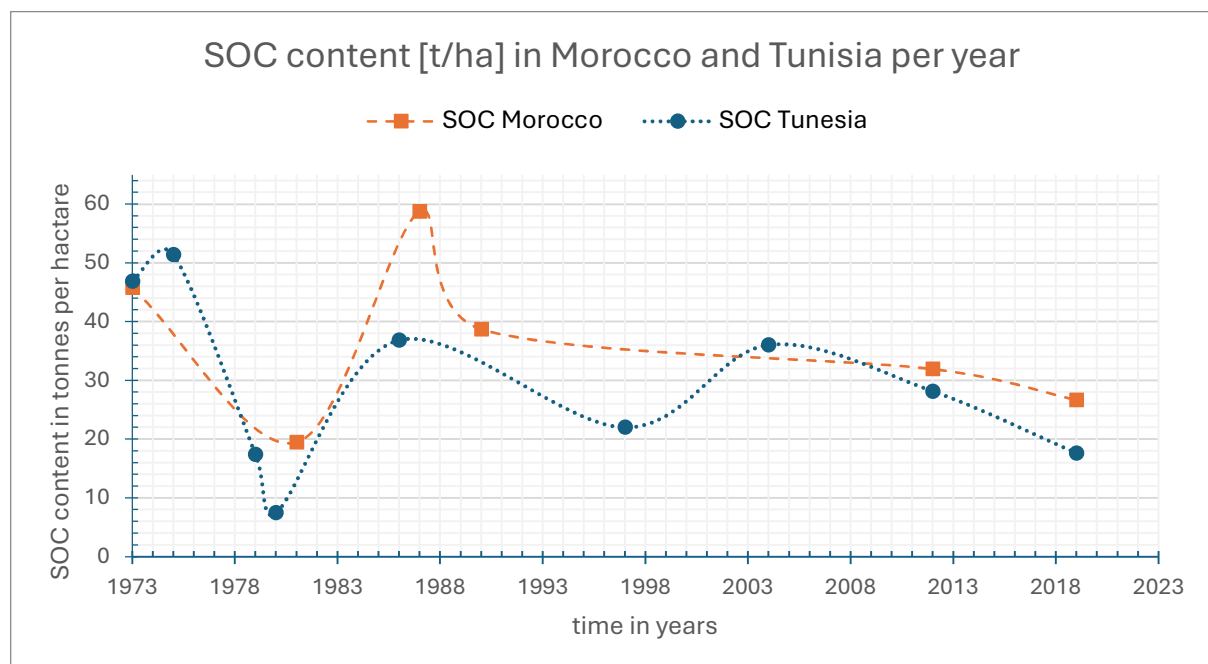


Figure 6: SOC content tonnes per hectare in Morocco and Tunisia per year.

Figure 7 displays the comparative trends for the Ivory Coast and Nigeria. While the Ivory Coast's slightly increasing trendline pre-dating its FTA implementation in 2008, afterwards, is maintained as a modest upward trend in SOC content, Nigeria's SOC content exhibited a steady decline before and after this period. Furthermore, considering a longer timeframe prior to FTA implementation, the Ivory Coast consistently maintained a higher baseline level of SOC content relative to Nigeria.

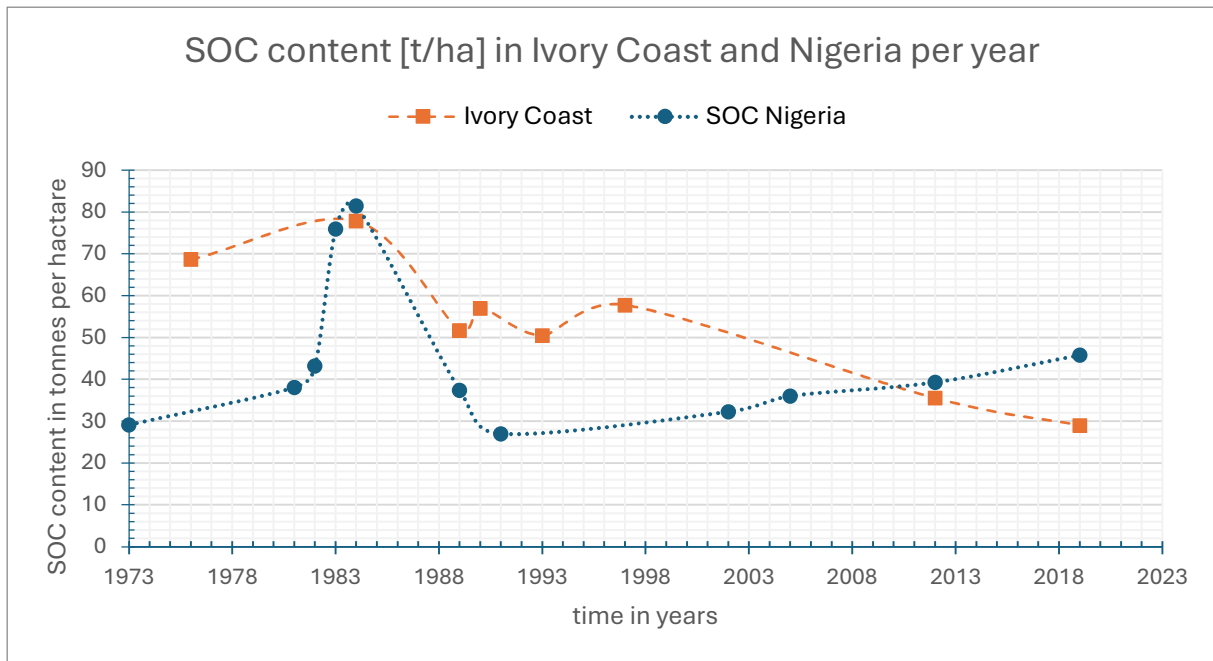


Figure 7: SOC content tonnes per hectare in Ivory Coast and Nigeria per year.

Figure 8 presents the trajectories for Peru and Bolivia. While Peru's increasing trendline pre-dating its FTA implementation in 2013 subsequently stabilised into a more stagnant SOC trajectory, Bolivia's slightly declining SOC content shifted into a steep upward trend. Furthermore, considering a longer timeframe prior to FTA implementation, Peru's SOC content showed a single distinct peak around the 1980s, whereas Bolivia experienced pronounced peaks in both 1979 and 1992.

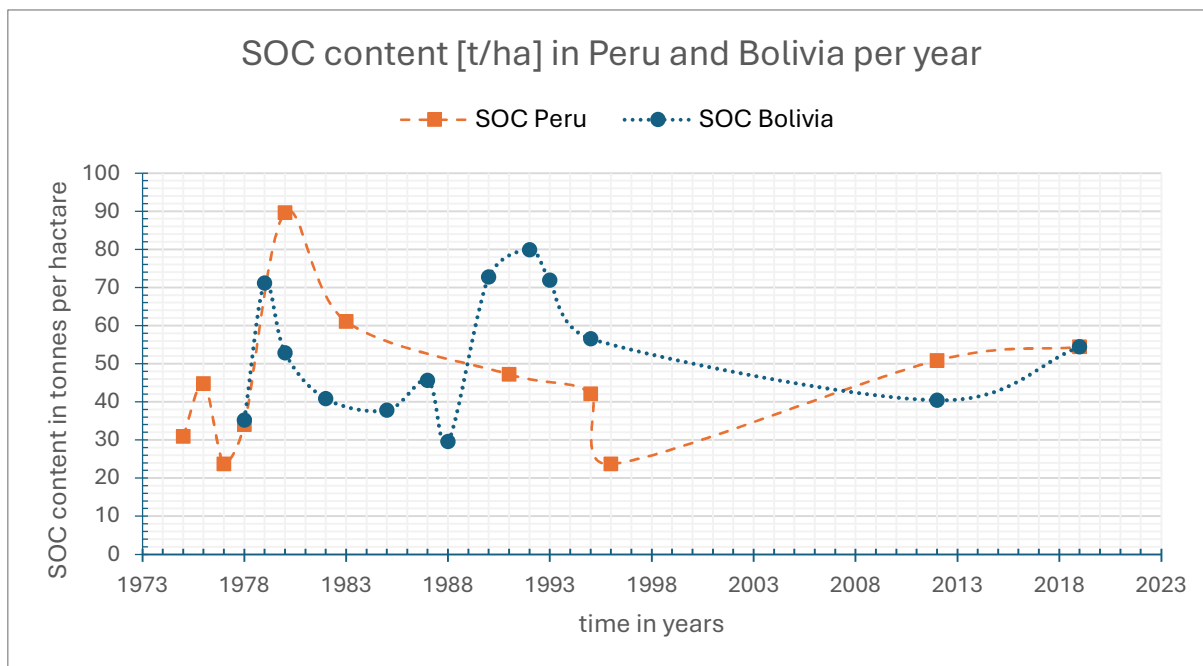


Figure 8: SOC content tonnes per hectare in Peru and Bolivia per year.

Figure 9 maps the trends for Colombia and Brazil. While Colombia's slightly increasing trendline pre-dating its FTA implementation in 2013, afterwards, shifted into a steep downward trajectory in SOC content, Brazil's steeply decreasing SOC content transitioned into a slight upward slope. Furthermore, considering a longer timeframe prior to FTA implementation reveals that Colombia followed a less predictable, more fluctuant, and overall higher baseline path than Brazil.

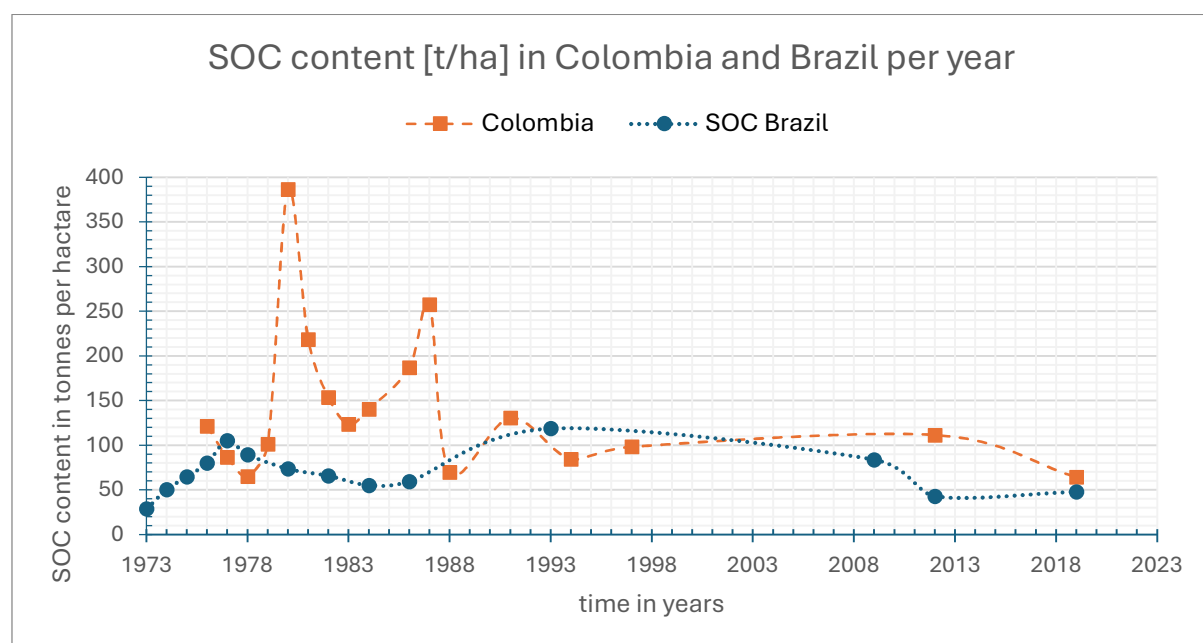


Figure 9: SOC content tonnes per hectare in Colombia and Brazil per year.

6.2 SECONDARY ANALYSED DATA: STAGGERED SYNTHDiD

In this next section, the secondary analysis of the data will be presented, as the output of the staggered synthetic Difference-in-Difference package of RStudio. Presentation is done via Boxes with the direct RStudio output, corresponding graphical plots, and accompanying elaborations on the key issues.

6.2.1 Cohort 2016; Ukraine

Box 9 presents the SynthDiD output for the 2016 cohort (Ukraine). The primary result is the *\$estimate*, which represents the average treatment effect on the treated (ATT). This value signifies the estimated change in SOC storage [t/ha] directly attributable to the FTA implementation, relative to the synthetic control group. The analysis reveals that the implementation of Ukraine's FTA led to a reduction of 5.47 tonnes of SOC per hectare of topsoil.

BOX 9 – FTA ADOPTION COHORT: 2016

```
$estimate
[1] -5.470692

$controls      estimate 1
Kazakhstan      0.695
Bolivia         0.154
Brazil          0.113

$periods      estimate 1
2015            0.788
1979            0.129

$dimensions
N1      N0      N0.effective      T1      T0      T0.effective
1.0      5.000      1.919      4.000      43.000      1.554
```

The *\$controls* section identifies the untreated units used to construct the synthetic counterfactual and their respective weights. Firstly, Kazakhstan (69,5%) acts as the primary contributor to the synthetic control. This substantial weight validates the initial case selection, confirming that Kazakhstan serves as a highly fitting match for Ukraine's trajectory. Secondly, Bolivia (15,4%) and Brazil (11,3%) serve as complementary donors. Lastly, the remaining donors (Nigeria and Tunisia) contribute a combined residual weight of 3,8% ($1 - 0,695 - 0,154 - 0,113$), indicating minimal resemblance to Ukraine's soil carbon trends.

The synthetic counterfactual was further refined by weighting pre-treatment periods, as detailed in *\$periods*. The model systematically prioritises recent observations to ensure the synthetic trend mirrors the treated unit's trajectory immediately prior to treatment. For the Ukraine cohort, the model identified three primary temporal anchors:

- 2015: The model assigned 78.8% of the weight to the year 2015, as the situation in 2015 is, naturally, the strongest indicator of what 2016 and later years would have been.
- 1979: Despite the temporal distance, the model identified 12.9% structural similarities between 1979 of the treatment and non-treatment group to tune the synthetic trend.
- 1984: As visualised in [Figure 10](#), the model assigns minor weight to 1984 to finalise the counterfactual construction.

Lastly, the *\$dimensions* section clarifies the model's structural configuration:

- The cohort features one treated unit, namely Ukraine (*N1;1.0*), against a donor pool of five untreated units (*N0;5.000*). An effective number of controls (*N0.effective*) of 1,919 indicates a targeted, selective, precise matching strategy that "zooms in" on the most structurally similar counterparts – primarily Kazakhstan – and indicates a high-quality, targeted match with Ukraine – rather than attempting a broad, undifferentiated average.
- The analysis includes four post-treatment years (*T1;4.000*; 2016–2019), and the total number of pre-treatment years the model had access to was 43 (*T0;43.000*; 1973–2015). The effective pre-treatment period (*T0.effective*) of 1,554 highlights that the model prioritised the years depicted in *\$periods* to predict the trajectory of the treated country, thus finding a strong, stable trend in the recent data without needing to over-fit by trying to force the counterfactual to match noise from the 1970s.

[Figure 10](#) is a visual representation by RStudio depicting the same output of the SynthDiD-analysis. The blue 'treated' line represents the SOC content of Ukraine over the years, while the orange 'synthetic control' represents the created and weighted counterfactual. The black line at the bottom of the figure, parallel to the X-axis, depicts the weighted years, where height of red triangles shows the weight of each used year. Lastly, the downwards arrows display the treatment effect.

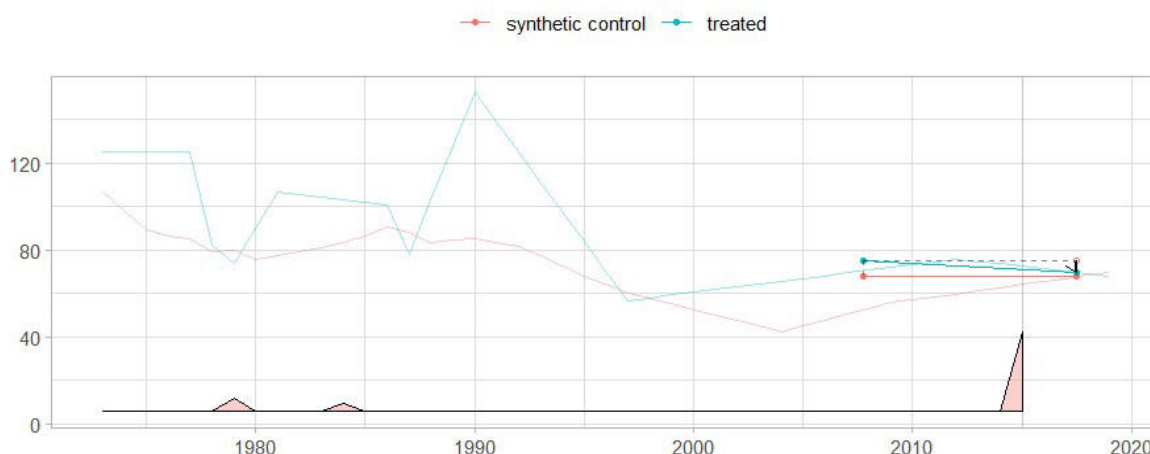


Figure 10: Plot of the staggered synthetic Difference-in-Difference analysis for the 2016 cohort by RStudio.

6.2.2 Cohort 1996: Morocco

The analysis for the 1996 cohort depicted in [Box 10](#), centred on Morocco, yields an *\$estimate* of 4,999 t/ha, suggesting that FTA implementation was associated with an minor increase in SOC storage compared to the synthetic control, which can be seen in [Figure 11](#).

The *\$controls* section indicates a broad matching strategy, distributing weights across all five untreated units: Tunisia (26,3%), Kazakhstan (24,6%), Nigeria (21,1%), Brazil (14,1%), and Bolivia (14,0%). Unlike the Ukraine cohort, this high level of donor diversification is reflected in an *NO.effective* of 4,687. This indicates that the synthetic control is composed of a well-balanced weighted average of the entire donor pool, while Morocco's selected pair, Tunisia, still acts as the primary contributor to the control, validating the initial case selection.

BOX 10 – FTA ADOPTION COHORT: 1996

\$estimate
[1] 4.999207

<i>\$controls</i>	<i>estimate 1</i>
Tunesia	0.263
Kazakhstan	0.246
Nigeria	0.211
Brazil	0.141
Bolivia	0.140

<i>\$periods</i>	<i>estimate 1</i>
1995	0.523
1984	0.306
1992	0.141

<i>\$dimensions</i>					
<i>N1</i>	<i>N0</i>	<i>N0.effective</i>	<i>T1</i>	<i>T0</i>	<i>T0.effective</i>
1.000	5.000	4.687	24.000	23.000	2.573

The *\$periods* weights prioritise 1995 (52,3%) and 1984 (30,6%), with minor adjustments from 1992 (14,1%). Thus, similarly to Ukraine's case, the year directly pre-dating FTA implementation was the primary contributor to the pre-treatment period. The *\$dimensions* reveal that the model utilized 24 post-treatment years ($\tau_1; 24,000$) against 23 pre-treatment years ($\tau_0; 23,000$). An effective pre-treatment period ($\tau_0.effective$) of 2,573 confirms that the model based its structural trend on the relevant years depicted in *\$periods*.

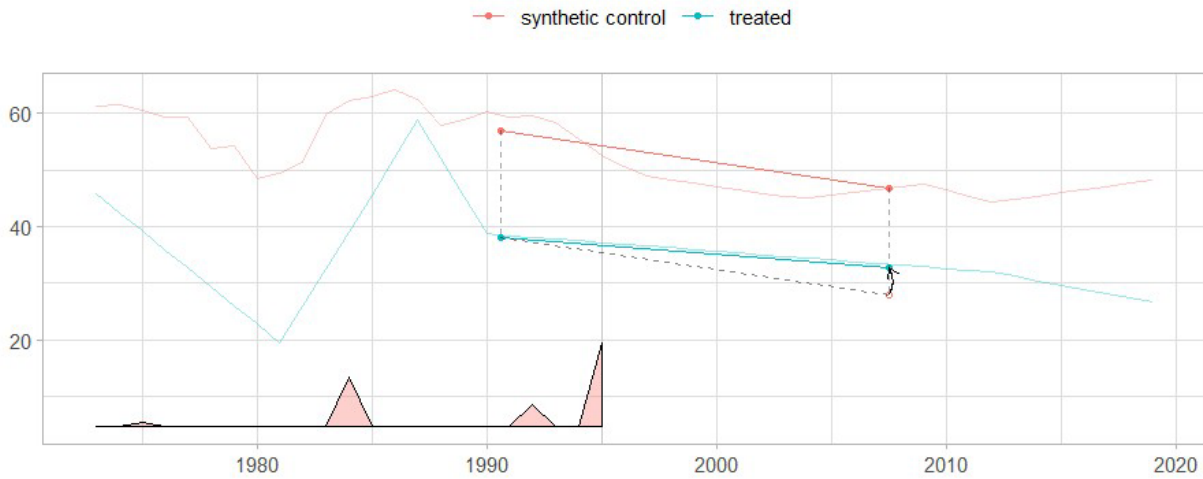


Figure 11: Plot of the staggered synthetic Difference-in-Difference analysis for the 1996 cohort by RStudio.

6.2.3 Cohort 2008: Ivory Coast

For the 2008 cohort (Ivory Coast), the *\$estimate* in [Box 11](#) shows a reduction of 21,78 t/ha. The *\$controls* output highlights a balanced reliance on the donor pool, led by Kazakhstan (30,8%) and Nigeria (29,1%), complemented by Bolivia (16,3%), Brazil (12,2%), and Tunisia (11,6%). This diversification is evidenced by an *no.effective* of 4,262, suggesting that the Ivory Coast's pre-treatment soil carbon trajectory closely mirrored the aggregate trend of the control group.

Temporal weighting in *\$periods* follows a logical progression, with 2004 (33,9%) and 1984 (29,9%) serving as the primary anchors for the counterfactual construction, followed by earlier years, as shown in [Figure 12](#). The configuration in *\$dimensions* uses 12 post-treatment years ($\tau_1; 12.000$) and 35 pre-treatment years ($\tau_0; 35.000$). An effective pre-treatment period ($\tau_0.effective$) of 3,690 indicates that the model utilized a relatively wide historical window to establish the stability of the synthetic control trend.

BOX 11 – FTA ADOPTION COHORT: 2008

\$estimate
[1] -21.7807

\$controls *estimate 1*
Kazakhstan 0.308
Nigeria 0.291
Bolivia 0.163
Brazil 0.122
Tunisia 0.116

\$periods *estimate 1*
2004 0.339
1984 0.299
1979 0.206
1973 0.157

\$dimensions
N1 N0 N0.effective T1 T0 T0.effective
1.000 5.000 4.262 12.000 35.000 3.690

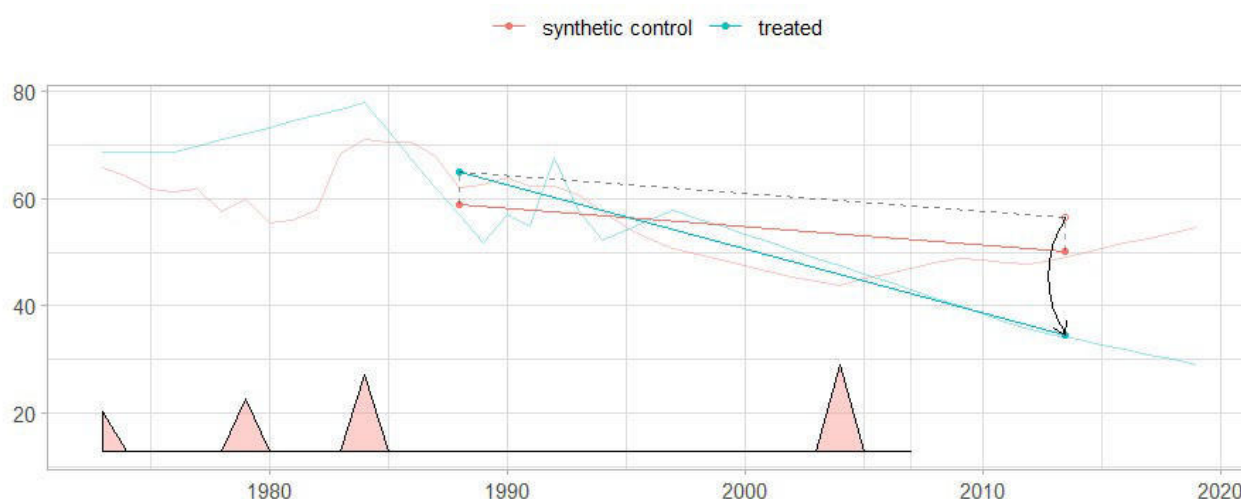


Figure 12: Plot of the staggered synthetic Difference-in-Difference analysis for the 2008 cohort by RStudio.

6.2.4 Cohort 2013: Peru and Colombia

The final cohort encompasses the joint FTA implementation of Peru and Colombia in 2013, resulting in an *\$estimate* of a reduction of 14,39 tonnes per hectare. Similarly to the cohort, the output of the staggered synthetic Difference-in-Difference analysis can be seen in [Box 12](#), and its visual representations in the plot of [Figure 13](#).

BOX 12 – FTA ADOPTION COHORT: 2013

\$estimate
[1] -14.38934

<i>\$controls</i>	<i>estimate 1</i>
Nigeria	0.450
Kazakhstan	0.308
Bolivia	0.243

<i>\$periods</i>	<i>estimate 1</i>
2012	0.659
1979	0.197
1984	0.132

<i>\$dimensions</i>					
<i>N1</i>	<i>N0</i>	<i>N0.effective</i>	<i>T1</i>	<i>T0</i>	<i>T0.effective</i>
2.000	5.000	2.811	7.000	40.000	2.039

The *\$controls* section shows that the synthetic counterfactual is primarily derived from Nigeria (45,0%), Kazakhstan (30,8%), and Bolivia (24,3%). This selective matching is confirmed by an *N0.effective* of 2,811, indicating that the model focused on these three units to approximate the joint trajectory of Peru and Colombia. The fact that Brazil is missing from the *\$controls* section, indicates that the SOC content trend present in Brazil is not a fitting structural match for the combination of trends in Colombia and Peru, although it was classified as pair to Colombia in section [5.3.4. Colombia vs. Brazil: Tropical Commodity Competitors](#)

Regarding temporal alignment, the *\$periods* weights are logically concentrated on 2012 (65,9%), followed by 1979 (19,7%) and 1984 (13,2%). The model configuration in *\$dimensions* includes seven post-treatment years (*T1*; 7.000) and 40 pre-treatment years (*T0*; 40.000). An effective pre-treatment period (*T0.effective*) of 2,039 demonstrates that, despite the long historical dataset, the algorithm used the most recent data to construct a comparison for this dual cohort.

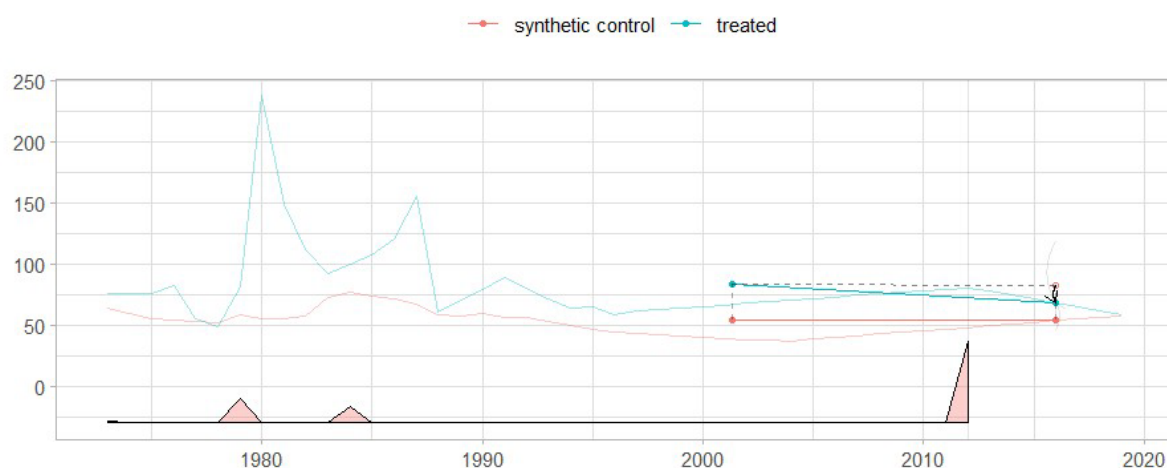


Figure 13: Plot of the staggered synthetic Difference-in-Difference analysis for the 2008 cohort by RStudio.

6.2.5 Average Treatment Effect

Box 13 shows that the final aggregated average treatment effect on the treated' is a reduction of 9,922 tonnes of soil organic carbon content of topsoil per hectare after implementation of a Free-Trade Agreement.

BOX 13 – FINAL AGGREGATED ATT

[1] -9.922

6.3 SECONDARY ANALYSED DATA: PAIRWISE SYNTHDiD

To validate the findings from the primary synthetic control analysis, pairwise Difference-in-Differences models were conducted, comparing each treated unit directly against its selected control. The results of the pairwise estimations are summarised below and shown in Box 14:

- *Ukraine vs. Kazakhstan*: This analysis yields a significant negative effect of -22,11 t/ha ($p < 0,05$), aligning with the direction of the primary synthetic control result and confirming a substantial reduction in SOC following FTA implementation.
- *Morocco vs. Tunisia*: The estimate of -2,62 t/ha shows a reduction in SOC contrary to the increase in SOC shown by the staggered Synth-DiD; however, the result lacks statistical significance ($p = 0,192$), indicating a less certain effect compared to the other cohorts.

- *Ivory Coast vs. Nigeria*: This pair displays the most statistically robust negative effect, with a decrease of 28,92 t/ha and a highly significant t-value ($p < 0,001$), reinforcing the strong negative impact observed in the staggered SynthDiD-analysis.
- *Peru vs. Bolivia*: The analysis indicates a positive estimate of 8,23 t/ha. Despite this, the result is not statistically significant ($p = 0,262$), indicating that there is no definitive evidence of an FTA-induced increase in SOC for this pair using the pairwise DiD-method.
- *Colombia vs. Brazil*: This comparison results in an estimate of -0,19 t/ha. With a t-value near zero and a high p-value ($p = 0,994$), this pairwise analysis offer close to no certainly or significance in the resulting change in soil carbon storage attributable to the FTA.

BOX 14 – PAIRWISE DIFFERENCE-IN-DIFFERENCE METHODE

--- Pairwise DiD Effect: Ukraine vs Kazakhstan ---

Estimate	Std. Error	t value	Pr(> t)
-22.11162791	8.91864373	-2.47925902	0.01697803

--- Pairwise DiD Effect: Morocco vs Tunesia ---

Estimate	Std. Error	t value	Pr(> t)
-2.6247101	1.9813795	-1.3246883	0.1919627

--- Pairwise DiD Effect: Ivory Coast vs Nigeria ---

Estimate	Std. Error	t value	Pr(> t)
-2.892371e+01	3.944792e+00	-7.332126e+00	3.286638e-09

--- Pairwise DiD Effect: Peru vs Bolivia ---

Estimate	Std. Error	t value	Pr(> t)
8.2258571	7.2405164	1.1360871	0.2619345

--- Pairwise DiD Effect: Colombia vs Brazil ---

Estimate	Std. Error	t value	Pr(> t)
-0.187500000	25.716147533	-0.007291139	0.994214792

7 DISCUSSION

This research set out to assess the impact of the European Union's Common Agricultural Policy (CAP) and associated Free Trade Agreements (FTAs) on Soil Organic Carbon (SOC) storage in partner countries. Through the application of a staggered Synthetic Difference-in-Differences (SynthDiD) framework, complemented by pairwise DiD validation, this study has moved beyond descriptive trends to evaluate the causal environmental externalities of trade-agriculture policies.

The empirical results reveal a complex and predominantly negative relationship between FTA implementation and soil carbon sequestration. The final aggregated Average Treatment Effect on the Treated (ATT) of -9,92 t/ha highlights a substantial, overall reduction in SOC. However, this average masks significant heterogeneity across cohorts, which ranged from a positive effect of +5,00 t/ha to a severe decrease of -21,78 t/ha.

A defining feature of this analysis was the strong synthetic match observed in the 2016 cohort. The substantial weight assigned to Kazakhstan (69,5%) suggests that it shares deep structural similarities in its agricultural system compared to Ukraine, likely stemming from their comparable post-Soviet agricultural legacies and vast, semi-arid steppe ecosystems. This strong match combined with statistical significance in its pairwise DiD analysis provides considerable credibility to the observed SOC reduction in Ukraine of 5,47 tonnes per hectare, indicating that the negative outcome is not a result of poor donor matching but rather a reflection of genuine environmental degradation following intensified trade engagement.

In contrast, Morocco stands as the exception to the general negative trend, exhibiting a positive ATT of 5,00 t/ha. This result warrants critical consideration. Morocco's agricultural sector is unique among the studied cohorts, characterised by long-standing EU-Morocco trade cooperation and investments in soil conservation and water management policies. It is plausible that Morocco's resilience to trade-induced agricultural expansion allowed it to decouple trade growth from soil degradation, a feat the other countries struggled to achieve.

The Ivory Coast, meanwhile, represents the most alarming case of soil degradation, with a consistent and severe decrease in SOC across both the staggered SynthDiD and statistically significant pairwise models. The Ivory Coast's agricultural economy is heavily reliant on export commodities, and the influx of trade-oriented agricultural pressure appears to have accelerated the depletion of organic matter, likely through the transition to monoculture cropping patterns that leave the soil vulnerable to erosion.

The methodological sensitivity of the Colombia-Brazil pair also provides a critical discussion point. Colombia exhibited intense fluctuations in its SOC trend, which rendered Brazil effectively non-functional as a stable control unit within the staggered model, with other control units filling this gap. As the pairwise DiD for Colombia and Brazil yielded a result with near-zero significance, the sheer instability in the SOC data suggests that Colombia's agriculture is operating under such high-intensity variability that standard counterfactuals struggle to stabilise.

This sensitivity reinforces the utility of the pairwise DiD as a stress test for the primary SynthDiD findings. Notably, for both Ukraine and the Ivory Coast, the pairwise models consistently yielded more negative estimates than the staggered models. While the pairwise DID showed reductions of 22,11 and 28,922 t/ha, the SynthDiD-method provided 21,78 and 5,47 tonnes of SOC reduction per hectare. This indicates that the current SynthDiD results may be inherently conservative, potentially underestimating the total negative environmental impact of FTA-induced agricultural intensification.

7.1 COMPARISON WITH EXISTING LITERATURE

The findings of this research align with the broader scepticism expressed in existing literature regarding the environmental sustainability of the EU's agricultural-trade framework. As reviewed in [Chapter 2](#), many scholars argue that the externalisation of environmental costs is a consequence of trade liberalisation when environmental standards are not strictly enforced.

The positive result for Morocco somewhat echoes literature emphasising "environmental policy convergence," where certain developing nations successfully implement protective measures alongside trade agreements ([Boellstorff & Benito, 2005](#); [Cantore, 2012](#); [Matthews, 2018](#); [Moreddu et al., 2011](#)). However, for the majority of the cohorts, the results provide empirical weight to the externalisation of environmental costs. The [literature frequently suggests](#) that the EU's consumption-based model necessitates high-yield agricultural inputs from abroad, and the results of this thesis confirm that the associated costs are being paid in soil degradation in partner countries.

While most studies focus on deforestation, this thesis contributes a novel, soil-specific quantitative analysis that supports the critical consensus that trade-driven pressures, without ecological safeguards, remain incompatible with long-term soil health.

7.2 POLICY RECOMMENDATIONS

The results suggest that the EU trade-agriculture framework, in its current state, acts as a transmitter for soil degradation. To prevent the further externalisation of environmental costs, a shift in the EU's approach to trade diplomacy is required.

- *First, implementing more robust environmental safeguards in FTAs:*

This could include the deployment of so-called, usually unpopular, mirror clauses. These clauses would require that imported agricultural goods meet the same ecological and production standards as those required of internal EU producers. By ensuring a level playing field, the EU could prevent the competitive advantage currently enjoyed by unsustainable agricultural practices in partner countries ([Kornher & Von Braun, 2020](#); [Matthews, 2018](#)).

- *Second, shifting towards incentivising sustainable consumption within EU borders:*

Reducing the domestic demand for carbon-depleting commodities is a sustainable way to alleviate the production pressure placed on trading partners ([Kornher & Von Braun, 2020](#)). This requires a rethink of the EU's agricultural policy to prioritise low-impact farming over export-led intensification.

- *Third, initiating stronger, EU-led certification schemes for soil health:*

Some trade partners currently lack the economic incentives to prioritise SOC. If the EU were to facilitate the development of a soil-carbon verification system, it could create a market for agricultural goods that maintain or increase soil organic carbon ([Meemken et al., 2019](#)). Rather than treating trade and soil health as competing interests, these certification schemes could transform the trade relationship into a collaborative undertaking for soil restoration.

In conclusion, this research confirms that the environmental cost of trade is written into the very soil of our partner countries. Without a policy transformation that embeds ecological integrity, the current trends of degradation observed in Ukraine, the Ivory Coast, Peru, and Colombia are likely to persist, undermining the global foundations of food security and carbon stability.

8 CONCLUSION

This thesis has researched the environmental implications of the European Union's Common Agricultural Policy (CAP) and its Free Trade Agreements (FTAs) by examining their impact on Soil Organic Carbon (SOC) in key partner countries. By deploying a staggered Synthetic Difference-in-Differences (SynthDiD) analysis, this study sought to isolate the causal effect of these policy frameworks on soil health, a vital yet frequently overlooked dimension of the global carbon budget.

8.1 SUMMARY OF FINDINGS

The empirical evidence presented in this research leads to the conclusion that, in the majority of cases, trade liberalisation through EU-associated FTAs combined with the EU's agricultural policies has acted as a catalyst for topsoil degradation in partner countries. The final aggregated Average Treatment Effect on the Treated (ATT) of -9,92 t/ha demonstrates a trend of SOC depletion. These findings suggest that a push for export-led agricultural intensification and extensification, often encouraged or facilitated by FTAs, comes at the expense of the topsoil's capacity to store carbon.

While the results exhibit heterogeneity – ranging from the resilience observed in Morocco's soil systems (+5,00 t/ha) to the severe carbon depletion in the Ivory Coast (21,78 t/ha) – the overarching narrative is one of negative environmental externalisation. The pairwise DiD analysis reinforces this conclusion, suggesting that the current institutional framework governing the EU's CAP and FTA relations fails to internalise the ecological costs of agricultural production.

Consequently, the research question is answered in the negative regarding the current sustainability of the trade-agriculture relationship: the existing framework does not sufficiently protect partner countries' topsoil resources. Instead, it incentivises agricultural trajectories that harm long-term pedological stability. To reverse this, the EU must engage in more active ecological stewardship, ensuring that future trade and agricultural policy serves as a tool for global soil restoration rather than a driver of structural topsoil depletion to safeguard global food security and carbon stability.

8.2 SIGNIFICANCE AND APPLICATION

The results of this thesis are of political and ecological significance as the EU transitions toward an "Open, Sustainable, and Assertive" trade policy. This strategic shift emphasises a rules-based system where sustainability interests are intended to govern free trade agreements ([Eliasson & Garcia-Duran, 2023](#); [García, 2023](#)). The fact that CAP-FTA interaction is found to reduce SOC storage implies that current Sustainability Impact Assessments (SIAs) are insufficient in protecting global carbon sinks. Identifying this causal relationship benefits policymakers by providing the evidence needed to integrate targeted green conditionalities into trade negotiations, such as mandatory conservation, biodynamic agriculture, and soil management standards.

This is notably important given that the CAP's domestic 'greening' rules are designed to reduce greenhouse gas emissions within the EU, theoretically creating positive externalities for other countries, particularly developing countries and the Global South ([Cantore, 2012](#); [Blanco, 2018](#)). However, a serious risk of carbon leakage exists where domestic climate mitigation is partially offset by the relocation of carbon-intensive production to partner countries. This research suggests that EU agricultural demand induces SOC depletion elsewhere, thus effectively externalising the carbon footprint of EU consumption. Additionally, this research clarifies soil-related ecological impacts, offering useful insights for the implementation of current and negotiation of future trade agreements.

The economic and social costs of not implementing these thesis results are the potential for soil degradation in key global agricultural exporters like Ukraine, where millions of hectares are already exposed to harmful erosion, leading to 224 million dollars in economic losses ([Drobitko et al., 2022](#)). Left unaddressed, soil degradation triggers a cascade of desertification, reduced water infiltration, and nutrient loss, which jeopardises long-term food security and biodiversity. Ultimately, these environmental pressures increase the burden on EU climate adaptation and humanitarian aid, while undermining international development programs ([Matthews, 2015](#); [Schulmeister, 2015](#); [Blanco, 2018](#); [Kornher & Von Braun, 2020](#)).

To conclude, this thesis provides a dual benefit: it assists the EU in amending its trade policy to minimise negative environmental externalities and supports partner countries by identifying the agricultural trade mechanisms that could threaten their soil capital.

8.3 RECOMMENDATIONS FOR FURTHER RESEARCH

Building on the insights gathered from this study, several recommendations for further research present themselves, offering the potential to deepen understanding of cause-effect processes and improve trade and agricultural policies.

- *Decoupling extensive versus intensive pressures:*

Future research should aim to decouple the transmission mechanisms of trade-driven SOC loss. This involves investigating whether the dominant impact occurs extensively, through the conversion of natural high-carbon soil-ecosystems into agricultural land, or intensively, via the adoption of high-tillage, monoculture soil-management practices.

- *Locating the internal cause of external pressures:*

Moreover, there is an opportunity for qualitative research to distinguish the impact of specific CAP instruments from the broader EU socio-economic system or 'green trade' agenda, such as the EU Deforestation Regulation or environmental chapters in FTAs. Such research would clarify whether the 'greening' of EU trade diplomacy effectively mitigates the carbon leakage identified in this study or merely shifts the environmental burden to other unobserved sectors, as the broader EU socio-economic system would inadvertently push environmental externalisation.

- *Quantifying inherent external pressures of the CAP:*

Furthermore, it is recommended to investigate the 'purity' assumption on the counterfactual. While the currently used SynthDiD model assumes that the absence of an FTA prevents the influence of the CAP on the soil health of partner countries from being realised, this assumption is not inviolable. Quantifying the indirect and inherent external influence of internal measures like the CAP could generate practical insights to improve the climate and environmental leadership position the EU often claims.

- *Clarifying the causes for Morocco's diversion from topsoil degradation:*

Lastly, Morocco's increase in topsoil organic carbon of 5,00 tonnes per hectare compared to the predominant decrease in SOC provides a profound research case. Better understanding which domestic policies or environmental circumstances led to the increase in Morocco's soil health could support repetition of this success elsewhere.

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ANNEX I: SOIL DATA

country	year	SOC	treat	treatment_cohort
Ukraine	1973	125,29	0	2016
Ukraine	1974	125,29	0	2016
Ukraine	1975	125,29	0	2016
Ukraine	1976	125,29	0	2016
Ukraine	1977	125,29	0	2016
Ukraine	1978	82,02	0	2016
Ukraine	1979	74,06	0	2016
Ukraine	1980	90,25	0	2016
Ukraine	1981	106,44	0	2016
Ukraine	1982	105,33	0	2016
Ukraine	1983	104,23	0	2016
Ukraine	1984	103,12	0	2016
Ukraine	1985	102,02	0	2016
Ukraine	1986	100,91	0	2016
Ukraine	1987	78,00	0	2016
Ukraine	1988	102,81	0	2016
Ukraine	1989	127,62	0	2016
Ukraine	1990	152,43	0	2016
Ukraine	1991	138,76	0	2016
Ukraine	1992	125,09	0	2016
Ukraine	1993	111,41	0	2016
Ukraine	1994	97,74	0	2016
Ukraine	1995	84,07	0	2016
Ukraine	1996	70,40	0	2016
Ukraine	1997	56,73	0	2016
Ukraine	1998	58,01	0	2016
Ukraine	1999	59,28	0	2016
Ukraine	2000	60,56	0	2016
Ukraine	2001	61,83	0	2016
Ukraine	2002	63,11	0	2016
Ukraine	2003	64,38	0	2016
Ukraine	2004	65,66	0	2016
Ukraine	2005	66,93	0	2016
Ukraine	2006	68,21	0	2016
Ukraine	2007	69,49	0	2016
Ukraine	2008	70,76	0	2016
Ukraine	2009	72,04	0	2016
Ukraine	2010	73,31	0	2016
Ukraine	2011	74,59	0	2016
Ukraine	2012	75,86	0	2016
Ukraine	2013	74,74	0	2016
Ukraine	2014	73,62	0	2016
Ukraine	2015	72,50	0	2016
Ukraine	2016	71,37	1	2016
Ukraine	2017	70,25	1	2016
Ukraine	2018	69,13	1	2016
Ukraine	2019	68,01	1	2016

Morocco	1973	45,80	0	1996
Morocco	1974	42,51	0	1996
Morocco	1975	39,22	0	1996
Morocco	1976	35,92	0	1996
Morocco	1977	32,63	0	1996
Morocco	1978	29,34	0	1996
Morocco	1979	26,05	0	1996
Morocco	1980	22,75	0	1996
Morocco	1981	19,46	0	1996
Morocco	1982	26,01	0	1996
Morocco	1983	32,57	0	1996
Morocco	1984	39,12	0	1996
Morocco	1985	45,67	0	1996
Morocco	1986	52,22	0	1996
Morocco	1987	58,78	0	1996
Morocco	1988	52,09	0	1996
Morocco	1989	45,41	0	1996
Morocco	1990	38,72	0	1996
Morocco	1991	38,41	0	1996
Morocco	1992	38,10	0	1996
Morocco	1993	37,80	0	1996
Morocco	1994	37,49	0	1996
Morocco	1995	37,18	0	1996
Morocco	1996	36,87	1	1996
Morocco	1997	36,56	1	1996
Morocco	1998	36,25	1	1996
Morocco	1999	35,94	1	1996
Morocco	2000	35,63	1	1996
Morocco	2001	35,32	1	1996
Morocco	2002	35,01	1	1996
Morocco	2003	34,70	1	1996
Morocco	2004	34,40	1	1996
Morocco	2005	34,09	1	1996
Morocco	2006	33,78	1	1996
Morocco	2007	33,47	1	1996
Morocco	2008	33,16	1	1996
Morocco	2009	32,85	1	1996
Morocco	2010	32,54	1	1996
Morocco	2011	32,23	1	1996
Morocco	2012	31,92	1	1996
Morocco	2013	31,17	1	1996
Morocco	2014	30,42	1	1996
Morocco	2015	29,67	1	1996
Morocco	2016	28,91	1	1996
Morocco	2017	28,16	1	1996
Morocco	2018	27,41	1	1996
Morocco	2019	26,66	1	1996

Ivory Coast	1973	68,68	0	2008
Ivory Coast	1974	68,68	0	2008
Ivory Coast	1975	68,68	0	2008
Ivory Coast	1976	68,68	0	2008
Ivory Coast	1977	69,83	0	2008
Ivory Coast	1978	70,98	0	2008
Ivory Coast	1979	72,12	0	2008
Ivory Coast	1980	73,27	0	2008
Ivory Coast	1981	74,42	0	2008
Ivory Coast	1982	75,57	0	2008
Ivory Coast	1983	76,71	0	2008
Ivory Coast	1984	77,86	0	2008
Ivory Coast	1985	72,63	0	2008
Ivory Coast	1986	67,40	0	2008
Ivory Coast	1987	62,17	0	2008
Ivory Coast	1988	56,94	0	2008
Ivory Coast	1989	51,71	0	2008
Ivory Coast	1990	57,02	0	2008
Ivory Coast	1991	54,86	0	2008
Ivory Coast	1992	67,66	0	2008
Ivory Coast	1993	57,80	0	2008
Ivory Coast	1994	52,35	0	2008
Ivory Coast	1995	54,17	0	2008
Ivory Coast	1996	55,98	0	2008
Ivory Coast	1997	57,80	0	2008
Ivory Coast	1998	56,32	0	2008
Ivory Coast	1999	54,83	0	2008
Ivory Coast	2000	53,35	0	2008
Ivory Coast	2001	51,87	0	2008
Ivory Coast	2002	50,39	0	2008
Ivory Coast	2003	48,90	0	2008
Ivory Coast	2004	47,42	0	2008
Ivory Coast	2005	45,94	0	2008
Ivory Coast	2006	44,46	0	2008
Ivory Coast	2007	42,97	0	2008
Ivory Coast	2008	41,49	1	2008
Ivory Coast	2009	40,01	1	2008
Ivory Coast	2010	38,53	1	2008
Ivory Coast	2011	37,04	1	2008
Ivory Coast	2012	35,56	1	2008
Ivory Coast	2013	34,63	1	2008
Ivory Coast	2014	33,69	1	2008
Ivory Coast	2015	32,76	1	2008
Ivory Coast	2016	31,83	1	2008
Ivory Coast	2017	30,89	1	2008
Ivory Coast	2018	29,96	1	2008
Ivory Coast	2019	29,03	1	2008

Peru	1973	30,98	0	2013
Peru	1974	30,98	0	2013
Peru	1975	30,98	0	2013
Peru	1976	44,82	0	2013
Peru	1977	23,74	0	2013
Peru	1978	34,08	0	2013
Peru	1979	61,86	0	2013
Peru	1980	89,64	0	2013
Peru	1981	80,13	0	2013
Peru	1982	70,62	0	2013
Peru	1983	61,10	0	2013
Peru	1984	59,37	0	2013
Peru	1985	57,64	0	2013
Peru	1986	55,90	0	2013
Peru	1987	54,17	0	2013
Peru	1988	52,44	0	2013
Peru	1989	50,70	0	2013
Peru	1990	48,97	0	2013
Peru	1991	47,24	0	2013
Peru	1992	45,95	0	2013
Peru	1993	44,67	0	2013
Peru	1994	43,39	0	2013
Peru	1995	42,11	0	2013
Peru	1996	23,70	0	2013
Peru	1997	25,40	0	2013
Peru	1998	27,10	0	2013
Peru	1999	28,79	0	2013
Peru	2000	30,49	0	2013
Peru	2001	32,19	0	2013
Peru	2002	33,89	0	2013
Peru	2003	35,59	0	2013
Peru	2004	37,29	0	2013
Peru	2005	38,98	0	2013
Peru	2006	40,68	0	2013
Peru	2007	42,38	0	2013
Peru	2008	44,08	0	2013
Peru	2009	45,78	0	2013
Peru	2010	47,48	0	2013
Peru	2011	49,18	0	2013
Peru	2012	50,87	0	2013
Peru	2013	51,38	1	2013
Peru	2014	51,89	1	2013
Peru	2015	52,40	1	2013
Peru	2016	52,90	1	2013
Peru	2017	53,41	1	2013
Peru	2018	53,92	1	2013
Peru	2019	54,43	1	2013

Colombia	1973	121,39	0	2013
Colombia	1974	121,39	0	2013
Colombia	1975	121,39	0	2013
Colombia	1976	121,39	0	2013
Colombia	1977	86,59	0	2013
Colombia	1978	65,27	0	2013
Colombia	1979	101,24	0	2013
Colombia	1980	386,82	0	2013
Colombia	1981	218,51	0	2013
Colombia	1982	153,75	0	2013
Colombia	1983	123,66	0	2013
Colombia	1984	140,47	0	2013
Colombia	1985	157,28	0	2013
Colombia	1986	186,98	0	2013
Colombia	1987	257,71	0	2013
Colombia	1988	69,89	0	2013
Colombia	1989	90,18	0	2013
Colombia	1990	110,46	0	2013
Colombia	1991	130,74	0	2013
Colombia	1992	115,29	0	2013
Colombia	1993	99,84	0	2013
Colombia	1994	84,38	0	2013
Colombia	1995	89,04	0	2013
Colombia	1996	93,69	0	2013
Colombia	1997	98,34	0	2013
Colombia	1998	99,22	0	2013
Colombia	1999	100,09	0	2013
Colombia	2000	100,97	0	2013
Colombia	2001	101,85	0	2013
Colombia	2002	102,72	0	2013
Colombia	2003	103,60	0	2013
Colombia	2004	104,48	0	2013
Colombia	2005	105,36	0	2013
Colombia	2006	106,23	0	2013
Colombia	2007	107,11	0	2013
Colombia	2008	107,99	0	2013
Colombia	2009	108,86	0	2013
Colombia	2010	109,74	0	2013
Colombia	2011	110,62	0	2013
Colombia	2012	111,49	0	2013
Colombia	2013	104,75	1	2013
Colombia	2014	98,01	1	2013
Colombia	2015	91,27	1	2013
Colombia	2016	84,53	1	2013
Colombia	2017	77,79	1	2013
Colombia	2018	71,05	1	2013
Colombia	2019	64,31	1	2013

Kazachstan	1973	138,35	0	9999
Kazachstan	1974	122,72	0	9999
Kazachstan	1975	107,09	0	9999
Kazachstan	1976	101,46	0	9999
Kazachstan	1977	95,84	0	9999
Kazachstan	1978	90,21	0	9999
Kazachstan	1979	84,59	0	9999
Kazachstan	1980	84,92	0	9999
Kazachstan	1981	88,93	0	9999
Kazachstan	1982	92,94	0	9999
Kazachstan	1983	96,96	0	9999
Kazachstan	1984	100,97	0	9999
Kazachstan	1985	104,98	0	9999
Kazachstan	1986	108,99	0	9999
Kazachstan	1987	104,15	0	9999
Kazachstan	1988	99,30	0	9999
Kazachstan	1989	94,45	0	9999
Kazachstan	1990	89,61	0	9999
Kazachstan	1991	84,76	0	9999
Kazachstan	1992	79,92	0	9999
Kazachstan	1993	75,07	0	9999
Kazachstan	1994	70,22	0	9999
Kazachstan	1995	65,38	0	9999
Kazachstan	1996	60,53	0	9999
Kazachstan	1997	55,68	0	9999
Kazachstan	1998	52,44	0	9999
Kazachstan	1999	49,20	0	9999
Kazachstan	2000	45,96	0	9999
Kazachstan	2001	42,72	0	9999
Kazachstan	2002	39,48	0	9999
Kazachstan	2003	36,23	0	9999
Kazachstan	2004	32,99	0	9999
Kazachstan	2005	37,45	0	9999
Kazachstan	2006	41,90	0	9999
Kazachstan	2007	46,35	0	9999
Kazachstan	2008	50,80	0	9999
Kazachstan	2009	55,26	0	9999
Kazachstan	2010	59,71	0	9999
Kazachstan	2011	64,16	0	9999
Kazachstan	2012	68,61	0	9999
Kazachstan	2013	70,17	0	9999
Kazachstan	2014	71,73	0	9999
Kazachstan	2015	73,29	0	9999
Kazachstan	2016	74,85	0	9999
Kazachstan	2017	76,41	0	9999
Kazachstan	2018	77,97	0	9999
Kazachstan	2019	79,53	0	9999

Tunesia	1973	46,88	0	9999
Tunesia	1974	49,14	0	9999
Tunesia	1975	51,41	0	9999
Tunesia	1976	42,91	0	9999
Tunesia	1977	34,40	0	9999
Tunesia	1978	25,90	0	9999
Tunesia	1979	17,40	0	9999
Tunesia	1980	7,49	0	9999
Tunesia	1981	12,39	0	9999
Tunesia	1982	17,28	0	9999
Tunesia	1983	22,18	0	9999
Tunesia	1984	27,07	0	9999
Tunesia	1985	31,97	0	9999
Tunesia	1986	36,86	0	9999
Tunesia	1987	35,51	0	9999
Tunesia	1988	34,16	0	9999
Tunesia	1989	32,81	0	9999
Tunesia	1990	31,46	0	9999
Tunesia	1991	30,11	0	9999
Tunesia	1992	28,76	0	9999
Tunesia	1993	27,40	0	9999
Tunesia	1994	26,05	0	9999
Tunesia	1995	24,70	0	9999
Tunesia	1996	23,35	0	9999
Tunesia	1997	22,00	0	9999
Tunesia	1998	24,01	0	9999
Tunesia	1999	26,01	0	9999
Tunesia	2000	28,02	0	9999
Tunesia	2001	30,03	0	9999
Tunesia	2002	32,03	0	9999
Tunesia	2003	34,04	0	9999
Tunesia	2004	36,05	0	9999
Tunesia	2005	35,06	0	9999
Tunesia	2006	34,07	0	9999
Tunesia	2007	33,08	0	9999
Tunesia	2008	32,09	0	9999
Tunesia	2009	31,11	0	9999
Tunesia	2010	30,12	0	9999
Tunesia	2011	29,13	0	9999
Tunesia	2012	28,14	0	9999
Tunesia	2013	26,64	0	9999
Tunesia	2014	25,14	0	9999
Tunesia	2015	23,64	0	9999
Tunesia	2016	22,14	0	9999
Tunesia	2017	20,64	0	9999
Tunesia	2018	19,14	0	9999
Tunesia	2019	17,64	0	9999

Nigeria	1973	29,14	0	9999
Nigeria	1974	30,26	0	9999
Nigeria	1975	31,38	0	9999
Nigeria	1976	32,50	0	9999
Nigeria	1977	33,62	0	9999
Nigeria	1978	34,74	0	9999
Nigeria	1979	35,86	0	9999
Nigeria	1980	36,98	0	9999
Nigeria	1981	38,10	0	9999
Nigeria	1982	43,22	0	9999
Nigeria	1983	75,97	0	9999
Nigeria	1984	81,51	0	9999
Nigeria	1985	72,69	0	9999
Nigeria	1986	63,88	0	9999
Nigeria	1987	55,06	0	9999
Nigeria	1988	46,24	0	9999
Nigeria	1989	37,43	0	9999
Nigeria	1990	32,24	0	9999
Nigeria	1991	27,05	0	9999
Nigeria	1992	27,52	0	9999
Nigeria	1993	28,00	0	9999
Nigeria	1994	28,47	0	9999
Nigeria	1995	28,95	0	9999
Nigeria	1996	29,42	0	9999
Nigeria	1997	29,90	0	9999
Nigeria	1998	30,37	0	9999
Nigeria	1999	30,84	0	9999
Nigeria	2000	31,32	0	9999
Nigeria	2001	31,79	0	9999
Nigeria	2002	32,27	0	9999
Nigeria	2003	33,53	0	9999
Nigeria	2004	34,78	0	9999
Nigeria	2005	36,04	0	9999
Nigeria	2006	36,50	0	9999
Nigeria	2007	36,97	0	9999
Nigeria	2008	37,44	0	9999
Nigeria	2009	37,91	0	9999
Nigeria	2010	38,38	0	9999
Nigeria	2011	38,84	0	9999
Nigeria	2012	39,31	0	9999
Nigeria	2013	40,24	0	9999
Nigeria	2014	41,17	0	9999
Nigeria	2015	42,10	0	9999
Nigeria	2016	43,03	0	9999
Nigeria	2017	43,95	0	9999
Nigeria	2018	44,88	0	9999
Nigeria	2019	45,81	0	9999

Bolivia	1973	35,3	0	9999
Bolivia	1974	35,3	0	9999
Bolivia	1975	35,3	0	9999
Bolivia	1976	35,3	0	9999
Bolivia	1977	35,3	0	9999
Bolivia	1978	35,3	0	9999
Bolivia	1979	71,20	0	9999
Bolivia	1980	52,82	0	9999
Bolivia	1981	46,82	0	9999
Bolivia	1982	40,82	0	9999
Bolivia	1983	39,81	0	9999
Bolivia	1984	38,81	0	9999
Bolivia	1985	37,80	0	9999
Bolivia	1986	41,73	0	9999
Bolivia	1987	45,66	0	9999
Bolivia	1988	29,60	0	9999
Bolivia	1989	51,16	0	9999
Bolivia	1990	72,73	0	9999
Bolivia	1991	76,33	0	9999
Bolivia	1992	79,93	0	9999
Bolivia	1993	71,90	0	9999
Bolivia	1994	64,24	0	9999
Bolivia	1995	56,57	0	9999
Bolivia	1996	55,63	0	9999
Bolivia	1997	54,68	0	9999
Bolivia	1998	53,73	0	9999
Bolivia	1999	52,78	0	9999
Bolivia	2000	51,83	0	9999
Bolivia	2001	50,88	0	9999
Bolivia	2002	49,93	0	9999
Bolivia	2003	48,98	0	9999
Bolivia	2004	48,03	0	9999
Bolivia	2005	47,08	0	9999
Bolivia	2006	46,13	0	9999
Bolivia	2007	45,18	0	9999
Bolivia	2008	44,23	0	9999
Bolivia	2009	43,28	0	9999
Bolivia	2010	42,34	0	9999
Bolivia	2011	41,39	0	9999
Bolivia	2012	40,44	0	9999
Bolivia	2013	42,44	0	9999
Bolivia	2014	44,44	0	9999
Bolivia	2015	46,45	0	9999
Bolivia	2016	48,45	0	9999
Bolivia	2017	50,46	0	9999
Bolivia	2018	52,46	0	9999
Bolivia	2019	54,46	0	9999

Brazil	1973	28,76	0	9999
Brazil	1974	50,34	0	9999
Brazil	1975	64,9	0	9999
Brazil	1976	80,3	0	9999
Brazil	1977	105,26	0	9999
Brazil	1978	89,59	0	9999
Brazil	1979	81,63	0	9999
Brazil	1980	73,67	0	9999
Brazil	1981	69,73	0	9999
Brazil	1982	65,79	0	9999
Brazil	1983	60,51	0	9999
Brazil	1984	55,24	0	9999
Brazil	1985	57,40	0	9999
Brazil	1986	59,56	0	9999
Brazil	1987	68,01	0	9999
Brazil	1988	76,47	0	9999
Brazil	1989	84,93	0	9999
Brazil	1990	93,38	0	9999
Brazil	1991	101,84	0	9999
Brazil	1992	110,30	0	9999
Brazil	1993	118,75	0	9999
Brazil	1994	116,57	0	9999
Brazil	1995	114,40	0	9999
Brazil	1996	112,22	0	9999
Brazil	1997	110,04	0	9999
Brazil	1998	107,86	0	9999
Brazil	1999	105,69	0	9999
Brazil	2000	103,51	0	9999
Brazil	2001	101,33	0	9999
Brazil	2002	99,15	0	9999
Brazil	2003	96,98	0	9999
Brazil	2004	94,80	0	9999
Brazil	2005	92,62	0	9999
Brazil	2006	90,45	0	9999
Brazil	2007	88,27	0	9999
Brazil	2008	86,09	0	9999
Brazil	2009	83,91	0	9999
Brazil	2010	70,27	0	9999
Brazil	2011	56,62	0	9999
Brazil	2012	42,98	0	9999
Brazil	2013	43,69	0	9999
Brazil	2014	44,40	0	9999
Brazil	2015	45,11	0	9999
Brazil	2016	45,82	0	9999
Brazil	2017	46,53	0	9999
Brazil	2018	47,24	0	9999
Brazil	2019	47,95	0	9999

country	year	SOC	treat	treatment_cohort
Ukraine	1973	125,29	0	2016
Ukraine	1974	125,29	0	2016
Ukraine	1975	125,29	0	2016
Ukraine	1976	125,29	0	2016
Ukraine	1977	125,29	0	2016
Ukraine	1978	82,02	0	2016
Ukraine	1979	74,06	0	2016
Ukraine	1980	90,25	0	2016
Ukraine	1981	106,44	0	2016
Ukraine	1982	105,33	0	2016
Ukraine	1983	104,23	0	2016
Ukraine	1984	103,12	0	2016
Ukraine	1985	102,02	0	2016
Ukraine	1986	100,91	0	2016
Ukraine	1987	78,00	0	2016
Ukraine	1988	102,81	0	2016
Ukraine	1989	127,62	0	2016
Ukraine	1990	152,43	0	2016
Ukraine	1991	138,76	0	2016
Ukraine	1992	125,09	0	2016
Ukraine	1993	111,41	0	2016
Ukraine	1994	97,74	0	2016
Ukraine	1995	84,07	0	2016
Ukraine	1996	70,40	0	2016
Ukraine	1997	56,73	0	2016
Ukraine	1998	58,01	0	2016
Ukraine	1999	59,28	0	2016
Ukraine	2000	60,56	0	2016
Ukraine	2001	61,83	0	2016
Ukraine	2002	63,11	0	2016
Ukraine	2003	64,38	0	2016
Ukraine	2004	65,66	0	2016
Ukraine	2005	66,93	0	2016
Ukraine	2006	68,21	0	2016
Ukraine	2007	69,49	0	2016
Ukraine	2008	70,76	0	2016
Ukraine	2009	72,04	0	2016
Ukraine	2010	73,31	0	2016
Ukraine	2011	74,59	0	2016
Ukraine	2012	75,86	0	2016
Ukraine	2013	74,74	0	2016
Ukraine	2014	73,62	0	2016
Ukraine	2015	72,50	0	2016
Ukraine	2016	71,37	1	2016
Ukraine	2017	70,25	1	2016
Ukraine	2018	69,13	1	2016
Ukraine	2019	68,01	1	2016

Notes

Ukraine	
1977	125,29
1978	82,02
1979	74,06
1981	106,44
1986	100,91
1987	78,00
1990	152,43
1997	56,73
2012	75,86
2019	68,01

Morocco	1973	45,80	0	1996
Morocco	1974	42,51	0	1996
Morocco	1975	39,22	0	1996
Morocco	1976	35,92	0	1996
Morocco	1977	32,63	0	1996
Morocco	1978	29,34	0	1996
Morocco	1979	26,05	0	1996
Morocco	1980	22,75	0	1996
Morocco	1981	19,46	0	1996
Morocco	1982	26,01	0	1996
Morocco	1983	32,57	0	1996
Morocco	1984	39,12	0	1996
Morocco	1985	45,67	0	1996
Morocco	1986	52,22	0	1996
Morocco	1987	58,78	0	1996
Morocco	1988	52,09	0	1996
Morocco	1989	45,41	0	1996
Morocco	1990	38,72	0	1996
Morocco	1991	38,41	0	1996
Morocco	1992	38,10	0	1996
Morocco	1993	37,80	0	1996
Morocco	1994	37,49	0	1996
Morocco	1995	37,18	0	1996
Morocco	1996	36,87	1	1996
Morocco	1997	36,56	1	1996
Morocco	1998	36,25	1	1996
Morocco	1999	35,94	1	1996
Morocco	2000	35,63	1	1996
Morocco	2001	35,32	1	1996
Morocco	2002	35,01	1	1996
Morocco	2003	34,70	1	1996
Morocco	2004	34,40	1	1996
Morocco	2005	34,09	1	1996
Morocco	2006	33,78	1	1996
Morocco	2007	33,47	1	1996
Morocco	2008	33,16	1	1996
Morocco	2009	32,85	1	1996
Morocco	2010	32,54	1	1996
Morocco	2011	32,23	1	1996
Morocco	2012	31,92	1	1996
Morocco	2013	31,17	1	1996
Morocco	2014	30,42	1	1996
Morocco	2015	29,67	1	1996
Morocco	2016	28,91	1	1996
Morocco	2017	28,16	1	1996
Morocco	2018	27,41	1	1996
Morocco	2019	26,66	1	1996

Morocco

1973	45,80
1981	19,46
1987	58,78
1990	38,72
2012	31,92
2019	26,66

Ivory Coast	1973	68,68	0	2008
Ivory Coast	1974	68,68	0	2008
Ivory Coast	1975	68,68	0	2008
Ivory Coast	1976	68,68	0	2008
Ivory Coast	1977	69,83	0	2008
Ivory Coast	1978	70,98	0	2008
Ivory Coast	1979	72,12	0	2008
Ivory Coast	1980	73,27	0	2008
Ivory Coast	1981	74,42	0	2008
Ivory Coast	1982	75,57	0	2008
Ivory Coast	1983	76,71	0	2008
Ivory Coast	1984	77,86	0	2008
Ivory Coast	1985	72,63	0	2008
Ivory Coast	1986	67,40	0	2008
Ivory Coast	1987	62,17	0	2008
Ivory Coast	1988	56,94	0	2008
Ivory Coast	1989	51,71	0	2008
Ivory Coast	1990	57,02	0	2008
Ivory Coast	1991	54,86	0	2008
Ivory Coast	1992	67,66	0	2008
Ivory Coast	1993	57,80	0	2008
Ivory Coast	1994	52,35	0	2008
Ivory Coast	1995	54,17	0	2008
Ivory Coast	1996	55,98	0	2008
Ivory Coast	1997	57,80	0	2008
Ivory Coast	1998	56,32	0	2008
Ivory Coast	1999	54,83	0	2008
Ivory Coast	2000	53,35	0	2008
Ivory Coast	2001	51,87	0	2008
Ivory Coast	2002	50,39	0	2008
Ivory Coast	2003	48,90	0	2008
Ivory Coast	2004	47,42	0	2008
Ivory Coast	2005	45,94	0	2008
Ivory Coast	2006	44,46	0	2008
Ivory Coast	2007	42,97	0	2008
Ivory Coast	2008	41,49	1	2008
Ivory Coast	2009	40,01	1	2008
Ivory Coast	2010	38,53	1	2008
Ivory Coast	2011	37,04	1	2008
Ivory Coast	2012	35,56	1	2008
Ivory Coast	2013	34,63	1	2008
Ivory Coast	2014	33,69	1	2008
Ivory Coast	2015	32,76	1	2008
Ivory Coast	2016	31,83	1	2008
Ivory Coast	2017	30,89	1	2008
Ivory Coast	2018	29,96	1	2008
Ivory Coast	2019	29,03	1	2008

Ivory Coast

1976	68,68
1984	77,86
1989	51,71
1990	57,02
1993	50,54
1997	57,80
2012	35,56
2019	29,03

Peru	1973	30,98	0	2013
Peru	1974	30,98	0	2013
Peru	1975	30,98	0	2013
Peru	1976	44,82	0	2013
Peru	1977	23,74	0	2013
Peru	1978	34,08	0	2013
Peru	1979	61,86	0	2013
Peru	1980	89,64	0	2013
Peru	1981	80,13	0	2013
Peru	1982	70,62	0	2013
Peru	1983	61,10	0	2013
Peru	1984	59,37	0	2013
Peru	1985	57,64	0	2013
Peru	1986	55,90	0	2013
Peru	1987	54,17	0	2013
Peru	1988	52,44	0	2013
Peru	1989	50,70	0	2013
Peru	1990	48,97	0	2013
Peru	1991	47,24	0	2013
Peru	1992	45,95	0	2013
Peru	1993	44,67	0	2013
Peru	1994	43,39	0	2013
Peru	1995	42,11	0	2013
Peru	1996	23,70	0	2013
Peru	1997	25,40	0	2013
Peru	1998	27,10	0	2013
Peru	1999	28,79	0	2013
Peru	2000	30,49	0	2013
Peru	2001	32,19	0	2013
Peru	2002	33,89	0	2013
Peru	2003	35,59	0	2013
Peru	2004	37,29	0	2013
Peru	2005	38,98	0	2013
Peru	2006	40,68	0	2013
Peru	2007	42,38	0	2013
Peru	2008	44,08	0	2013
Peru	2009	45,78	0	2013
Peru	2010	47,48	0	2013
Peru	2011	49,18	0	2013
Peru	2012	50,87	0	2013
Peru	2013	51,38	1	2013
Peru	2014	51,89	1	2013
Peru	2015	52,40	1	2013
Peru	2016	52,90	1	2013
Peru	2017	53,41	1	2013
Peru	2018	53,92	1	2013
Peru	2019	54,43	1	2013

Peru

1975	30,98
1976	44,82
1977	23,74
1978	34,08
1980	89,64
1983	61,10
1991	47,24
1995	42,11
1996	23,70
2012	50,87
2019	54,43

Colombia	1973	121,39	0	2013
Colombia	1974	121,39	0	2013
Colombia	1975	121,39	0	2013
Colombia	1976	121,39	0	2013
Colombia	1977	86,59	0	2013
Colombia	1978	65,27	0	2013
Colombia	1979	101,24	0	2013
Colombia	1980	386,82	0	2013
Colombia	1981	218,51	0	2013
Colombia	1982	153,75	0	2013
Colombia	1983	123,66	0	2013
Colombia	1984	140,47	0	2013
Colombia	1985	157,28	0	2013
Colombia	1986	186,98	0	2013
Colombia	1987	257,71	0	2013
Colombia	1988	69,89	0	2013
Colombia	1989	90,18	0	2013
Colombia	1990	110,46	0	2013
Colombia	1991	130,74	0	2013
Colombia	1992	115,29	0	2013
Colombia	1993	99,84	0	2013
Colombia	1994	84,38	0	2013
Colombia	1995	89,04	0	2013
Colombia	1996	93,69	0	2013
Colombia	1997	98,34	0	2013
Colombia	1998	99,22	0	2013
Colombia	1999	100,09	0	2013
Colombia	2000	100,97	0	2013
Colombia	2001	101,85	0	2013
Colombia	2002	102,72	0	2013
Colombia	2003	103,60	0	2013
Colombia	2004	104,48	0	2013
Colombia	2005	105,36	0	2013
Colombia	2006	106,23	0	2013
Colombia	2007	107,11	0	2013
Colombia	2008	107,99	0	2013
Colombia	2009	108,86	0	2013
Colombia	2010	109,74	0	2013
Colombia	2011	110,62	0	2013
Colombia	2012	111,49	0	2013
Colombia	2013	104,75	1	2013
Colombia	2014	98,01	1	2013
Colombia	2015	91,27	1	2013
Colombia	2016	84,53	1	2013
Colombia	2017	77,79	1	2013
Colombia	2018	71,05	1	2013
Colombia	2019	64,31	1	2013

Colombia

1976	121,39
1977	86,59
1978	65,27
1979	101,24
1980	386,82
1981	218,51
1982	153,75
1983	123,66
1984	140,47
1986	186,98
1987	257,71
1988	69,89
1991	130,74
1994	84,38
1997	98,34
2012	111,49
2019	64,31

Kazachstan	1973	138,35	0	9999
Kazachstan	1974	122,72	0	9999
Kazachstan	1975	107,09	0	9999
Kazachstan	1976	101,46	0	9999
Kazachstan	1977	95,84	0	9999
Kazachstan	1978	90,21	0	9999
Kazachstan	1979	84,59	0	9999
Kazachstan	1980	84,92	0	9999
Kazachstan	1981	88,93	0	9999
Kazachstan	1982	92,94	0	9999
Kazachstan	1983	96,96	0	9999
Kazachstan	1984	100,97	0	9999
Kazachstan	1985	104,98	0	9999
Kazachstan	1986	108,99	0	9999
Kazachstan	1987	104,15	0	9999
Kazachstan	1988	99,30	0	9999
Kazachstan	1989	94,45	0	9999
Kazachstan	1990	89,61	0	9999
Kazachstan	1991	84,76	0	9999
Kazachstan	1992	79,92	0	9999
Kazachstan	1993	75,07	0	9999
Kazachstan	1994	70,22	0	9999
Kazachstan	1995	65,38	0	9999
Kazachstan	1996	60,53	0	9999
Kazachstan	1997	55,68	0	9999
Kazachstan	1998	52,44	0	9999
Kazachstan	1999	49,20	0	9999
Kazachstan	2000	45,96	0	9999
Kazachstan	2001	42,72	0	9999
Kazachstan	2002	39,48	0	9999
Kazachstan	2003	36,23	0	9999
Kazachstan	2004	32,99	0	9999
Kazachstan	2005	37,45	0	9999
Kazachstan	2006	41,90	0	9999
Kazachstan	2007	46,35	0	9999
Kazachstan	2008	50,80	0	9999
Kazachstan	2009	55,26	0	9999
Kazachstan	2010	59,71	0	9999
Kazachstan	2011	64,16	0	9999
Kazachstan	2012	68,61	0	9999
Kazachstan	2013	70,17	0	9999
Kazachstan	2014	71,73	0	9999
Kazachstan	2015	73,29	0	9999
Kazachstan	2016	74,85	0	9999
Kazachstan	2017	76,41	0	9999
Kazachstan	2018	77,97	0	9999
Kazachstan	2019	79,53	0	9999

Kazakhstan

1973	138,3533
1975	107,0866
1979	84,59
1980	84,92
1986	108,99
1997	55,68
2004	32,99
2012	68,61
2019	79,53

Tunesia	1973	46,88	0	9999
Tunesia	1974	49,14	0	9999
Tunesia	1975	51,41	0	9999
Tunesia	1976	42,91	0	9999
Tunesia	1977	34,40	0	9999
Tunesia	1978	25,90	0	9999
Tunesia	1979	17,40	0	9999
Tunesia	1980	7,49	0	9999
Tunesia	1981	12,39	0	9999
Tunesia	1982	17,28	0	9999
Tunesia	1983	22,18	0	9999
Tunesia	1984	27,07	0	9999
Tunesia	1985	31,97	0	9999
Tunesia	1986	36,86	0	9999
Tunesia	1987	35,51	0	9999
Tunesia	1988	34,16	0	9999
Tunesia	1989	32,81	0	9999
Tunesia	1990	31,46	0	9999
Tunesia	1991	30,11	0	9999
Tunesia	1992	28,76	0	9999
Tunesia	1993	27,40	0	9999
Tunesia	1994	26,05	0	9999
Tunesia	1995	24,70	0	9999
Tunesia	1996	23,35	0	9999
Tunesia	1997	22,00	0	9999
Tunesia	1998	24,01	0	9999
Tunesia	1999	26,01	0	9999
Tunesia	2000	28,02	0	9999
Tunesia	2001	30,03	0	9999
Tunesia	2002	32,03	0	9999
Tunesia	2003	34,04	0	9999
Tunesia	2004	36,05	0	9999
Tunesia	2005	35,06	0	9999
Tunesia	2006	34,07	0	9999
Tunesia	2007	33,08	0	9999
Tunesia	2008	32,09	0	9999
Tunesia	2009	31,11	0	9999
Tunesia	2010	30,12	0	9999
Tunesia	2011	29,13	0	9999
Tunesia	2012	28,14	0	9999
Tunesia	2013	26,64	0	9999
Tunesia	2014	25,14	0	9999
Tunesia	2015	23,64	0	9999
Tunesia	2016	22,14	0	9999
Tunesia	2017	20,64	0	9999
Tunesia	2018	19,14	0	9999
Tunesia	2019	17,64	0	9999

Tunesia

1973	46,9
1975	51,408
1979	17,40
1980	7,49
1986	36,86
1997	22,00
2004	36,05
2012	28,14
2019	17,64

Nigeria	1973	29,14	0	9999
Nigeria	1974	30,26	0	9999
Nigeria	1975	31,38	0	9999
Nigeria	1976	32,50	0	9999
Nigeria	1977	33,62	0	9999
Nigeria	1978	34,74	0	9999
Nigeria	1979	35,86	0	9999
Nigeria	1980	36,98	0	9999
Nigeria	1981	38,10	0	9999
Nigeria	1982	43,22	0	9999
Nigeria	1983	75,97	0	9999
Nigeria	1984	81,51	0	9999
Nigeria	1985	72,69	0	9999
Nigeria	1986	63,88	0	9999
Nigeria	1987	55,06	0	9999
Nigeria	1988	46,24	0	9999
Nigeria	1989	37,43	0	9999
Nigeria	1990	32,24	0	9999
Nigeria	1991	27,05	0	9999
Nigeria	1992	27,52	0	9999
Nigeria	1993	28,00	0	9999
Nigeria	1994	28,47	0	9999
Nigeria	1995	28,95	0	9999
Nigeria	1996	29,42	0	9999
Nigeria	1997	29,90	0	9999
Nigeria	1998	30,37	0	9999
Nigeria	1999	30,84	0	9999
Nigeria	2000	31,32	0	9999
Nigeria	2001	31,79	0	9999
Nigeria	2002	32,27	0	9999
Nigeria	2003	33,53	0	9999
Nigeria	2004	34,78	0	9999
Nigeria	2005	36,04	0	9999
Nigeria	2006	36,50	0	9999
Nigeria	2007	36,97	0	9999
Nigeria	2008	37,44	0	9999
Nigeria	2009	37,91	0	9999
Nigeria	2010	38,38	0	9999
Nigeria	2011	38,84	0	9999
Nigeria	2012	39,31	0	9999
Nigeria	2013	40,24	0	9999
Nigeria	2014	41,17	0	9999
Nigeria	2015	42,10	0	9999
Nigeria	2016	43,03	0	9999
Nigeria	2017	43,95	0	9999
Nigeria	2018	44,88	0	9999
Nigeria	2019	45,81	0	9999

Nigeria

1973	29,14
1981	38,10
1982	43,22
1983	75,97
1984	81,51
1989	37,43
1991	27,05
2002	32,27
2005	36,04
2012	39,31
2019	45,81

Bolivia	1973	35,3	0	9999
Bolivia	1974	35,3	0	9999
Bolivia	1975	35,3	0	9999
Bolivia	1976	35,3	0	9999
Bolivia	1977	35,3	0	9999
Bolivia	1978	35,3	0	9999
Bolivia	1979	71,20	0	9999
Bolivia	1980	52,82	0	9999
Bolivia	1981	46,82	0	9999
Bolivia	1982	40,82	0	9999
Bolivia	1983	39,81	0	9999
Bolivia	1984	38,81	0	9999
Bolivia	1985	37,80	0	9999
Bolivia	1986	41,73	0	9999
Bolivia	1987	45,66	0	9999
Bolivia	1988	29,60	0	9999
Bolivia	1989	51,16	0	9999
Bolivia	1990	72,73	0	9999
Bolivia	1991	76,33	0	9999
Bolivia	1992	79,93	0	9999
Bolivia	1993	71,90	0	9999
Bolivia	1994	64,24	0	9999
Bolivia	1995	56,57	0	9999
Bolivia	1996	55,63	0	9999
Bolivia	1997	54,68	0	9999
Bolivia	1998	53,73	0	9999
Bolivia	1999	52,78	0	9999
Bolivia	2000	51,83	0	9999
Bolivia	2001	50,88	0	9999
Bolivia	2002	49,93	0	9999
Bolivia	2003	48,98	0	9999
Bolivia	2004	48,03	0	9999
Bolivia	2005	47,08	0	9999
Bolivia	2006	46,13	0	9999
Bolivia	2007	45,18	0	9999
Bolivia	2008	44,23	0	9999
Bolivia	2009	43,28	0	9999
Bolivia	2010	42,34	0	9999
Bolivia	2011	41,39	0	9999
Bolivia	2012	40,44	0	9999
Bolivia	2013	42,44	0	9999
Bolivia	2014	44,44	0	9999
Bolivia	2015	46,45	0	9999
Bolivia	2016	48,45	0	9999
Bolivia	2017	50,46	0	9999
Bolivia	2018	52,46	0	9999
Bolivia	2019	54,46	0	9999

Bolivia

1978	35,3
1979	71,20
1980	52,82
1982	40,82
1985	37,80
1987	45,66
1988	29,60
1990	72,73
1992	79,93
1993	71,90
1995	56,57
2012	40,44
2019	54,46

Brazil	1973	28,76	0	9999
Brazil	1974	50,34	0	9999
Brazil	1975	64,9	0	9999
Brazil	1976	80,3	0	9999
Brazil	1977	105,26	0	9999
Brazil	1978	89,59	0	9999
Brazil	1979	81,63	0	9999
Brazil	1980	73,67	0	9999
Brazil	1981	69,73	0	9999
Brazil	1982	65,79	0	9999
Brazil	1983	60,51	0	9999
Brazil	1984	55,24	0	9999
Brazil	1985	57,40	0	9999
Brazil	1986	59,56	0	9999
Brazil	1987	68,01	0	9999
Brazil	1988	76,47	0	9999
Brazil	1989	84,93	0	9999
Brazil	1990	93,38	0	9999
Brazil	1991	101,84	0	9999
Brazil	1992	110,30	0	9999
Brazil	1993	118,75	0	9999
Brazil	1994	116,57	0	9999
Brazil	1995	114,40	0	9999
Brazil	1996	112,22	0	9999
Brazil	1997	110,04	0	9999
Brazil	1998	107,86	0	9999
Brazil	1999	105,69	0	9999
Brazil	2000	103,51	0	9999
Brazil	2001	101,33	0	9999
Brazil	2002	99,15	0	9999
Brazil	2003	96,98	0	9999
Brazil	2004	94,80	0	9999
Brazil	2005	92,62	0	9999
Brazil	2006	90,45	0	9999
Brazil	2007	88,27	0	9999
Brazil	2008	86,09	0	9999
Brazil	2009	83,91	0	9999
Brazil	2010	70,27	0	9999
Brazil	2011	56,62	0	9999
Brazil	2012	42,98	0	9999
Brazil	2013	43,69	0	9999
Brazil	2014	44,40	0	9999
Brazil	2015	45,11	0	9999
Brazil	2016	45,82	0	9999
Brazil	2017	46,53	0	9999
Brazil	2018	47,24	0	9999
Brazil	2019	47,95	0	9999

Brazil

1973	28,76
1974	50,34
1975	64,9
1976	80,3
1977	105,26
1978	89,59
1980	73,67
1982	65,79
1984	55,24
1986	59,56
1993	118,75
2009	83,91
2012	42,98
2019	47,95

Ukraine	48.28593°N, 22.72506°E						Luvisols	48.22029°N, 24.00824°E						Chernozem	48.96275°N, 22.92923°E						Vertisols			
1977	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]			
								0	0,07	86,9	1,41	122,53	8,577	85,770		0	0,12	65,8	1,41	92,78	11,133	111,334		
								0,35	0,07	33,67	1,41	47,48	10,920	109,196	0,4	0,12	0,3	32,31	1,41	45,56	8,201	82,009		
125,29														194,97								193,34		
1978		0	0,28	10,1	1,4	14,14	3,959	39,592																
	0,4	0,28	0,3	5,41	1,4	7,58	0,152	1,516																
82,02								41,11																
1979																								
74,06																								
1981																								
106,44																								
1986																								
100,91																								
1987																								
78,00																								
1990																								
152,43																								
1997																								
56,73																								
2012			SOC [%w]							SOC [%w]							SOC [%w]							
		0	0,3	2,22	1,4	31,08	9,324	93,24		0	0,3	1,54	1,41	21,71	6,5142	65,142		0	0,3	1,45	1,41	20,45	6,1335	61,335
75,86								93,24								65,142							61,335	
2019																								
68,01							60,34								106,84								110,12	

49.19407°N, 23.18794°E							49.68615°N, 23.09581°E							48.35658°N, 26.42370°E							
Chernozem							Regosol							Chernozem							
	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	
0,45	0	0,22	16,1	1,41	22,70	4,994									0	0,26	13,9	1,37	19,04	4,951	49,512
	0,22	0,3	8,73	1,41	12,31	0,985								0,4	0,26	6,48	1,37	8,87	0,355	3,548	
	59,79												53,06								
							0	0,3	20	1,37	27,40	8,220	82,200								
							82,20														
SOC [%w]							SOC [%w]							SOC [%w]							
0	0,3	1,45	1,41	20,45	6,1335	61,335	0	0,3	1,6	1,37	21,92	6,576	65,76	0	0,3	1,6	1,37	21,92	6,576	65,76	
61,335							65,76							65,76							
77,4							46,51							57,6							

50.80921°N, 24.90148°E						51.56614°N, 24.00882°E						50.52533°N, 26.07714°E						Chernozem		
Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]			
0	0,3	14,75	1,41	20,80	62,393															
62,39																				
												0	0,3	12,9	1,37	17,67	5,302	53,019		
53,02																				
						0	0,28	47,7	1,67	79,66	22,305	223,045								
						0,56	0,28	0,3	49,90	1,67	83,33	1,667	16,665							
						239,71														
SOC [%w]						SOC [%w]						SOC [%w]								
0	0,3	2,13	1,41	30,03	9,010	90,10	0	0,3	2,02	1,67	33,73	10,1202	101,202	0	0,3	1,6	1,37	21,92	6,576	65,76
						90,10							101,202							65,76
						41,4							52,41							41,51

48.17389°N, 30.14281°E							45.58328°N, 29.34021°E							Kastanozem				46.25886°N, 30.02548°E				Kastanozem			
Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]					
0	0,3	23,1	1,36	31,42	9,425	94,248		0	0,27	16,9	1,24	20,96	5,658	56,581											
							0,4	0,27	0,3	14,09	1,24	17,47	0,524	5,241											
						94,25													61,82						
														0	0,25	16	1,24	19,84	4,960	49,600					
														0,8	0,25	0,3	15,63	1,24	19,38	0,969	9,688				
																				59,29					
SOC [%w]							SOC [%w]							SOC [%w]											
0	0,3	1,68	1,36	22,85	6,8544	68,544	0	0,3	2,1	1,24	26,04	7,812	78,12	0	0,3	2,1	1,24	26,04	7,812	78,12					
						68,544															78,12				
						83,53																	61,07		

[illegible]

49.56887°N, 35.28911°E							Fluvisol	51.79996°N, 34.30206°E							Fluvisol
Depth [m]			SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	
1880	0	0,3	32,75	1,35	44,21	13,264	132,638								
132,64															
								0	0,3	15,85	1,37	21,71	6,514	65,144	
								65,14							
			SOC [%w]								SOC [%w]				
0	0,3	2,09	1,35	28,22	8,4645	84,645		0	0,3	1,6	1,37	21,92	6,576	65,76	
84,645							65,76								
83,62							71,6								

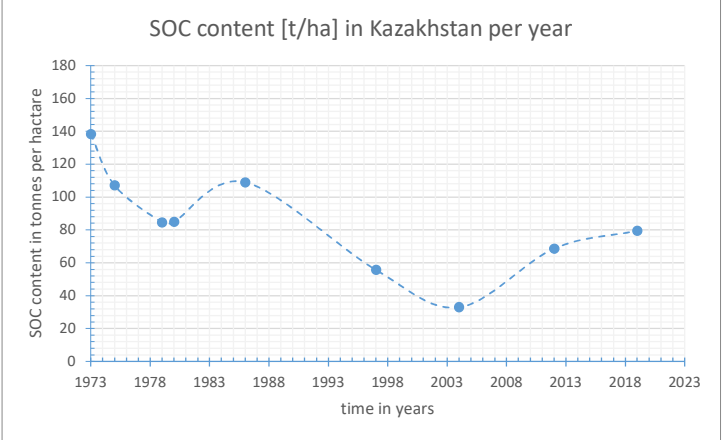
Kazakhstan	46.89719°N, 56.34938°E						Solonetz	54.94501°N, 69.11944°E						Kastanozems	54.94501°N, 69.11944°E						Kastanozems
1973	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	
138,4																					
1975																					
107,09																					
1979																					
84,588																					
1980	0	0,25	3,1	1,42	4,40	1,101	11,005														
84,92							11,01														
1986																					
108,99																					
1997															0	0,25	23,84	1,33	31,71	7,927	79,268
55,68																				79,27	
2004								0	0,25	10,775	1,33	14,33	3,583	35,827							
32,99														35,83							
2012			SOC [%w]							SOC [%w]							SOC [%w]				
	0	0,3	0,4	1,42	5,68	1,704	17,04	0	0,3	2,01	1,33	26,73	8,0199	80,199	0	0,3	2,01	1,33	26,73	8,0199	80,199
68,61							17,04							80,20						80,20	
2019																					
79,53							25,57							105,41						103,51	

[illegible]

[illegible]

52.90998°N, 70.27954°E						52.73348°N, 70.73657°E						52.24117°N, 71.13528°E					
Xerosols						Xerosols						Xerosols					
Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]
0	0,25	37,67	1,33	50,10	125,253												
					125,25							0	0,25	25,81	1,33	34,33	85,818
																	85,82
						0	0,25	9,28	1,3	12,06	3,016						
											30,160						
											30,16						
		SOC [%w]						SOC [%w]						SOC [%w]			
0	0,3	2,15	1,33	28,60	85,785	0	0,3	1,75	1,3	22,75	6,825	68,25	0	0,3	1,8	1,33	71,82
					85,79						68,25						71,82
											68,25						
					105,47						69,75						67,31

51.21895°N, 71.78369°E							Chernozem							50.93934°N, 72.07251°E							Chernozem							50.81740°N, 72.24610°E							Chernozem						
Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]							
0	0,25	30,75	1,38	42,44	10,609	106,088																																			
						106,09																																			

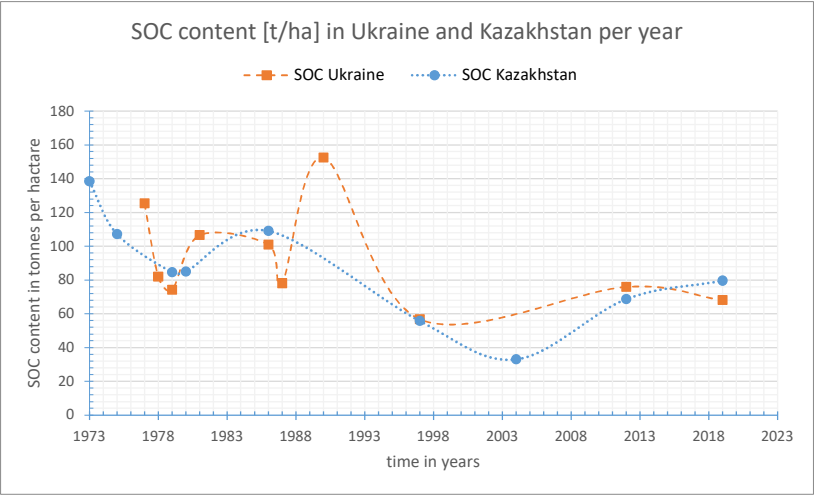


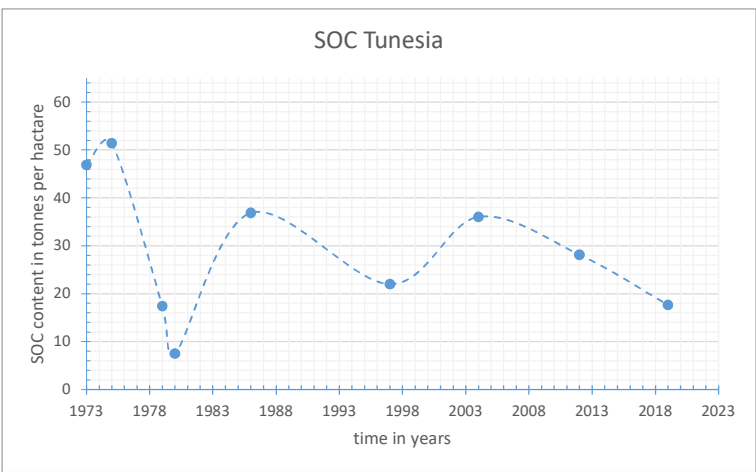
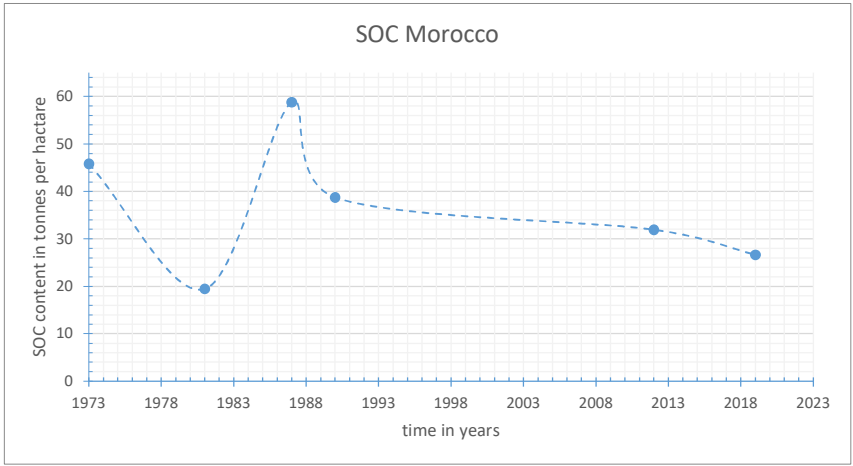
Ukraine

1977	125,29
1978	82,02
1979	74,06
1981	106,44
1986	100,91
1987	78,00
1990	152,43
1997	56,73
2012	75,86
2019	68,01

Kazakhstan

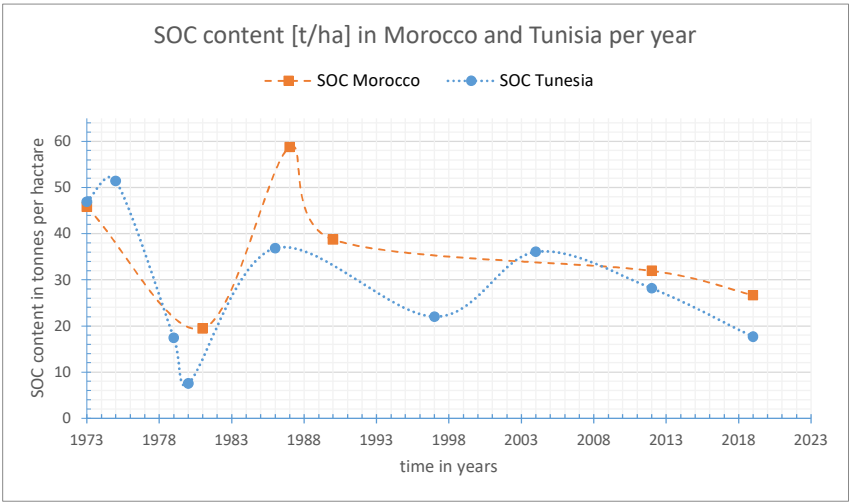
1973	138,3533
1975	107,0866
1979	84,59
1980	84,92
1986	108,99
1997	55,68
2004	32,99
2012	68,61
2019	79,53





Morocco	
1973	45,80
1981	19,46
1987	58,78
1990	38,72
2012	31,92
2019	26,66

Tunisia	
1973	46,9
1975	51,408
1979	17,40
1980	7,49
1986	36,86
1997	22,00
2004	36,05
2012	28,14
2019	17,64



9.67051°N, 6.90848°W							Luvisol		9.62094°N, 6.91989°W						Luvisol		9.59267°N, 6.92228°W						Luvisol	
Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]				
0	0,20	8,10	1,4	11,34	2,27	22,68	0	0,20	8,10	1,4	11,34	2,27	22,68	0	0,20	19,60	1,4	27,44	5,49	54,88				
0,20	0,3	6,77	1,4	9,47	0,95	9,47	0,20	0,3	5,93	1,4	8,30	0,83	8,30	0,20	0,3	13,62	1,4	19,06	1,91	19,06				
32,15							30,98							73,94										

SOC [%w]							SOC [%w]							SOC [%w]						
0	0,3	0,98	1,4	13,72	4,116	41,16	0	0,3	0,98	1,4	13,72	4,116	41,16	0	0,3	0,98	1,4	13,72	4,116	41,16
						41,16							41,16							41,16
						29,86							29,29							28,97

6.83620°N, 2.92258°E							Vertisol			6.98598°N, 3.00723°E			Luvisol			8.51181°N, 3.48532°E			Luvisol			
Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		
							0		0,15		14		1,56		21,84		3,276		32,760			
							0,35		0,23		0,3		8,4		1,56		13,06		0,914		9,142	
													41,90									
							0		0,23		36		1,56		56,16		12,917		129,168			
0,41		0,23		0,3		13,5		1,56		21,12		1,478		14,782								
													143,95									

		0	0,28	9,4	1,41	13,25	3,711	37,111
	0,45	0,28	0,3	5,5	1,41	7,71	0,154	1,542
								38,65

SOC [%w]							SOC [%w]							SOC [%w]						
0	0,3	0,61	1,56	9,52	2,8548	28,548	0	0,3	0,61	1,56	9,52	2,8548	28,548	0	0,3	0,74	1,41	10,43	3,1302	31,302
						28,55							28,55							31,30
						46,6							47,24							35,84

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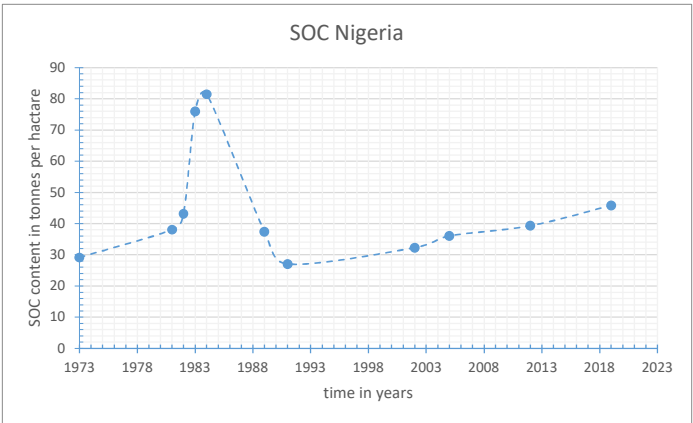
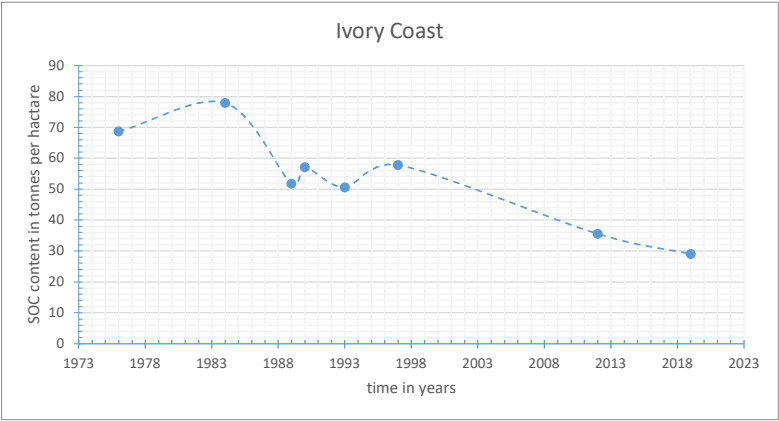
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4.89545°N, 6.22922°E				Fluvisol			
Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	
	0	0,15	20,7	1,39	28,77	4,316	43,160
	0,15	0,3	7,8	1,39	10,84	1,626	16,263
							59,42

	0	0,14	16,2	1,39	22,52	3,040	30,399
0,80	0,14	0,3	11,3	1,39	15,72	2,593	25,931
							56,33

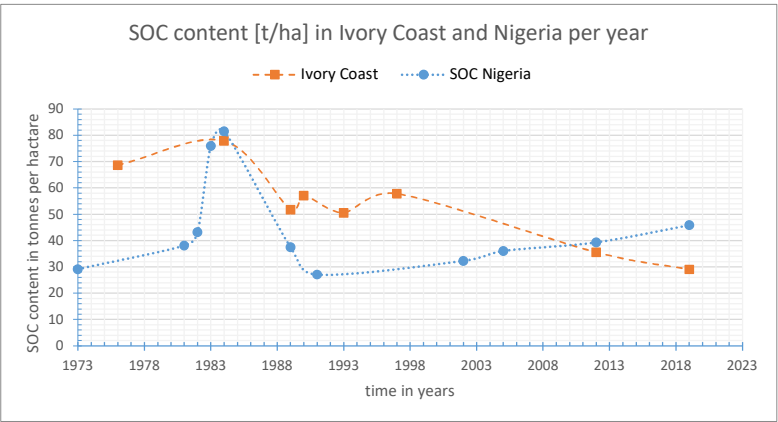
SOC [%w]							
	0	0,3	1,27	1,39	17,65	5,2959	52,959
							52,96

73,74



Ivory Coast	
1976	68,68
1984	77,86
1989	51,71
1990	57,02
1993	50,54
1997	57,80
2012	35,56
2019	29,03

Nigeria	
1973	29,14
1981	38,10
1982	43,22
1983	75,97
1984	81,51
1989	37,43
1991	27,05
2002	32,27
2005	36,04
2012	39,31
2019	45,81



Peru	3.06176°S, 71.02019°W						3.77940°S, 73.20975°W						3.88008°S, 73.32333°W						Gleysol			
	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	
1975																						
30,98																						
1976	0	0,10	17,8	1,42	25,28	2,53	25,28															
	0,1	0,20	7,8	1,42	11,08	1,11	11,08															
	0,35	0,2	0,3	5,96	1,42	8,46	0,85	8,46														
44,82																						
1977																						
23,74																						
1978																						
34,08																						
1980								0	0,06	60,75	1,21	73,51	4,41	44,10								
								0,06	0,27	16,25	1,21	19,66	4,03	40,31								
								0,45	0,27	0,3	12,34	1,21	14,93	0,52	5,23							
89,64																						
1983																						
61,10																						
1991								0	0,05	20,8	1,21	25,17	1,26	12,58	0	0,13	20,8	1,21	25,17	3,33	33,35	
								0,05	0,13	3,1	1,21	3,75	0,30	3,00	0,13	0,24	5,33	1,21	6,44	0,71	7,14	
								0,51	0,13	0,3	3,05	1,21	3,69	0,63	0,56	0,24	0,3	4,75	1,21	5,75	0,34	3,45
47,24																						
1995															21,85							
1995																0	0,15	6	1,21	7,26	1,09	10,89
																0,46	0,15	0,3	4,83	1,21	5,84	0,88
42,11																						
1996																0	0,05	11,6	1,21	14,04	0,70	7,02
																0,35	0,05	0,3	5,51	1,21	6,67	1,67
23,70																						
2012			SOC [%w]							SOC [%w]							SOC [%w]					
50,87	0	0,3	1,91	1,42	27,12	8,14	81,37	0	0,3	1,42	1,21	17,18	5,15	51,55	0	0,3	1,42	1,21	17,18	5,15	51,55	
2019																						
54,43							66,81							60,52							60,23	

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Bolivia			10.27693°S, 65.68068°W					Acrisol			10.54984°S, 67.33389°W					Gleysol			11.04542°S, 67.39699°W					Ferralsol		
	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]			
1978																										
35,3																										
1979																										
71,20																										
1980																										
52,82																										
1982																										
40,82																										
1985																										
37,80																										
1987																										
45,66																										
1988																										
29,60																										
1990																										
72,73																										
1992	0	0,15	22	1,26	27,72	4,16	41,58	0,50	0	0,13	19	1,5	28,50	3,71	37,05	0,55	0	0,25	22	1,55	34,10	8,53	85,25			
79,93	0,46	0,15	0,3	13,52	1,26	17,04	2,56		0,13	0,3	11,20	1,5	16,80	2,86	28,56		0,25	0,3	17,64	1,55	27,34	1,37	13,67			
1993							67,14								65,61								98,92			
71,90																										
1995																										
56,57																										
2012			SOC [%w]								SOC [%w]								SOC [%w]							
40,44	0	0,3	1,55	1,26	19,53	5,86	58,59		0	0,3	1,16	1,5	17,40	5,22	52,20		0	0,3	0,1	1,55	1,55	0,47	4,65			
2019							58,59								52,20								4,65			
54,46							49,52								63,92								65,09			

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14.63559°S, 60.48125°W							14.61118°S, 61.32679°W						16.11921°S, 62.12184°W						Luvisol			
Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	Depth [m]		SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		
0	0,10	14	1,31	18,34	1,83	18,34	0	0,07	13	1,43	18,59	1,30	13,01									
0,10	0,3	9,00	1,31	11,79	2,36	23,58	0,07	0,3	9,00	1,43	12,87	2,96	29,60									
41,92													42,61									
															0	0,11	17	1,43	24,31	2,67	26,74	
															0,11	0,25	8	1,38	11,04	1,55	15,46	
															0,39	0,25	0,3	8,69	1,38	11,99	0,60	6,00
															48,19							
SOC [%w]							SOC [%w]							SOC [%w]								
0	0,3	1,02	1,31	13,36	4,01	40,09	0	0,3	0,94	1,43	13,44	4,03	40,33	0	0,3	0,88	1,38	12,14	3,64	36,43		
40,09							40,33							36,43								
58,28							59,79							68,08								

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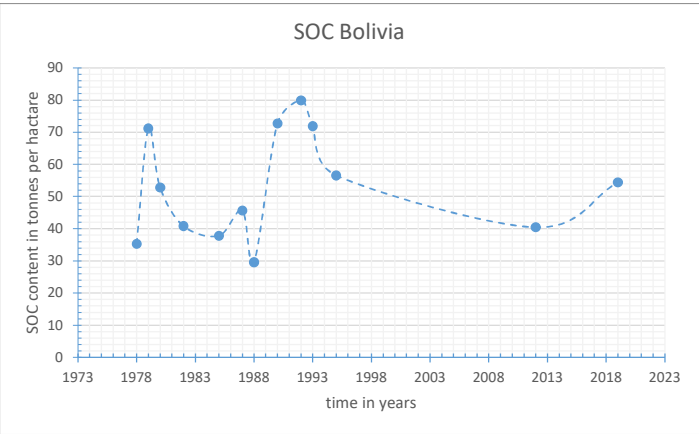
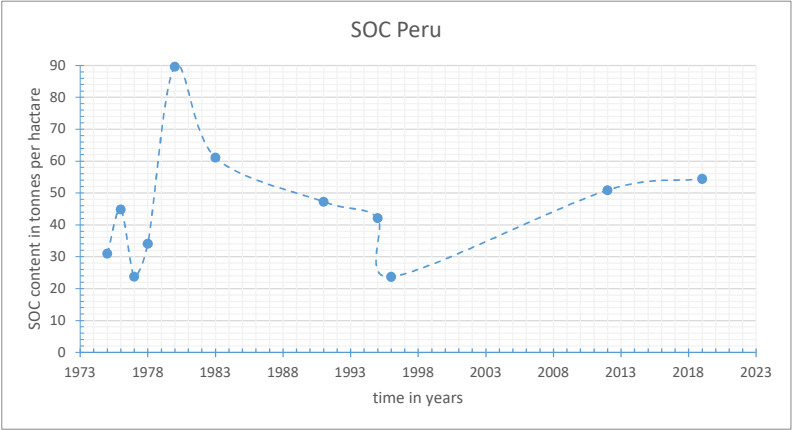
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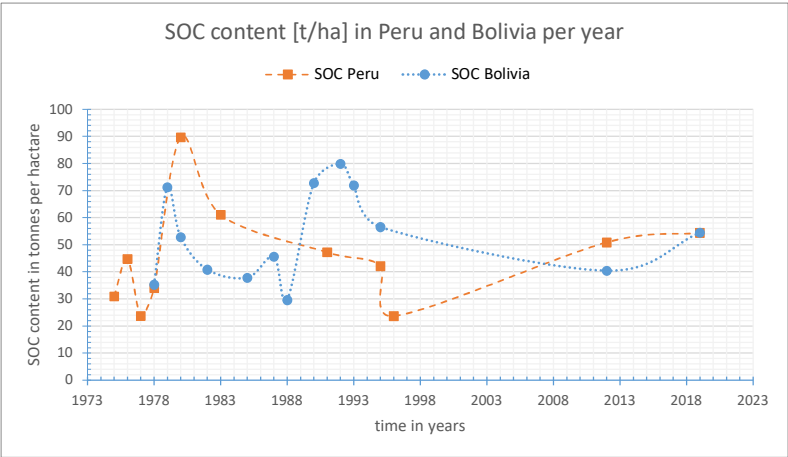
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Peru	
1975	30,98
1976	44,82
1977	23,74
1978	34,08
1980	89,64
1983	61,10
1991	47,24
1995	42,11
1996	23,70
2012	50,87
2019	54,43



Bolivia	
1978	35,3
1979	71,20
1980	52,82
1982	40,82
1985	37,80
1987	45,66
1988	29,60
1990	72,73
1992	79,93
1993	71,90
1995	56,57
2012	40,44
2019	54,46

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

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[illegible]

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[illegible]

[illegible]

[illegible]

[illegible]

Brazil		1.12436°S, 69.07685°W						1.65691°N, 68.87601°W						0.40495°N, 66.19804°W							
	Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]		Depth [m]	SOC [g/kg]	ρ [kg/dm3]	SOC [kg/m3]	SOC [kg/m2]	SOC [t/ha]	
1973																					
28,76																					
1974																					
50,34																					
1975														0,00	0,12	9,7	1,95	18,92	2,27	22,70	
														0,12	0,25	9,1	1,95	17,75	2,31	23,07	
													0,4	0,25	0,30	8,20	1,95	15,99	0,80	8,00	
64,9																				53,76	
1976							0,00	0,065	49,6	1,94	96,22	6,25	62,55	0,00	0,10	10,6	1,95	20,67	2,07	20,67	
						0,325	0,065	0,3	32,29	1,94	62,65	14,72	147,22	0,10	0,30	5,80	1,95	11,31	2,26	22,62	
80,3													209,77							43,29	
1977	0	0,10	24,6	1,26	31,00	3,10	31,00														
	0,10	0,250	16,5	1,26	20,79	3,12	31,19														
0,5	0,250	0,3	14,25	1,26	17,96	0,90	8,98														
105,26							71,16														
1978																					
89,59																					
1980																					
73,67																					
1982																					
65,79																					
1984																					
55,24																					
1986																					
59,56																					
1993																					
118,75																					
2009																					
83,91																					
2012			SOC [%w]						SOC [%w]							SOC [%w]					
	0	0,3	1,36	1,26	17,14	5,14	51,41	0	0,3	0,35	1,94	6,79	2,04	20,37	0	0,3	0,34	1,95	6,63	1,99	19,89
42,98							51,41							20,37						19,89	
2019														20,37							
47,95						56,42						45,52								54,96	

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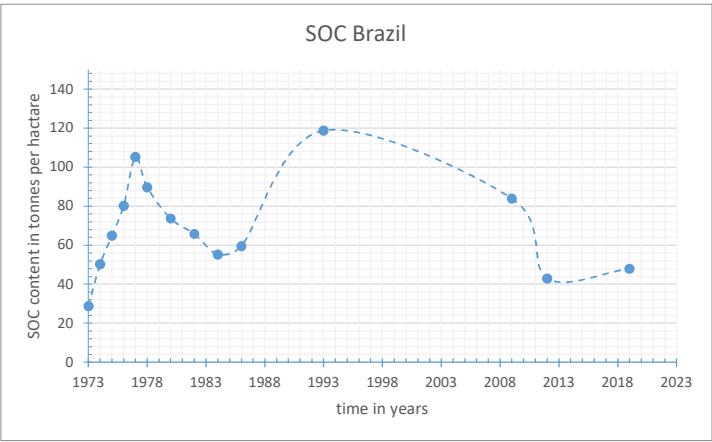
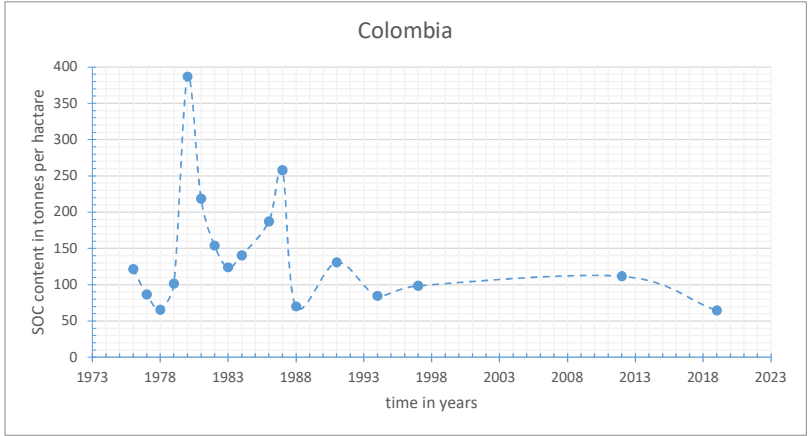
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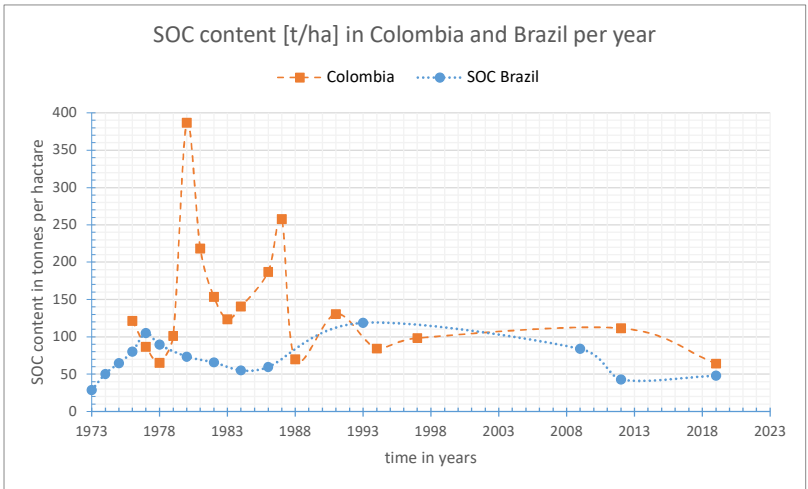
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Colombia	
1976	121,39
1977	86,59
1978	65,27
1979	101,24
1980	386,82
1981	218,51
1982	153,75
1983	123,66
1984	140,47
1986	186,98
1987	257,71
1988	69,89
1991	130,74
1994	84,38
1997	98,34
2012	111,49
2019	64,31



Brazil	
1973	28,76
1974	50,34
1975	64,9
1976	80,3
1977	105,26
1978	89,59
1980	73,67
1982	65,79
1984	55,24
1986	59,56
1993	118,75
2009	83,91
2012	42,98
2019	47,95