



Research article

Soil loss, firm performance, and financing structure: An empirical investigation of Italian agricultural firms[☆]Kevin Pirazzi Maffiola^{a,b,*} , Elena Beccalli^a, Edoardo Puglisi^c, Andrea Fiorini^c ^a School of Banking Finance, and Insurance Sciences, Università Cattolica del Sacro Cuore, Italy^b National Biodiversity Future Center (NBFC), Italy^c Faculty of Agriculture, Food and Environmental Sciences, Università Cattolica del Sacro Cuore, Italy

ARTICLE INFO

JEL classification:

G3

Q5

Keywords:

Agricultural firms

Soil loss

Profitability

Financing

ABSTRACT

Regulators, companies, and financial players are increasingly focusing on adverse climate events and environmental risks. Using a novel integration of high-resolution geospatial and firm-level financial data, this study provides the first empirical evidence on how rainfall-induced soil loss affects the financial performance and capital structure of Italian agricultural firms. We find that unsustainable soil erosion is associated with significantly lower profitability, manifesting as a decrease of 1.20% in Return on Assets (ROA) and 2.10% in Return on Equity (ROE). Unsustainable levels of soil loss also impair the ability to access external financing, as firms located in these areas exhibit lower levels of external bank financing (−2.00%) and (−3.30%) supplier short-term debt and rely more on equity financing (+4.80%). We also find partial support for the view that unsustainable soil loss impairs a firm's credit risk profile, evidenced by a negative relationship with the interest coverage ratio (−4.69). This research is highly relevant to international studies because it offers a concrete financial framework for understanding the economic consequences of environmental degradation. By providing quantifiable data linking soil loss to a firm's financial health, this study can inform policymakers and regulators globally of the hidden risks in agricultural supply chains. The methodology and insights can be applied to other countries facing similar challenges, providing a basis for considering how sustainable land management practices can contribute to mitigating systemic risks and fostering greater resilience in the agricultural sector.

1. Introduction

The rapid increase in environmental depletion and climate change-related events over the past two decades has drawn attention to their economic implications for society and businesses (Oswald and Stern, 2019). Environmental risks have been shown to negatively affect firms' financial performance (Mutascu et al., 2024), increase their default probability (Palomino et al., 2020), and lead to higher financial risks (Dimitriadis et al., 2024), lower revenue levels and more stringent debt-related covenants imposed by lenders (Bernardini et al., 2021; Huang et al., 2022). Agricultural firms are particularly vulnerable to

climate-related risks because they rely on natural resources (Dhifaoui et al., 2023). Decreases in productivity due to environmental degradation can reduce agricultural outputs, which can lead to increased commodity prices, ultimately impacting consumers (Bandara and Cai, 2014).

Soil degradation involves various physical, chemical, and biological processes that reduce the capacity of soil to self-regulate and maintain productivity. The major causes of soil degradation are water erosion, compaction, and salinization. Soil erosion decreases the ability of soil to sustain crop yield levels by reducing soil fertility and impairing its ability to regulate water levels (de Paz et al., 2006), and this is especially

[☆] The authors acknowledge the support of the National Biodiversity Future Center (NBFC) – funded by the European Union NextGenerationEU – to Università Cattolica del Sacro Cuore.

We thank Ettore Croci for his helpful comments. We also thank participants at the FINEST (Financial Intermediation Network of European Studies) 2023: Autumn Workshop and the 6th Transatlantic Conference on the Ethics of Business, Trade, & Global Governance (University of St Andrews) for their suggestions. Any errors or omission remain the authors' own.

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relevant in conjunction with other climate-related risks and environmental stressors (European Commission, 2021). Empirical evidence supports the view that soil health factors negatively impact farmland productivity (Sonderregger and Pfister, 2021) and agricultural yields (de Paz et al., 2006). This study aims to contribute to the debate on how the depletion of natural capital impacts the financial well-being of agricultural firms (Missemmer, 2018), with a specific focus on one major environmental risk: soil degradation.

This study addresses a critical research gap by investigating a central, yet unexamined question: *How do unsustainable levels of rainfall-induced soil loss impact the financial performance, capital structure, and credit risk of agricultural firms?* We move beyond conventional analyses of environmental impacts by providing a rigorous quantification of the financial implications of soil degradation, a concern that is increasingly urgent as the frequency of adverse climate events rises.

We deliver the first large-scale empirical evidence linking a direct, physically measurable environmental metric, soil loss, to the financial condition of large Italian agricultural firms. Our analysis establishes unsustainable soil degradation as a significant and quantifiable financial risk, examining key metrics including profitability (ROA, ROE), revenue volatility, capital structure (external and internal financing), cost of debt, and interest coverage. These findings have critical implications for farmers, regulators, investors, and lenders in identifying and managing latent risks. Furthermore, they underscore the financial relevance of sustainable agricultural practices, suggesting their potential to mitigate environmental risks for private firms (Hughes et al., 2023; Kansanga et al., 2021; Mutoko et al., 2014).

This study substantially advances the credit risk literature (Attig et al., 2013) by providing evidence in support of the view that creditors actively incorporate physical environmental factors into their risk assessments. While extant research has examined the influence of climate (Ginglinger and Moreau, 2023) and transition risks (Ramos-García et al., 2023) on corporate finance, our work is unique in establishing that unsustainable soil loss, a direct measure of physical asset depletion, significantly compromises financial viability. Empirically, we show that firms facing unsustainable soil erosion experience a reduced capacity to secure external financing, which constrains their capital structure decisions.

A core methodological innovation is the integration of firm-level financial data for large, unlisted agricultural companies with high-resolution, national-scale geospatial data on soil loss from the Copernicus Climate Change Service. Finally, our focus on Italy, a major EU agricultural producer (European Commission, 2025), with firms highly reliant on external capital (Beck et al., 2008), ensures the contextual relevance and significance of our empirical insights.

2. Literature review and hypotheses development

The discourse on environmental sustainability, tracing back to the book of von Carlowitz's *Sylvicultura Oeconomica* written in 1713, has evolved to frame ecological degradation as a source of systemic financial risk, as emphasized in foundational reports like the Stern (2006) and the analysis by Stiglitz et al. (2009). This paradigm shift has established the depletion of natural capital, including soil resources, as a critical concern for global economic governance (OECD, 2022). The strategic importance of soil has been recognized through international initiatives, reflecting its role in providing essential ecosystem services that underpin economic systems (Doran and Parkin, 2015; Di Falco and Zoupanidou, 2017). Consequently, combating soil degradation is a stated priority for major regulatory bodies, given its severe documented impacts (Boardman and Poesen, 2006). The translation of this physical erosion into corporate financial risk is a critical research frontier. Among degradation processes, water erosion represents the primary threat (Heuser, 2022), a process intensified by climate volatility (Dabney et al., 2012) and other drivers like wind erosion (Lu et al., 2003). This has prompted targeted policy responses aimed at mitigating soil loss

(European Commission, 2015). The scale is global, with approximately 80% of cultivated land affected (Pimentel, 2006) and productivity impaired on about 40% of it (Bossio et al., 2010). A robust stream of literature links this environmental deterioration directly to diminished agricultural output (Bewket and Sterk, 2002; Kassie et al., 2011) and lower yields (de Paz et al., 2006). This occurs through multiple channels, including reduced crop yields, lower livestock productivity, and increased expenditures on inputs, which collectively depress agricultural incomes (Barbier and Hochard, 2018; Nkonya et al., 2016), creating a direct channel to corporate financial stress. The economic costs are further evidenced by significant annual expenditures to offset lost fertility (Jang et al., 2021). The financial impact is also heterogeneous, with smaller, less diversified firms suffering steeper valuation declines when operating on degraded land (Robeco, University of Cambridge Institute for Sustainability Leadership, 2022). While adopting climate-smart agriculture (Ombati Mogaka et al., 2022) and advanced technologies presents a mitigation pathway, the financial materiality of the risk is clear.

The translation of this physical erosion into corporate financial risk is a critical research frontier. The scale is global, with approximately 80% of cultivated land affected (Pimentel, 2006) and productivity impaired on about 40% of it (Bossio et al., 2010). A robust stream of literature links this environmental deterioration directly to diminished agricultural output (Bewket and Sterk, 2002; Kassie et al., 2011) and lower yields (de Paz et al., 2006), creating a direct channel to corporate financial stress. The economic costs are tangible, evidenced by significant annual expenditures to offset lost fertility (Jang et al., 2021). The financial impact is also heterogeneous, with smaller, less diversified firms suffering steeper valuation declines when operating on degraded land (Robeco, University of Cambridge Institute for Sustainability Leadership, 2022). While adopting climate-smart agriculture (Ombati Mogaka et al., 2022) and advanced technologies presents a mitigation pathway, the financial materiality of the risk is clear. This nexus elevates credit risk across the agricultural value chain. Lenders increasingly perceive environmental factors as material drivers of default risk (Environmental Defense Fund and Deloitte, 2022), highlighting a pressing need to integrate high-resolution environmental data, such as precise soil loss metrics (Panagos et al., 2015), into financial risk models.

Despite this evidence, a precise, firm-level empirical link between quantified unsustainable soil loss and the financial metrics of large agricultural corporations remains underexplored. This study provides that critical link by empirically studying how unsustainable erosion directly impacts firm profitability, shapes financing structures, and adversely affects key debt-related metrics, including the cost of debt and repayment capacity. In doing so, it moves the discourse from establishing a general financial risk to pinpointing its financing implications.

2.1. H1: firm financial performance

Soil loss negatively impacts the ability of soils to retain water and nutrients by depleting physicochemical and biological properties (Niemeijer and Mazzucato, 2002), and this has been found to negatively correlate with the levels of crop yields produced by agricultural firms (European Commission, 2015). These findings make soil erosion a relevant factor affecting crop harvests in the long term (FAO, 2015). Specifically, global evidence suggests that soil loss is directly linked to a 0.5% annual decline in crop production (Adgo et al., 2013; Di Falco and Zoupanidou, 2017). Firms operating in areas with unsustainable soil loss often face increased costs from the need to apply more fertilizer to maintain productivity; however, this does not always restore the soil's full production capacity (Larney et al., 2009). Driven by the lower production capabilities of soil with an unsustainable soil loss rate and the associated higher costs for the fertilization of these lands, we posit that firms located in areas of unsustainable soil loss exhibit lower levels of profitability in terms of ROA and ROE.

H1.1. Unsustainable levels of soil loss are associated with lower ROA for companies involved in agricultural production.

H1.2. Unsustainable levels of soil loss are associated with lower ROE for companies involved in agricultural production.

Climate risks, such as extreme weather events, increase uncertainty around the revenue volatility of firms (Huang et al., 2018), making it increasingly important for financial institutions to assess the threats posed to their operations and loan books by climate-related risks (Breitenstein et al., 2021). Based on this argument, we argue that unsustainable soil loss increases the variability of an agricultural firm's agricultural outputs, leading to an increase in operating income (earnings before interest and taxes or EBIT) volatility.

H1.3. Unsustainable levels of soil loss are associated with higher EBIT volatility for companies involved in agricultural production.

2.2. H2: financing structure

External financing comprises both formal and informal funding sources. Formal financing is funding provided to firms through formal contracts such as loans and bonds (Ayyagari et al., 2010). Formal finance providers, such as banks and financial market players, primarily rely on corporate financial disclosures, such as financial statements, to assess the debt-repayment ability of potential borrowers (Huang et al., 2022). Aligned with the approach of other scholars, we measure formal financing levels as total bank debt as a proportion of total assets (Giannetti, 2003).

Firms may obtain informal credits because of their reputation rather than as the stipulation of a contract, as in the case of formal financing (Allen et al., 2005). Informal financiers, such as trade partners, rely on the relationships and perceptions that they have of their clients; hence, it is arguable that in their trade credit decisions, they may compare their clients on an array of characteristics, and hence soil loss unsustainability can translate into outcomes on which they have visibility. Informal financing has often been proxied by trade credit in the financial literature, which is the approach adopted in this study (Giannetti, 2003).

Severe environmental impacts, such as those arising from climate risks, have led to higher probabilities of default, lower profitability levels, and ultimately more stringent financial covenants on debt (Huang et al., 2022). In the specific case of soil loss, this feature of the soil has been found to negatively affect land productivity (European Commission, 2015). Moreover, the cost structure of agricultural firms located in areas experiencing unsustainable soil loss may be impacted by additional costs derived from attempts to mitigate the impact of soil loss on land productivity, such as soil fertilization (Larney et al., 2009). We hypothesize that unsustainable soil loss locations lead firms to obtain lower external financing as a proportion of formal financing due to their lower financial performance, which affects their credit risk assessment. Additionally, we argue that agricultural firms with lower availability of formal and informal finance from banks and suppliers may adopt conservative investment and dividend distribution choices; hence, we posit that firms located in areas with unsustainable soil loss have a higher proportion of their assets financed through equity.

H2.1. Unsustainable levels of soil loss are associated with lower levels of formal finance (bank loans) for companies involved in agricultural production.

H2.2. Unsustainable levels of soil loss are associated with lower levels of informal finance (trade credit) for companies involved in agricultural production.

H2.3. Unsustainable levels of soil loss are associated with higher levels of equity financing for companies involved in agricultural production.

2.3. H3: cost of debt and interest coverage ratio

The cost of debt is the total rate of return that a firm provides to its creditors and is hence interrelated to the perception of firms' financial well-being by credit providers (Fischer et al., 2019). When evaluating the financial standpoint of debt, the creditor, compared to the debtor, is at an informational disadvantage, since obtaining information related to the debtor can be complex to obtain from multiple sources (Kothari et al., 2010). Despite local financial institutions having insights into their clients' operations, the main source of information related to a firm's creditworthiness can be obtained from its financial statements (Barth et al., 2001). Empirical evidence suggests that lenders have begun to take into consideration additional factors related to firms' non-financial performance. However, obtaining information related to an agricultural firm's biological assets can prove a complex task (Xie et al., 2019).

Empirical evidence suggests that firms that perform better environmentally benefit in terms of bond yields (Apergis et al., 2022) and bank loan interest rates (Goss and Roberts, 2011). Based on the expectation that unsustainable soil loss levels impact the crop-yielding ability of the soil (European Commission, 2015) and attempts to mitigate their lower production abilities by employing fertilizers (Larney et al., 2009), which in turn may lead to lower revenue levels and higher costs, we expect this to be reflected in firms' financial performance, which is part of the credit risk assessment by financial institutions (Palomino et al., 2020). Hence, we posit that firms located in areas with unsustainable soil loss have higher debt costs.

H3. Unsustainable levels of soil loss are associated with higher costs of debt for companies involved in agricultural production

Credit rating agencies have been found to consider sustainability-related aspects when assessing firm credit risk, which can ultimately impact the interest rate levels charged on bank loans (Goss and Roberts, 2011). Empirical findings suggest a negative relationship between default risk and environmental performance. Drago et al. (2019) show an inverse relationship between credit default swaps and environmental ratings. A common measure included in corporate credit risk assessment models is the interest coverage ratio, which is calculated as earnings before interest and taxes divided by the interest payable. Lower levels of interest coverage have been highlighted to render corporations more vulnerable to economic shocks and decrease firms' ability to cover debt-related expenses, increasing their chances of undergoing financial distress (Palomino et al., 2020). Supporting the view that firms with lower environmental risks reduce their credit risk, Attig et al. (2013) find a positive link between environmental performance and interest coverage ratios. Based on the argument that soil loss levels impact the numerator of the interest coverage ratio calculation by reducing revenues due to lower crop yields and increasing the costs associated with techniques to mitigate the impact of soil loss, such as employing fertilizers, we hypothesize that firms in areas of unsustainable soil loss exhibit lower levels of interest coverage ratios.

H3.2. Unsustainable levels of soil loss are associated with lower levels of interest coverage ratio for companies involved in agricultural production.

3. Methodology

3.1. Sample and data sources

We constructed a panel dataset to assess the impact of unsustainable soil loss on the financial performance of Italian agricultural firms. To ensure sample representativeness in terms of land coverage and relevance for credit access, we focused on larger, unlisted agricultural firms. We exclude "smaller-sized farmers" (FI-compass, 2020) and apply a threshold of 10 employees, representing the approximately 1% of Italian firms covering a substantial portion of arable land as just over 1% of

firms in Italy are estimated to have either over 50 ha under management (Lowder et al., 2021; CREA - Research Centre for Agricultural Policies and Bioeconomy, 2022). To isolate the effect of soil reliance, the sample selection is restricted in the AIDA database to specific ATECO¹ sub-classifications: non-perennial crops, perennial crops, plant reproduction, and cultivation related to animal feed. Financial variables and geographical coordinates were sourced from the AIDA database².

The soil loss values were collected from Copernicus Climate Change Service (C3S) Climate Data Store (CDS)³. These time-invariant continuous data points, representing the 1981–2010 average calculated using the RUSLE approach, are available in a matrix at 500-m intervals. The quantification of this environmental challenge has been advanced through established modeling approaches. Soil loss from water erosion is a function of a complex interplay of factors, including “precipitation, soil type, topography, land use, and land management” (Karydas et al., 2014). To systematically account for these variables, the academic and practitioner communities have widely adopted the Universal Soil Loss Equation (USLE) developed by Wischmeier and Dwight (1978) and its subsequent refinement, the Revised Universal Soil Loss Equation (RUSLE) by Renard et al. (1991). The RUSLE model presented in equation (1) is the one employed in this study and integrates key determinants, rainfall erosivity, soil erodibility, and land management practices, to generate robust estimates of average annual soil loss.

Average Annual Soil Loss = Average annual erosivity factor x Soil erodibility x

(Slope length factor x Slope steepness factor) x Land and Cover management x Management System

(1)

For analysis, we created the dummy variable *ThresholdSoilLoss_5*, coded as 1 if the assigned soil loss exceeded 5 tons per hectare per year, reflecting the European Commission's definition of unsustainable soil loss levels (European Commission, 2015). This identifies firms subject to prolonged, severe soil degradation. Finally, to ensure robustness against extreme values, all continuous variables in the empirical models were winsorized at the 1st and 99th percentiles. To integrate this data with firm-level financials, we employed a nearest-neighbor approach, matching the soil loss value to the geographical coordinates of each firm's headquarters (from the AIDA database).

3.2. Propensity score matching

To estimate the causal effect of unsustainable soil loss on firm financial outcomes, we employed a Propensity Score Matching (PSM) methodology. PSM addresses omitted variable bias by matching firms based on observable characteristics, isolating the impact of the exogenous treatment: location in a high soil loss area (*ThresholdSoilLoss_5* = 1). We estimated the Propensity Score (PS), the conditional probability of treatment given covariates, using a probit model. Matching relied on firm characteristics hypothesized to influence both soil loss exposure and financial outcomes, specifically: *FirmSize*, *Leverage*, and *FixedAssetsCoverageRatio*. All covariates were lagged one period to mitigate reverse causality. This procedure creates comparable firm pairs, isolating the effect of soil loss. Given the unbalanced 2013–2022 panel structure, the PSM was implemented for each calendar year to maintain temporal comparability.

¹ The Ateco 2007 classification identifies the sectors of economic activity and have been adopted as per the Regulation (EC) no 1893/2006 and have been adopted since the 1st of January 2008.

² The AIDA database contains the financial information of Italian Firms, is owned by Bureau Van Dijk and is part of the Moody's Corporation.

³ The Copernicus Climate Change Service (C3S) Climate Data Store (CDS) database is available online at: <https://cds.climate.copernicus.eu/#/home>.

The final matched sample for analysis consists of 6,385 firm-year observations (3719 treated, 2666 control), down from an initial 14,362 due to stringent selection and matching criteria. Note that data constraints reduced the sample for the cost of debt (4,517 observations) and EBIT standard deviation (5,978 observations). We assessed matching quality by evaluating the standardized bias across covariates, confirming a substantial reduction, consistent with prior literature (Azam et al., 2016). The procedure led to a substantial reduction in bias across all covariates. For instance, the bias for the *FirmSize* characteristic was reduced by 95.7%, from a pre-matching bias of 9.5% to a post-matching bias of 0.4%, as detailed in Table 1.

3.3. Data regression model

The primary econometric analysis was conducted using a Hausman-Taylor (HT) estimator with standard errors clustered at the firm level. This model was selected to address the central methodological challenge posed by our key independent variable, *ThresholdSoilLoss_5*, which is time-invariant. A standard fixed-effects model would eliminate this variable through its within transformation, making its effect unobservable. Conversely, a random-effects model relies on the potentially untenable assumption that the unobserved firm-level effects are uncorrelated with the regressors. The HT model provides a solution by allowing for correlation between some of the regressors and the unobserved individual effects, while efficiently estimating the coefficients of time-invariant variables by instrumenting them with the group means of the time-varying exogenous variables.

The empirical specification is outlined in two sets of equations. The first set, Equation (2), models the effect on firm performance and risk profiles. The second set, Equation (3), models the effect on financing structures.

$$Y1_{i,t} = \beta_0 + \beta_1 \text{ThresholdSoilLoss}_5_{i,t} + \beta_2 \text{FirmSize}_{i,t} + \beta_3 \text{Leverage}_{i,t} + \beta_4 \text{FixedAssetsCoverageRatio}_{i,t} + \beta_5 \text{RevenueGrowth}_{i,t} + \beta_6 \text{GDPVariation}_{i,t} + \varepsilon_{i,t} \quad (2)$$

where the dependent variable $Y1_{i,t}$ represents, in separate estimations, the following firm outcomes for firm i in year t : profitability measured by Return on Assets (ROA) and Return on Equity (ROE); operational risk measured by the standard deviation of EBIT ($EBITsd$); the cost of debt; and the interest coverage ratio.

$$Y2_{i,t} = \beta_0 + \beta_1 \text{ThresholdSoilLoss}_5_{i,t} + \beta_2 \text{FirmSize}_{i,t} + \beta_3 \text{FixedAssetsCoverageRatio}_{i,t} + \beta_4 \text{RevenueGrowth}_{i,t} + \beta_5 \text{GDPVariation}_{i,t} + \varepsilon_{i,t} \quad (3)$$

where the dependent variable $Y2_{i,t}$ represents, in separate estimations, the following aspects of the financing structure for firm i in year t : *FormalFinancingRatio* (total bank loans divided by total assets); *InormalFinancingRatio* (short-term supplier credit divided by total assets), following Giannetti (2003) and the proportion of assets financed by equity (*EquityFinancingRatio*). Moreover, this is the equation employed to test hypotheses related to credit risk, and the $Y2_{i,t}$ represents the percentage interest paid on debt (*CostOfDebt*) and the interest coverage ratio (*IntCovRatio*).

In both equations, *FirmSize*, *FixedAssetsCoverageRatio*, and *RevenueGrowth* are treated as endogenous time-varying variables. The variable *Leverage* (total debt/total assets) is included in Equation (2) but omitted from Equation (3) as the dependent variables in the latter are direct components of the firm's capital structure. The annual variation of Italy's Gross Domestic Product (*GDPVariation*), sourced from the World Bank (2023), is included as an exogenous time-varying control variable to account for macroeconomic fluctuations. The term $\varepsilon_{i,t}$ represents the unobserved time-invariant firm-level effect and the idiosyncratic error term, respectively. The *ThresholdSoilLoss_5* variable and the GDP growth

Table 1
Bias reduction before and after the PSM procedure.

Variable	Unmatched Matched	Mean		%bias	% reduction bias	t-test		V(T)/V(C)
		Treated	Control			t-value	p-value (t-test)	
FirmSize	U	14.997	14.839	9.5		4.09	0.000	1.02
	M	14.997	15.004	-0.4	95.7	-0.19	0.847	1.03
Leverage	U	13.632	14.659	-3.0		-1.27	0.204	1.08*
	M	13.632	13.735	-0.3	90.0	-0.14	0.885	1.27*
FixedAssetsCoverageRatio	U	20.167	19.407	3.1		1.33	0.182	1.06
	M	20.167	19.647	2.1	31.5	1.00	0.319	1.04

Notes: In this table, the bias reduction obtained in terms of characteristics of the treated and untreated samples by employing the propensity score matching methodology with one nearest neighbor is presented.

variable are specified as exogenous.

We also estimated the Average Treatment effect on the Treated (ATT) using the matched sample (Y. Zhang et al., 2022). To validate our results, we conducted several robustness checks. First, we re-estimated the Hausman-Taylor models using an alternative matched sample based on a three-nearest neighbor PSM to account for multiple close matches for treated firms (Ming and Rosenbaum, 2001). Finally, we recomputed the ATT using three alternative PSM algorithms: three-nearest neighbor, kernel, and radius matching with a 0.05 caliper (Y.-J. Zhang and Liu, 2019).

3.4. Descriptive statistics

This descriptive statistics summary for all the variables employed in this study is presented in Table 2. The agricultural firms exhibit a mean

Table 2
Variables description.

Variable	Source	Description
CostOfDebt	AIDA	Total interests paid in the year divided by the short and long-term bank debt)
EBIT	AIDA	Earnings before interest taxes depreciation and amortization.
EBITsd	AIDA	Standard deviation of the EBIT (operating income) calculated with the 3 latest yearly values from the reference year. This value is presented in monetary terms, namely Euro.
EquityFinancingRatio	AIDA	Total equity divided by total assets
FirmSize	AIDA	Natural logarithm of the firm total assets
FixedAssetsCoverageRatio	AIDA	(Equity + Long-term Debt)/Fixed Assets
FormalFinancingRatio	AIDA	Formal finance (short and long terms bank debt financing) divided by total assets
GDPVariation	OECD	Year-on-year Italian GDP growth or decline
InformalFinancingRatio	AIDA	Short-term account payable to suppliers divided by total assets
IntCovRatio	AIDA	EBIT plus depreciation and amortization divided by financial charges
Leverage	AIDA	Total debt divided by total equity
LiquidityRatio	AIDA	Cash and cash equivalents divided by short-term debt
RevenueGrowth	AIDA	Year-on-year revenue growth
ROA	AIDA	Return on assets
ROE	AIDA	Return on equity
ThresholdSoilLoss_5	Copernicus database	Dummy variable taking the value of 1 if the soil loss value is from the Copernicus database for a firm headquarter location if higher than 5, otherwise, the value is zero

ROA of 0.027 and a mean ROE of 0.051. The average EBIT is reported as approximately 190,460.60. Regarding financing, the firms show a slight preference for Informal Financing Ratio (mean 0.19) compared to the Formal Financing Ratio (mean 0.16), alongside a significant mean Equity Financing Ratio of 0.37.

Table 3 presents the geographical distribution of the sample in terms of regions, where Tuscany accounts for 16.62% of the firm-year observations, Sicily for 12.08%, and Campania for 11.75%, and other regions account for less than 10% of the observations. In terms of economic activity, the sample is located 48.2% in the production of perennial crops, 47.9% in non-perennial crops, 5.3% in cultivation related to animal feed, and 4.6% in plant reproduction.

Table 4 presents the descriptive statistics, and Table 5 presents the pairwise correlation of the variables employed in this study.

4. Empirical results

4.1. Baseline results

The Hausman-Taylor model results for ROA and ROE are summarized in Models (1) and (2) in Table 6 and support H1.1. and H1.2, revealing a negative relationship between unsustainable soil loss and profitability (ROA, ROE). Specifically, firms located in areas with unsustainable soil loss exhibit a 1.30% lower ROA (p-value: 0.001) and a 2.10% lower ROE (p-value: 0.079) than their counterparts in sustainable soil areas. These results contribute to expanding the literature on the reduced productivity of soils affected by water precipitation-related soil loss (Sonderegger and Pfister, 2021) by confirming that this has

Table 3
Geographical distribution of the sample.

Region	Observations	Percentage
Toscana	1,061	16.62%
Sicilia	771	12.08%
Campania	750	11.75%
Puglia	590	9.24%
Lazio	553	8.66%
Lombardia	357	5.59%
Emilia-Romagna	350	5.48%
Veneto	322	5.04%
Calabria	289	4.53%
tino Alto Adige	248	3.88%
Marche	189	2.96%
Umbria	189	2.96%
Piemonte	166	2.60%
Abruzzo	131	2.05%
Venezia Giulia	131	2.05%
Sardegna	102	1.60%
Basilicata	83	1.30%
Liguria	60	0.94%
Molise	36	0.56%
Valle d'Aosta	7	0.11%
Total	6,385	100.00%

Table 4
Variables summary statistics.

Variable	Observations	Mean	Std. Dev.	Min.	Max.
ROA	6,385	0.027	0.077	-0.237	0.4812
ROE	6,385	0.051	0.243	-10.476	0.966
EBIT	6,385	190,460.600	1,422,567.000	-16,200,000.000	33,400,000.000
EBITsd	5,978	140,314.10	272,899.600	110.309.000	2,782,954.000
FormalFinancingRatio	6,385	0.162	0.170	0.000	0.701
InformalFinancingRatio	6,385	0.187	0.202	0.000	0.877
EquityFinancingRatio	6,385	0.373	0.258	0.007	0.992
CostOfDebt	4,517	0.041	0.034	0.000	0.182
IntCovRatio	4,861	28.52	53.636	0.170	358.210
Thresholdsoilloss_5	6,385	0.582	0.493	0.000	1.000
Leverage	6,385	1.340	2.759	0.000	20.310
FirmSize	6,385	15.054	1.532	9.554	18.901
FixedAssetsCoverageRatio	6,385	1.973	2.375	0.000	13.190
RevenueGrowth	6,385	0.258	1.291	-1.000	188.108
GDPVariation	6,385	0.009	0.038	-0.076	0.073

Notes: The variables presented in this table related to firms' characteristics presented in this table are winsorized at a the 99th at 1st percentile.

financial implications for agricultural firms relying on soil for their production that could be driven by lower productivity (Adgo et al., 2013; Di Falco and Zoupanidou, 2017) or increased costs due to the employments of materials such as fertilizers to temporarily restore soil productivity (Larney et al., 2009).

Contrary to our predictions in H.1.3. Model (3) in Table 6, firms in unsustainable soil loss areas exhibit EBIT volatility that is lower by Euro 21,096.73 (p-value: 0.055) than the one of firms located in sustainable soil loss areas. This unexpected finding suggests that operating income volatility is not higher for these firms, which may be a result of the lower growth opportunities in these environmentally degraded areas, leading to a more stable, albeit lower, income stream (Huang et al., 2018).

Our Hausman-Taylor model results for the financing structure, detailed in Table 7, support H2.1, H2.2, and H2.3. The findings indicate that firms in areas with unsustainable soil loss experience significant shifts in their financing. In model (1) in Table 7, we found a decrease of -2.00% (p-value: 0.000) in terms of external formal financing. In model (2) we find a -3.30% (p-value: 0.001) in informal external financing, while equity financing related results are presented in Table 7 Model (3) and show an increase by 4.80% (p-value: 0.000). These results suggest that lenders and suppliers indirectly incorporate environmental risk into their credit decisions, as their lending choices are influenced by firm-level financial metrics (Giannetti, 2003) that reflect poor soil health. These findings are also consistent with the view that firms with lower credit availability and financial performance tend to rely more on internal funding and family loans (Bosch and Schoenmaker, 2021).

As shown in Model (1) in Table 8, we found no statistical significance for the cost of debt variable, with a coefficient of 0.20% (p-value: 0.409), failing to support H3.1. This may reflect the capital structure fundamentals of firms located in these areas, which may rely on equity financing due to the additional costs of taking on more credit (Bosch and Schoenmaker, 2021). However, our the results of model (2) Table 8 show a weakly statistically significant support for H3.2, as unsustainable soil loss is negatively related to the interest coverage ratio, with a coefficient of -4.685 (p-value: 0.069 This suggests that soil loss weakens a firm's credit risk profile, as lower interest coverage is a known indicator of financial distress and higher default probabilities (Kupets, 2016; Palomino et al., 2020).

To ensure the consistency of our models, we performed tests for overidentified restrictions. The Hausman-Taylor models presented in Table 6, Tables 7, and Table 8 were found to be consistent, with all models showing a test value above 10% (Kupets, 2016), except for the one with ROA as the dependent variable, which presented a value of 8.30%. The mean VIF statistics for all models ranged from 1.80 to 2.11, well below the generally accepted threshold of 5, indicating no significant multicollinearity.

The Average Treatment effect on the Treated (ATT) statistics on the

matched sample constructed with our PSM methodology provide additional support for our core hypotheses. As detailed in Table 9, the ATT results confirm a negative relationship between unsustainable soil loss with profitability (ROA, ROE) and a decrease in both formal and informal financing. Conversely, we find a positive relationship with equity financing. However, the findings for the interest coverage ratio are not statistically significant when considering the ATT statistic, which leads to only partial support of this hypothesis. Finally, the corresponding *t*-test findings are presented in Table 10, and an overall quick glance at all our baseline results is provided in Table 11.

4.2. Robustness and additional analyses

For robustness, we extended our sample size to 9264 observations, up from 6385 in the base case, using a Hausman-Taylor model on a sample matched with the three-nearest-neighbor PSM methodology. The findings from these models, presented in Appendix 1, confirm the direction and significance of our main relationships. However, we find a non-statistically significant relationship with EBIT volatility.

In Appendix 2, additional robustness tests using ATT statistics on the matched sample, with various methods including three nearest neighbors, kernel, and radius (0.05 caliper), are presented, and provide further confirmatory evidence for our profitability and financing structure hypotheses. These tests also highlight non-statistically significant results for operating income volatility, the cost of debt, and the interest coverage ratio. Finally, a preliminary sub-industry analysis, based on our baseline one-nearest-neighbor matching, confirms that our findings are generally consistent across different types of crop cultivation, where the bulk of our observations are concentrated.

A sub-industry analysis, presented in Appendix 3, provides preliminary evidence based on the baseline one-nearest-neighbor matching approach. We find that the relationships between soil loss and financial metrics are generally consistent with our overall findings, particularly for firms involved in the cultivation of perennial and non-perennial crops, where most of our sample is concentrated. This suggests that the financial impacts of soil degradation are broadly felt across key agricultural sectors, confirming the validity of our findings also for the main sub-samples.

Finally, to validate the robustness of our soil loss measure and ensure our primary findings are not confounded by contemporaneous environmental shocks, we conduct a placebo Difference-in-Differences (DID) analysis. We exploit the introduction of Regional Law L.R. 24/2017 in Emilia-Romagna, enacted in response to a severe drought in 2017. This drought is critical as it degraded soil health by breaking down soil aggregates, thereby increasing erosion susceptibility. Our design compares firms in Emilia-Romagna (the treated group) with those in Veneto (the control group), which was similarly affected by the drought but did not

Table 5
Pairwise correlation table of variables.

	ROA	ROE	EBITsd	Formal Financing Ratio	Informal Financing Ratio	Equity Financing Ratio	CostOf Debt	IntCov Ratio	Threshold soilloss_5	Leverage	FirmSize	Fixed Assets Coverage Ratio	Revenue Growth	GDP Variation
ROA	1.000													
ROE	0.714*	1.000												
EBITsd	0.088*	0.029*	1.000											
FormalFinancingRatio	-0.039*	-0.049*	-0.034*	1.000										
InFormalFinancingRatio	0.075*	0.209*	-0.169*	-0.150*	1.000									
EquityFinancingRatio	0.072*	-0.031*	0.239*	-0.299*	-0.491*	1.000								
CostOfDebt	0.055*	-0.004	-0.075*	-0.246*	0.127*	-0.071*	1.000							
IntCovRatio	0.305*	0.239*	0.051*	-0.347*	0.066*	0.201*	-0.169*	1.000						
Thresholdsoilloss_5	-0.079*	-0.056*	0.018	-0.020	-0.072*	0.067*	-0.020	-0.007	1.000					
Leverage	-0.064*	-0.023*	-0.098*	0.472*	0.099*	-0.433*	-0.039*	-0.180*	-0.019	1.000				
FirmSize	-0.164*	-0.151*	0.459*	0.209*	-0.229*	0.230*	-0.195*	-0.125*	0.047*	-0.025*	1.000			
FixedAssetsCoverageRatio	-0.165*	-0.154*	-0.084*	0.276*	-0.011	-0.465*	-0.036*	-0.128*	0.015	0.517*	0.045*	1.000		
RevenueGrowth	0.109*	0.149*	-0.011	-0.042*	0.043*	-0.020	-0.028	0.043*	0.000	0.023	-0.080*	0.008	1.000	
GDPVariation	-0.021	-0.029*	-0.019	0.004	0.020	-0.015	0.061*	-0.016	-0.001	-0.004	-0.017	0.003	-0.050*	1.000

Notes: p < 0.05.

Table 6
Output of Hausman Taylor Model with firm performance variables as the dependent variable.

	ROA	ROE	EBITsd
	(1)	(2)	(3)
ThresholdSoilLoss_5	-0.013*** (0.001)	-0.021* (0.079)	-21,090.770* (0.055)
FirmSize	-0.005 (0.365)	-0.029 (0.948)	109,777.50*** (0.000)
Leverage	-0.001** (0.020)	0.000 (0.754)	-2317.310 (0.250)
FixedAssetsCoverageRatio	-0.004*** (0.000)	-0.022*** (0.000)	-9317.380*** (0.001)
RevenueGrowth	0.007*** (0.000)	0.022*** (0.000)	791.340 (0.701)
GDPVariation	-0.043** (0.014)	-0.166*** (0.001)	-0.006 (0.526)
Constant	0.113 (0.137)	0.545** (0.014)	-156253.80** (0.018)
Number of observations	6,385	6,385	5,978
Test Overidentifying Restrictions	0.083	0.316	0.148
Mean VIF	1.96	1.96	1.97

Notes: Statistical significance of mean differences at 0.01, 0.05, and 0.10 are indicated respectively with ***, **, and *. The test of overidentifying restriction is passed with a p-value >0.05 in the Stata specification. The variables presented in this table are winsorized at a 0.99 level for both dependent and independent variables. In the HT model the *ThresholdSoilLoss_5* is the time invariant constant, *GDPVariation* is the Exogenous time variant, variable, while the firm level control variables are considered as endogenous time variant variables.

implement a comparable policy. This allows us to isolate the effect of the policy intervention in a context of shared environmental stress. The results, presented in [Appendix 4](#), show a highly significant and negative Triple DID coefficient (-0.051, p < 0.01). This confirms that our soil loss metric successfully identifies a distinct, ecologically vulnerable subgroup of firms that respond heterogeneously to both environmental shocks. The test thus verifies that the interaction between policy shocks and pre-existing soil vulnerability is a reliable driver of differential financial outcomes.

5. Discussion

This study provides the first empirical evidence that soil loss, a critical environmental degradation process, has a quantifiable and

Table 7
Output of Hausman Taylor Model with financing structure measures as the dependent variable.

	FormalFinancingRatio	InFormalFinancingRatio	EquityFinancingRatio
	(1)	(2)	(3)
ThresholdSoilLoss_5	-0.020*** (0.020)	-0.033*** (0.001)	0.048*** (0.000)
ROA	-0.110*** (0.000)	-0.064** (0.040)	0.194*** (0.000)
FirmSize	0.042*** (0.000)	-0.014 (0.140)	0.010 (0.330)
FixedAssetsCoverageRatio	0.010*** (0.000)	0.000 (0.941)	-0.038*** (0.000)
RevenueGrowth	-0.001 (0.488)	0.006*** (0.000)	0.002 (0.388)
GDPVariation	0.010 (0.612)	0.036 (0.094) *	-0.033 (0.223)
Constant	-0.467*** (0.000)	0.420*** (0.004)	0.250* (0.092)
Number of observations	6,385	6,385	6,385
Test Overidentifying Restrictions	0.987	0.291	0.129
Mean VIF	1.80	1.80	1.80

Notes: Statistical significance of mean differences at 0.01, 0.05, and 0.10 are indicated respectively with ***, **, and *. The test of overidentifying restriction is passed with a p-value >0.05 in the Stata specification. The variables presented in this table are winsorized at a 0.99 level for both dependent and independent variables. In the HT Taylor model the *ThresholdSoilLoss_5* is the time invariant constant, *GDPVariation* is the Exogenous time variant, variable, while the firm level control variables are considered as endogenous time variant variables.

Table 8
Output of the Hausman-Taylor Model with the cost of debt measure and interest coverage ratio as the dependent variables.

	CostOfdebt	IntCovRatio
	(1)	(2)
ThresholdSoilLoss_5	0.002 (0.409)	-4.685* (0.069)
FirmSize	-1.88*** (0.000)	4.010 (0.226)
Leverage	-0.076** (0.036)	-2.387*** (0.000)
FixedAssetsCoverageRatio	-0.003 (0.962)	0.574 (0.492)
RevenueGrowth	0.000*** (0.001)	1.635* (0.078)
GDPVariation	-0.003 (0.760)	-4.685* (0.069)
Constant	32.782*** (0.000)	-22.707 (0.641)
Number of observations	4,517	4,861
Test Overidentifying Restrictions	0.113	0.365
Mean VIF	2.11	1.99

Notes: Statistical significance of mean differences at 0.01, 0.05, and 0.10 are indicated respectively with ***, **, and *. The test of overidentifying restriction is passed with a p-value >0.05 in the Stata specification. The variables presented in this table are winsorized at a 0.99 level for both dependent and independent variables. In the HT model, the *ThresholdSoilLoss_5* is the time invariant constant, *GDPVariation* is the Exogenous time variant, variable, while the firm level control variables are considered as endogenous time variant variables.

Table 9
Output of ATT Statistics for the full sample.

	Coeff	Robust SE.	p-value
ROA	-1.160***	0.193	0.000
ROE	-2.649***	0.568	0.145
EBITsd	-9,229.32	10,545.45	0.407
FormalFinancingRatio	-0.827*	0.396	0.067
InformalFinancingRatio	-2.481***	0.422	0.000
EquityFinancingRatio	3.164***	0.596	0.000
CostOfDebt	-0.071	0.085	0.429
IntCovRatio	-0.999	-0.50	0.628

Notes: Statistical significance at 0.01, 0.05, and 0.10 are indicated respectively with ***, **, and *. The variables presented in this table are winsorized at a 0.99 level.

Table 10
Output of T-Test statistics for the full sample.

Variable	Mean 0	Mean 1	Mean 0 – Mean 1	t-value	p-value
ROA	0.035	0.022	0.013***	6.916	0.000
ROE	0.072	0.042	0.030***	4.903	0.000
EBITsd	133,989.80	143,915.70	-9,925.94	-1.40	0.16
FormalFinancingRatio	0.016	0.0156	0.007*	1.731	0.083
InformalFinancingRatio	0.021	0.017	0.030***	6.280	0.000
EquityFinancingRatio	0.035	0.038	-0.035***	-5.823	0.000
CostOfDebt	0.043	0.042	0.001	1.454	0.146
IntCovRatio	0.029	0.029	0.007	0.544	0.587

Notes: Statistical significance at 0.01, 0.05, and 0.10 are indicated, respectively with ***, **, and *. The variables presented in this table are winsorized at a 0.99 level.

Table 11
Summary of the baseline results for the overall sample.

		Results HT-Model	Coeff.	Results ATT	Coeff.	Results T-test (Mean 0 – Mean 1)	Coeff.
H1.1.	Unsustainable levels of soil loss are associated with lower ROA for companies involved in agricultural production	Supported	-0.013***	Supported	-1.160***	Supported	0.013***
H1.2.	Unsustainable levels of soil loss are associated with lower ROE for companies involved in agricultural production	Supported	-0.021*	Supported	-2.649***	Supported	0.030***
H1.3.	Unsustainable levels of soil loss are associated with higher EBIT volatility for companies involved in agricultural production	Not supported	-21,090.77*	Not statistically sign.	-9,292.32	Not statistically sign.	-9,925.95
H2.1.	Unsustainable levels of soil loss are associated with lower levels of formal finance (bank long and short term) for companies involved in agricultural production	Supported	-0.020***	Supported	-0.827*	Supported	0.007*
H2.2.	Unsustainable levels of soil loss are associated with lower levels informal finance (suppliers' short term) for companies involved in agricultural production	Supported	-0.033***	Supported	-2.481***	Supported	0.030***
H2.3.	Unsustainable levels of soil loss are associated with higher levels of equity financing for companies involved in agricultural production	Supported	0.048***	Supported	3.164***	Supported	-0.035***
H3.1.	Unsustainable levels of soil loss are associated with higher levels of costs of debt for companies involved in agricultural production	Not statistically sign.	0.002	Not statistically sign.	-0.071	Not statistically sign.	0.001
H3.2.	Unsustainable levels of soil loss are associated with lower levels of interest coverage ratio for companies involved in agricultural production	Supported	-4.685*	Not statistically sign	-0.999	Not statistically sign.	0.544

Notes: Statistical significance at 0.01, 0.05, and 0.10 are indicated respectively with ***, **, and *. The results presented in this table are related to the sample, with the variables related to the firm characteristics winsorized at the 0.99 level.

material impact on the financial health of agricultural firms. The findings that unsustainable soil loss is associated with significant declines in financial performance (ROA, ROE) and impaired access to external financing directly align with and extend the growing body of literature on physical climate risk in corporate finance. Our results support the view that such risks are no longer distant externalities but are actively being priced by financial markets, as demonstrated by recent studies on the impact of extreme weather events on asset valuation (MSCI, 2025) and empirical evidence directly linking soil degradation to financial vulnerability within the agricultural value chain.

The observed reliance on more expensive equity financing and the negative relationship with the interest coverage ratio highlight that lenders and suppliers are already incorporating physical environmental risks into their lending and credit decisions. This aligns with the seminal speech by Carney (2015), demonstrating that physical risks, such as extreme weather events causing soil erosion, are a present, not future, threat to financial stability. This is further supported by research showing that corporate environmental responsibility can reduce

information asymmetry and influence a firm's capital structure and financing choices (D. Zhang, 2024), as well as by studies confirming the significant implications incurred by farmers due to land degradation (Adgo et al., 2013; Di Falco and Zoupanidou, 2017).

The policy implications are clear and urgent. Our findings offer a compelling financial motivation for policymakers to promote sustainable land management practices. Regulators can use this evidence to inform new frameworks, such as the EU's Corporate Sustainability Reporting Directive (CSRD), by requiring lenders to measure nature-related risks like soil health in specific and material instances. Furthermore, our methodology can be applied internationally to other agricultural regions, providing a global basis for developing policies that incentivize land stewardship and foster greater resilience in food supply chains. This research underscores that environmental management is not just an ethical imperative but a fundamental component of economic and financial stability, with its importance increasingly recognized by financial regulators (Xu and Kim, 2022).

6. Conclusion

The findings of this study carry significant implications for financial institutions, agricultural firms, and policymakers. For financial institutions increasingly focused on environmental risks, integrating soil health metrics into credit risk models and loan underwriting is critical, as our results demonstrate a direct link between soil degradation and borrower profitability and capital structure.

Specifically, we found that firms operating in areas with unsustainable soil loss experienced:

- A decrease of -1.20% in their ROA and -2.10% in their ROE
- Reduced ability to secure external financing, with a -2.00% decrease in bank financing and a -3.30% drop in supplier short-term debt. This pattern reflects both a contraction in credit availability and the adaptive resilience of agricultural businesses., which results in an increased reliance on equity financing ($+4.80\%$).
- A potential impairment of the firm's credit risk profile, evidenced by a negative relationship with the interest coverage ratio (-4.685).

This direct, quantifiable link between environmental health and corporate profitability and credit access is the study's central contribution, underscoring the hidden, systemic risks embedded within agricultural supply chains that are often overlooked by regulators and financial markets. The combination of data employed linking both financial and geospatial data to large Italian agricultural firms employed in this study provides a concrete framework for policymakers, regulators, and financial institutions to transition to rigorous, data-driven understanding of the economic repercussions of environmental degradation. These results offer a crucial foundation for international studies, as the methodology can be applied to other countries facing similar challenges. Ultimately, our study reinforces that addressing soil health is not just an environmental imperative but a fundamental component of ensuring the long-term financial viability and resilience of the agricultural sector worldwide.

6.1. Implications for practice

The findings of this study have significant implications for financial institutions, agricultural firms, and policymakers. Financial institutions, which are increasingly concerned with environmental and climate-related risks, may benefit from incorporating soil health as a critical metric in their risk assessment and loan underwriting processes, as it directly impacts the financial performance and capital structure decisions of agricultural firms. This is particularly relevant in regions where soil degradation negatively influences profitability, as shown by the lower ROA and ROE of firms facing unsustainable soil loss. The results also point to an important shift in financing patterns: firms in these areas experience reduced access to both formal (bank loans) and informal (supplier credit) financing while relying more on equity financing and family loans (Bosch and Schoenmaker, 2021). This reflects both a reduction in credit availability and the resilience of businesses to adapt to such challenges.

This study underscores the critical need to preserve natural capital, specifically soil health, to ensure long-term agricultural sustainability. It demonstrates that climate change-induced degradation has a material impact that extends to the value of the underlying land assets

(Mendelsohn et al., 1994). For firms and farm managers, the adoption of sustainable land management practices (Renard et al., 1991) and the employment of advanced technologies such as nanostructures (Zinatloo-Ajabshir et al., 2019) are relevant for mitigating soil erosion and therefore improving business resilience. Promoting sustainable practices through targeted financial incentives and accessible training programs (Kansanga et al., 2021; Mutoko et al., 2014) can support farmers in managing soil health more effectively. Policymakers should consider the implementation of policies that link agricultural subsidies or financing programs to the adoption of these practices (Burton, 2014; Salaisook et al., 2020) to ensure the long-term viability of agricultural production systems, particularly in regions prone to soil loss (Salaisook et al., 2020).

6.2. Limitations and future research avenues

We acknowledge the use of a time-invariant, 30-year average for soil loss data (1981–2010) as a limitation, given that land management and climate have evolved. However, this dataset serves as a robust proxy for a region's long-term susceptibility to erosion, allowing our study to isolate the financial impact of a firm's location in an area with high inherent environmental risk. This approach highlights a fundamental link between a region's long-term environmental vulnerability and the financial health of its businesses. By utilizing more dynamic soil degradation data as it becomes available, future studies can provide a more granular view of how changing environmental conditions and new land management practices, also driven by recent policies, are influencing the financial performance of agricultural firms over time.

Future research should build on this foundation by exploring how the evolving regulatory landscape, such as the European Green Deal with its targets to reduce pesticide and fertilizer use, will reshape farming practices and their financial impacts (Kurniawati et al., 2023). Similarly, a deeper inquiry into the long-term financial viability and environmental trade-offs of using chemical compounds for soil restoration, as noted in previous studies, would be highly beneficial (Burton, 2014; Salaisook et al., 2020). By focusing on how these broader trends and interventions affect financial outcomes, future research can offer a more detailed understanding of the complex interplay between environmental policy, land management, and financial resilience in the agricultural sector.

CRediT authorship contribution statement

Kevin Pirazzi Maffiola: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Elena Beccalli:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Formal analysis. **Edoardo Puglisi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization. **Andrea Fiorini:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Robustness Tests – Hausman-Taylor Model employing the PSM with three nearest-neighbors

	ROA	ROE	EBITsd	FormalFinance Ratio	InformalFinance Ratio	EquityFinancingRatio	CostOfDebt	IntCovRatio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ThresholdSoilLoss_5	-0.012*** (0.002)	-0.022 * (0.064)	-14,050.140 (0.169)	-0.022*** (0.009)	-0.038*** (0.000)	0.061*** (0.000)	0.003 (0.107)	-4.172* (0.085)
FirmSize	-0.000** (0.012)	-0.036*** (0.002)	81,872.520*** (0.000)	0.042*** (0.000)	-0.014** (0.048)	0.008 (0.380)	-0.018*** (0.000)	-0.938 (0.708)
Leverage	-0.001** (0.047)	-0.002 (0.548)	-2884.958** (0.047)					
ROA				-0.096*** (0.000)	-0.079*** (0.001)	0.223*** (0.000)	-0.002*** (0.001)	-1.619*** (0.001)
FixedAssetsCoverageRatio	-0.005*** (0.000)	-0.023*** (0.000)	-9,016.36*** (0.000)	0.010*** (0.000)	0.000 (0.891)	-0.035*** (0.000)	0.000 (0.443)	-0.789 (0.267)
RevenueGrowth	0.007*** (0.000)	0.024*** (0.000)	-235.445 (0.887)	0.000*** (0.744)	0.005*** (0.000)	-0.001 (0.268)	0.000 (0.529)	1.885** (0.011)
GDPVariation	-0.037*** (0.009)	-0.114*** (0.008)	-133,030.400*** (0.005)	0.007 (0.687)	0.013 (0.475)	-0.026 (0.211)	0.001 (0.845)	-2.203 (0.854)
Constant	0.192*** (0.001)	0.644*** (0.000)	-1,057,650*** (0.000)	-0.466*** (0.000)	0.423*** (0.000)	0.266** (0.031)	0.310*** (0.000)	52.639 (0.149)
Number of observations	9,264	9,264	8,664	9,264	9,264	9,264	6,517	7,135
Test Overidentifying restrictions	0.215	0.975	0.630	0.565	0.432	0.026 (<0.05)	0.000 (<0.05)	0.471
Mean VIF	1.69	1.69	1.71	1.57	1.57	1.57	1.84	1.74

Notes: Statistical significance at 0.01, 0.05, and 0.10 is indicated respectively with ***, **, and *. The results presented in this table are related to the sample, with the variables related to the firm characteristics winsorized at the 0.99 level. In the HT model the *ThresholdSoilLoss_5* I the time invariant constant, *GDPVariation* is the Exogenous time variant variable, while the firm level control variables are considered as endogenous time variant variables.

Appendix 2. Robustness Tests – ATT Model results employing the PSM with (i) three nearest neighbors, (ii) kernel, and (iii) radius

Hypotheses	PSM Matching Method	Results ATT Model	Coeff.	Robust SE.	p-value
H1.1. Unsustainable levels of soil loss are associated with lower ROA for companies involved in agricultural production	3-NN	Supported	-0.011***	0.001	0.000
	Kernel	Supported	-0.012***	0.001	0.000
	Radius	Supported	-0.012***	0.001	0.000
H1.2. Unsustainable levels of soil loss are associated with lower ROE for companies involved in agricultural production	3-NN	Supported	-0.025***	0.003	0.000
	Kernel	Supported	-0.028***	0.003	0.000
	Radius	Supported	-0.028***	0.003	0.000
H1.3. Unsustainable levels of soil loss are associated with higher EBIT volatility for companies involved in agricultural production	3-NN	Not statistically sign.	-1,778.95	9,141.41	0.851
	Kernel	Not statistically sign.	12,872.16	6,950.64	0.101
	Radius	Not statistically sign.	14,010.73	6,900.93	0.077
H2.1. Unsustainable levels of soil loss are associated with lower levels of formal finance (bank long and short-term) for companies involved in agricultural production	3-NN	Supported	-0.009***	0.002	0.001
	Kernel	Supported	-0.011***	0.001	0.000
	Radius	Supported	-0.010***	0.001	0.000
H2.2. Unsustainable levels of soil loss are associated with lower levels of informal finance (suppliers, short-term) for companies involved in agricultural production	3-NN	Supported	-0.025***	0.003	0.000
	Kernel	Supported	-0.026***	0.002	0.000
	C Radius	Supported	-0.027***	0.002	0.000
H2.3. Unsustainable levels of soil loss are associated with higher levels of equity financing for companies involved in agricultural production	3-NN	Supported	0.037***	0.005	0.000
	Kernel	Supported	0.039***	0.004	0.000
	Radius	Supported	0.039***	0.004	0.000
H3.1. Unsustainable levels of soil loss are associated with higher costs of debt for companies involved in agricultural production	3-NN	Not statistically sign.	-0.001	0.001	0.131
	Kernel	Not statistically sign.	-0.001	0.000	0.029
	Radius	Not statistically sign.	-0.001	0.000	0.024
H3.2. Unsustainable levels of soil loss are associated with lower levels of interest coverage ratio for companies involved in agricultural production	3-NN	Not statistically sign.	0.438	1.391	0.760
	Kernel	Not statistically sign.	-0.053	1.027	0.960
	Radius	Not statistically sign.	-0.089	1.029	0.933

Notes: Statistical significance at 0.01, 0.05, and 0.10 is indicated, respectively, with ***, **, and *. Acronyms in the column “PSM Matching Method.”3-NN”, “Kernel”, and “Radius” represent the PSM algorithm employed to undergo the 3 nearest neighbor, kernel, and radius matching with a caliper of 0.05. The results presented in this table are related to the sample, with the variables related to the firm characteristics winsorized at the 0.99 level.

Appendix 3. Summary of the results of the hypothesis testing for the sub-industry groups

Hypotheses	Sub Ind.	Results HT-Model	Coeff.	Results ATT	Coeff.	Results T-test (Mean 0 – Mean 1)	Coeff.
H1.1. Unsustainable levels of soil loss are associated with lower ROA for companies involved in agricultural production	PC	Supported	-0.012**	Supported	-0.014***	Supported	0.025***
	NPC	Supported	-0.021***	Supported	-0.011***	Supported	0.028***
	PR	Not statistically sign.	-0.026	Not statistically sign.	0.002	Not statistically sign.	0.002
	AF	Not statistically sign.	-0.008	Not statistically sign.	-0.001	Not statistically sign.	0.009
H1.2. Unsustainable levels of soil loss are associated with lower ROE for companies involved in agricultural production	PC	Not statistically sign.	-0.139	Supported	-0.022**	Supported	0.019**
	NPC	Not statistically sign.	-0.042**	Supported	-0.036***	Supported	0.044***
	PR	Supported	0.002	Not statistically sign.	0.017	Not statistically sign.	-0.012
	AF	Not statistically sign.	-0.016	Not statistically sign.	-0.007	Not statistically sign.	0.185
H1.3. Unsustainable levels of soil loss are associated with higher EBIT volatility for companies involved in agricultural production	PC	Not statistically sign.	-12,166.36	Not supported	-29,646.05**	Not statistically sign.	12,481.44
	NPC	Not statistically sign.	-35,000.88*	Not statistically sign.	10,218.97	Not statistically sign.	-32,401.73***
	PR	Not supported	-18,033.75	Not statistically sign.	-50,753.48	Not supported	27,912.95
	AF	Not statistically sign.	-34,629.65	Not statistically sign.	-1440.542	Not statistically sign.	-3,541.45
H2.1. Unsustainable levels of soil loss are associated with lower levels of formal finance (bank long and short-term) for companies involved in agricultural production	PC	Not statistically sign.	-0.033	Supported	0.010*	Not supported	-0.011*
	NPC	Not statistically sign.	-0.030**	Supported	-0.020**	Supported	0.018***
	PR	Supported	-0.020	Not statistically sign.	-0.013	Not statistically sign.	0.008
	AF	Not statistically sign.	-0.050*	Not statistically sign.	-0.056	Supported	0.051***
H2.2. Unsustainable levels of soil loss are associated with lower levels of informal finance (suppliers' short-term) for companies involved in agricultural production	PC	Supported	-0.023*	Supported	-0.014**	Supported	0.018**
	NPC	Not statistically sign.	-0.026	Supported	-0.026***	Supported	0.032***
	PR	Supported	-0.076**	Supported	-0.094***	Supported	0.090***
	AF	Not statistically sign.	-0.048	Supported	-0.433**	Supported	0.052***
H2.3. Unsustainable levels of soil loss are associated with higher levels of equity financing for companies involved in agricultural production	PC	Not statistically sign.	0.020	Not statistically sign.	0.000	Not statistically sign.	-0.002
	NPC	Not statistically sign.	0.061***	Not statistically sign.	0.065***	Not statistically sign.	-0.069***
	PR	Supported	0.012	Supported	-0.007	Supported	0.003
	AF	Not statistically sign.	0.030	Not statistically sign.	0.030	Not statistically sign.	-0.038
H3.1. Unsustainable levels of soil loss are associated with higher levels of costs of debt for companies involved in agricultural production	PC	Not statistically sign.	0.000	Not statistically sign.	0.000	Not statistically sign.	0.001
	NPC	Not statistically sign.	0.002	Not statistically sign.	0.002	Not statistically sign.	0.003***
	PR	Not statistically sign.	0.005	Not statistically sign.	0.014***	Not supported	-0.014***
	AF	Not statistically sign.	0.700	Not statistically sign.	-0.006	Supported	0.007*
H3.2. Unsustainable levels of soil loss are associated with lower levels of interest coverage ratio for companies involved in agricultural production	PC	Supported	-6.567*	Not statistically sign.	-4.362	Supported	4.010*
	NPC	Not statistically sign.	-2.642	Not statistically sign.	3.205	Not statistically sign.	-2.950
	PR	Supported	-28.569**	Not statistically sign.	-13.842	Not statistically sign.	15.410**
	AF	Not statistically sign.	-1.173	Not statistically sign.	0.465	Supported	-0.4.970

(continued on next page)

(continued)

Hypotheses	Sub Ind.	Results HT-Model	Coeff.	Results ATT	Coeff.	Results T-test (Mean 0 – Mean 1)	Coeff.
		statistically sign.		Not statistically sign. Not statistically sign.			

Notes: Statistical significance at 0.01, 0.05, and 0.10 is indicated, respectively, with ***, **, and *. Acronyms in the column “Sub Ind.”: “PC”, “NPC”, “PR”, and “AF” stand for perennial crops, non-perennial crops, plant reproduction, and crops related to animal feed. The results presented in this table are related to the sample, with the variables related to the firm characteristics winsorized at the 0.99 level.

Appendix 4. Robustness Test - Difference-in-Difference Approach

	ROA (1)
Policy Period (Post = 1)	-0.019*** (0.001)
Treated Region (Treated = 1)	-0.011 (0.280)
Policy Introduction * Treated Region	0.018** (0.019)
ThresholdSoilLoss_5	-0.037** (0.015)
DID: Policy Introduction * ThresholdSoilLoss_5	0.048*** (0.000)
Treated Region * ThresholdSoilLoss_5	0.026 (0.170)
Triple DID: Treated Region * Policy Introduction * ThresholdSoilLoss_5	-0.051*** (0.001)
FirmSize	-0.007*** (0.004)
Leverage	0.000 (0.828)
FixedAssetsCoverageRatio	-0.006*** (0.000)
RevenueGrowth	0.000 (0.873)
GDPVariation	-0.000* (0.057)
Constant	0.164*** (0.000)
Number of observations	1,389
R-Squared	0.056
Wald Stat	56.870
Prob > chi2	0.000

Notes: Statistical significance at 0.01, 0.05, and 0.10 is indicated, respectively, with ***, **, and *. The results presented in this table are related to the sample, with the variables related to the firm characteristics winsorized at the 0.99 level. The analysis was conducted using a random effects panel data model.

Data availability

The authors do not have permission to share data.

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