The impact of climate risks on the probability of bankruptcy: Evidence from agriculture firms in southern Europe

Abstract

Production in agricultural firms can be severely affected by the frequency and duration of extreme climate events, which can cause losses due to their impact on business-related natural capital. Physical climate effects are material dependencies for agricultural businesses that may severely affect performance and compromise survival. This study analyzes the effects of adverse climatic conditions in the area of the firm's headquarters, such as extreme maximum temperatures, heavy precipitation, and fires. Using logit regressions and the gradient-boosting ensemble method, agricultural firms' bankruptcy is found to be conditioned by these extreme weather events, indicating that the physical effects of climate change on firms' resources are already material for the agricultural sector's resilience and survival, although credit risk management still receives little attention.

Keywords

Physical climate risk, agricultural sector, bankruptcy, wildfire

1. Introduction

The temperature and precipitation trends analysis shows that climate change is visible worldwide, and its effects are expected to intensify in the coming years. European financial institutions (EIB, 2021; EIOPA, 2022) recognize that physical climate change risks require adaptation by institutions, businesses, and society to reduce vulnerability, moderate damage, and alleviate adverse effects. The IPCC (2021) report shows that Mediterranean countries are experiencing more extensive and longer agricultural and ecological droughts combined with floods from extreme rainfall. In addition to droughts and floods, a broad study performed by the EIOPA (2022) among European insurers identifies wildfires as one of the most dangerous and potentially disruptive risks in southern Europe from a current and forward-looking perspective. As wildfires are prevalent in rural areas, this study shows that most property and assets destroyed by wildfires belong to firms and agricultural businesses.

For many firms, interactions with nature have been considered no more than externalities and have not affected cash flows, assets, and risk profiles; hence, they have not translated into changes in the profit and loss account and/or the balance sheet (Natural Capital Coalition, 2016a). This is not the case for the agricultural sector, where nature (soil, water, atmospheric conditions, and ecosystems) is a significant part of the production process, derived from material dependencies. Identifying, measuring, and valuing changes in natural capital and dependencies is critical for agricultural firms to take action (Natural Capital Coalition, 2016a).

Climate change is the origin of critical changes in the natural capital used in agriculture, constituting one of these strong dependencies. For example, rain and temperature determine freshwater provision, and extreme conditions cause droughts and floods. In contrast, the combination of different humidity, temperature, and wind conditions determines the propensity of wildfires to intensify and extend. The resulting changes in consumptive natural capital range from the desiccation of the soil surface and freshwater, as well as damage/destruction of raw materials (grain and other harvests, trees) (Natural Capital Coalition, 2016b), to the deterioration or destruction of property, plant, and equipment (Monasterolo, 2020). The consequences of climate change dependency on the agricultural business are the increase in operational costs to access alternative freshwater and raw materials, loss of revenue from crops, reparation costs, and rebuilding investments, and even compromising the firm's resilience and survival in the most severe cases (Natural Capital Coalition, 2016b). Other consequences for the affected geographical area are unemployment and decreased GDP (Burke et al., 2018; Hsiang et al., 2017), threatening the stability of economic and financial systems.

To analyze the impact of physical risks from climate change on agricultural sector firms, this study establishes a necessary connection between the standpoints of firms' and their stakeholders.' From the firms' perspective, two theoretical approaches play a role in explaining how firms' financial health is affected: the resource-based theory (Barney and Clark, 2007; Berrone et al., 2013) and the resilience theory (Linnenluecke et al., 2012; Winn et al., 2011). From the stakeholders' perspective, this study builds on the theoretical exploration made by Ascui and Cojoianu (2019) of how natural capital credit risk assessment may be articulated in agricultural lending. Specifically, we advance the rating and costing stages[1] of the risk management process by identifying natural capital risks originating from climate change with a significant effect (materiality assessment) on the financial health of agricultural businesses.

This study focuses on the effects of climate-induced physical damage on firms' probability of bankruptcy. Therefore, credit risk management theory should be complemented by identifying climatic conditions and physical consequences that affect firms' resources and resilience, the measurement possibilities of risk drivers, and model proposals for risk assessment.

The main objective of this study is to analyze the comprehensive effect of climate change factors on firm bankruptcy for a sector of particular concern, agriculture, and a geographical area susceptible to climate change in southern Europe. Analyzing individual climate factors, such as excess rainfall and periods of abnormally high temperatures, the negative influence on firms' health is found to align with previous findings (Griffin et al., 2019; Nguyen et al., 2023), consistent with the dependency of agricultural resources and resilience on climate conditions. However, this study aims to contribute to the literature by exploring an element of climate change that has not not been previously analyzed as an inductor of financial health deterioration. To this end, we investigate wildfire effects on the agricultural business, which requires the joint impact of several climate factors: drought, high temperatures, and wind as the main inductors. According to our results, bankruptcy risk significantly increases for firms in areas affected by extremely high temperatures and rainfall, and also for firms in the area of influence of wildfires. The combination of these three climatic factors (drought, high temperatures, and wind) aggravates the negative effect of wildfires on firms' financial health. These results highlight the importance of studying geographical areas with specific climatic conditions and risks, suggesting that the influence of climatic factors is not straightforward. In southern Europe,

[1] The credit risk management process can be divided into five phases, comprising rating (or risk identification), costing (or risk evaluation), pricing, monitoring, and workout (Weber et al., 2008).

excess rainfall causes floods, a negative factor for agricultural production; however, scarce rainfall is the main inducer of droughts and a relevant climatic factor for wildfire risk.

This study contributes to the existing literature in several ways. First, it extends the emerging stream of research on the relationship between the physical effects of climate change and bankruptcy risk by establishing how this relationship affects the agricultural sector in southern Europe. Second, to the best of our knowledge, this is the first empirical study to analyze the effects of wildfires and their accentuated impacts in the presence of specific climatic conditions that climate change aggravates. Third, our results demonstrate the relevant role of the physical environment's risks on firms' financial health, showing that climate change factors affect the bankruptcy rates of companies in regions affected by exteme weather conditions and wildfires. Finally, our work links theoretical frameworks at two levels: at the agricultural firm level, the resource-based and resilience theories explain where and how firms' financial health is affected by physical climate risks. However, their application cannot quantify these risks individually. At the agricultural stakeholder level, the credit risk management theory incorporates financial environmental risks, including physical effects derived from climate change. It quantifies the risk for the concerned industries in broad geographical areas where these physical climate risks are endemic. The financial risk to agricultural businesses derived from climate change has implications for policymakers, regulators, investors, companies, and civil society (Caldecott, 2017; IRENA, 2017). In the case of financial firms, both creditors and insurers (Natural Capital Coalition, 2016c) are concerned about the deterioration of natural capital, which reduces income and increases costs, thus hampering the firms' capacity to repay credit and deteriorating their capital investment, which results in collateral abatement (ESRB, 2016).

The remainder of this paper is organized as follows. Section 2 reviews the literature on the physical effects of climate change on natural capital and how this impact may affect agricultural businesses and their bankruptcy risks. Section 3 describes the data, models, and variables used to test the proposed hypothesis. Section 4 reports and discusses the study's results. Section 5 presents robustness analyses, and Section 6 explains the conclusions derived from the results and their implications for agricultural firms, their stakeholders, and the financial industry.

2. Literature review

2.1. Climate change factors and physical effects on natural capital

As global warming intensifies, more frequent climate changes are observed, including hot extremes, heavy precipitation, intense tropical cyclones, and agricultural and ecological droughts, among other concerning changes (IPCC, 2021). All these disruptions in the natural environment induced by progressive warming require societal, productive systems, and institutional adaptation. Special incidences in primary sectors require strategic changes for resilience in areas with climate and weather extremes (Forino and Von Meding, 2021; Linnenluecke et al., 2013; Whiteman et al., 2012).

A temporal increase in extreme damage has been detected globally, with temperate zones showing stronger patterns of growing damage at the upper percentiles of the distribution (catastrophic events) and mounting economic impacts (Coronese et al., 2019). In the European Mediterranean area, temperature increases exceed the global mean, and precipitation varies widely, with mean values decreasing as the mean temperature rises (IPCC, 2021). Severe droughts are expected to become twice as frequent in Europe, and aridity levels may become desert-like in the Mediterranean region as warming progresses (Teuling, 2018). With high-temperature stress and limited water availability during the summer months in southern

Europe, the fire potential increases, which means more ignition, more extensive areas burned, and longer fire seasons (Lavalle et al., 2009).

Extreme weather events induced by climate change mainly refer to extreme temperatures, heavy rainfall (or lack thereof), and high wind speeds, which may result in compound extreme events such as droughts, floods, and cyclones (IPCC, 2021; Linnenluecke et al., 2012). The combination of specific extreme climatic conditions and phenomena that are not necessarily extreme can exacerbate their impacts (Teuling, 2018). Thus, heat, lack of air humidity, derived desiccation of the soil surface, and strong winds work to intensify and extend a specific disaster type, wildfires[2] (Sutanto et al., 2020).

Physical catastrophes due to climate change, including wildfires and other domino effects, give rise to compound risks and intensify soil erosion, water stress, and biodiversity loss (Monasterolo, 2020). The destruction of natural capital and productive tangible assets and the deterioration of property values have severe socioeconomic consequences, such as a reduction in GDP, growth prospects, employment, and agricultural production, and an increase in energy consumption, coastal destruction, crime incidence, and human mortality (Burke et al., 2018; Hsiang et al., 2017).

2.2. Physical climate effects and bankruptcy risk for agricultural business

The theory of financial environmental risk is a complex framework comprising three blocks (Gutiérrez-López et al., 2022): the transition costs to low-carbon production (LCP), which can be considered of systemic relevance in the European setting (Cahen-Fourot et al., 2019), firms' danger of being unsustainable once a low-carbon economy is reached (Caldecott and Dericks, 2018), and the already experienced or potential climate-induced physical damage to firms' capital (Romilly, 2007), which is the object of this study.

The physical impacts of climate-related risks are classified by European financial institutions (EIB, 2021; EIOPA, 2022) as acute risks (extreme weather events) and chronic risks (gradual global warming) and are expected to become the most prominent environmental hazards. Primary production sectors such as agriculture are strongly affected by their high dependence on natural capital (Ascui and Cojoianu, 2019). According to the resource-based theory, the direct effect on agricultural firms' resources negatively impacts firm performance**.** This theory states that a firm obtains a competitive advantage by exploiting its productive resources when imitation is challenging and generates valuable capabilities (Barney and Clark, 2007; Berrone et al., 2013).

Physical climate risks can damage or destroy productive resources (natural capital, a firm's physical assets, and even human capital health) (Monasterolo, 2020) to such a significant extent that a firm's survival can be compromised. Hence, we resort to resilience theory to complete the proposed theoretical framework.

Concerning the firm's resilience, business adaptation to the physical effects of extreme weather events has been mostly reactive due to their inability[3] to predict changes and variability in

[2] "Fire weather" alludes to weather conditions triggering and sustaining wildfires. As global warming intensify, scientists estimate more frequent fire weather conditions in the Mediterranean area with high confidence (IPPC, 2021, p. 1600).

[3] Some characteristics make climate risks different from other financial risks: non-linear impacts, forward-looking nature, large uncertainty, and complexity due to heterogeneous agents' behaviour (Linnenluecke et al., 2013).

climate at their locality, as well as expected impacts on their resources and activities and translation into costs and benefits (Berkhout, 2012; Winn et al., 2011). Adaptation is also conditioned by a firm's sense-making and learning processes related to climate change (Gasbarro and Pinkse, 2015; Zhang, 2022), with culture, institutions, information, and financial restrictions being as much of a determinant as costs and benefits.

Recent studies (Clement and Rivera, 2017; Linnenluecke et al., 2012; Winn et al., 2011) have expanded resilience theory to consider extreme weather events. Thus, firms advance from adaptation to transformative change to cope with adaptation limits as extreme weather events become more frequent and intense due to climate change. The adaptation process should allow the firm to recover and return to its original operational regime; however, when adaptation limits are surpassed, two other trajectories emerge: a new operational regime or cease of operations (Clement and Rivera, 2017).

Climate resilience expenses originating from climate risks concern operational disruptions, production adjustments, supply chain changes, and increased insurance premiums, whereas firms' asset value is reduced by direct asset destruction or deterioration (can be partly offset by insurance coverage) and market value reduction due to expected future climate risks (not covered by insurance) (Glinglinger and Moreau, 2023).

Since specific by-industry attributes may be critical to a successful and effective response to the physical impacts of climate change (Linnenluecke et al., 2013), we focus on the effects of climate change on agricultural business. Let us consider operational disruptions requiring agricultural production adjustments for achieving business resilience. As explained in the previous section, acute risks, such as extreme temperatures, droughts, and floods, cause issues in accessing water for irrigation, a negative effect on crop growth, loss of grain and other harvests (raw materials), degradation of fertile soil, and deterioration of livestock health and welfare, resulting in higher mortality rates, lower productivity, and deterioration of immobilized productive capital (property, plant, and equipment) (Ascui and Cojoianu, 2019; Grillakis, 2019; Monasterolo, 2020). Therefore, according to the Natural Capital Protocol, climatic factors are classified as dependencies on the agricultural sector (Natural Capital Coalition, 2016b).

Regarding the acute risk of fire, a primary consequence on agriculture is the destruction of crops and farmland. Fires can incinerate crops, devastate irrigation systems, and damage infrastructure, resulting in substantial losses for farmers and the agricultural sector. Another repercussion of agricultural fires is the degradation of fertile soil (Monasterolo, 2020). Fires can induce soil erosion and diminish the nutrient content of the soil, rendering it less adaptable for crop cultivation.

Gradual global warming is causing droughts, floods, and fires, which are more frequent and destructive in the Mediterranean area (chronic risks), generating costlier agricultural insurance premiums (EOPA, 2022) and incipient consideration of future climate risk incidence on the market value of firms' assets (EIB, 2021).

Consequently, the compound extreme event of wildfires must be regarded as a determinant of potential future losses and bankruptcy, critical factors in the climate resilience of agricultural firms in southern Europe.

However, the direct effect of climate-induced physical catastrophes on specific communities is not predictable despite the classification of some risks as "endemic" to particular regions (chronic risk), as it happens with the incidence of fires (McKnight and Linnenluecke, 2019). The low chance of expected recurrence in specific communities and their productive systems makes them adopt occasional reactive measures instead of incremental adaptations (Zhang, 2022). In addition to the previous factor, another concern is the backward-looking nature of financial risk metrics when climate change effects are growing, generating a general underestimation of climate change impacts on financial risk valuations (Monasterolo, 2020; Teuling, 2018). It is necessary to highlight the unprecedented extremes scientists expect in five metrics: magnitude, frequency, new regions, timing, and simultaneous occurrence (IPCC, 2021).

To develop a deductive focus that provides a general quantitative assessment in which individual firms' risks can be evaluated, we incorporate the agricultural stakeholders' standpoint, materialized in financial institutions' incorporation of climate change risks into credit risk assessment.

Evaluating physical climate risk has become increasingly critical for financial institutions, with significant implications for their operations and financial performance (EIB, 2021; EIOPA, 2022). Financial firms' resilience depends on how they measure the effect of the physical climate risk on the valuation of assets and clients' credit risk profiles. Therefore, regulators worldwide are increasingly focusing on climate risk, and financial institutions may be required to disclose their climate risk exposure and incorporate climate risk into their risk management processes. Non-compliance can result in regulatory penalties and reputational damage. However, financial risks from climate change have not received sufficient attention from financial institutions and their supervisors (Fabris, 2020).

This study addresses the need to incorporate physical climate risks into assessment methods to serve financial institutions' credit management (Georgopoulou et al., 2015). Specifically, we integrate climate risks into the credit risk assessment for agricultural businesses in southern Europe, a geographical area susceptible to climate change. To this aim, we adopt the theoretical framework developed by the Natural Capital Coalition (2016a) in their Natural Capital Protocol. Thus, in the "measure and value" stage, first, material dependencies are identified and measured; then, changes in the state and trends of business-related natural capital are measured. Finally, the value of these natural capital dependencies is assessed. Unlike floods, droughts, and extreme temperatures, wildfires, climate-related disasters with significant effects on agriculture, are mostly overlooked in the literature. However, the sector guide developed for the food and beverage sector (Natural Capital Coalition, 2016b) also applies to the agricultural sector and explicitly mentions wildfires as a cause of changes in natural capital.

In line with Ascui and Cojoianu (2019), we adopt a lender's perspective when considering climate-derived physical risk. The reason alluded to by resilience theory is the low chance of recurrence for a particular community and certain firms; hence, the low chance of recurrence is a reason for firms to only adopt reactive occasional measures (McKnight and Linnenluecke, 2019; Zhang, 2022). In contrast, lenders offer credit to wider geographical areas (normally countrywide), and are very likely to be affected by some adverse effects of physical climate risk if the lender's area of influence is endemically affected by climate risks, as countries in southern Europe are.

The question of interest is how to integrate these dependencies into credit risk management or the recently developed environmental credit risk management (ECRM) (UNEP FI, 2007). The risk assessment process comprises the following stages: identification, analysis, categorization, mitigation, and monitoring. To advance the stages of identification and analysis, we propose specific quantitative variables referring to extreme conditions of temperature, precipitation, and wind, as well as wildfires, to measure the physical climate change risk with damaging effects on agricultural resources. We hypothesize that they have a material incidence on firms' bankruptcy probability.

H1. Physical climate change factors exert a material effect on agricultural firms' bankruptcy risk in southern Europe.

To date, a limited number of studies have integrated environmental risk into credit risk management performed by financial firms (Coulson, 2009; Labatt and White, 2002; Mengze and Wei, 2015; UNEP FI, 2007; Weber, 2012, 2005; Weber et al., 2008, 2010; White, 1996), and previous studies addressing physical climate risk in credit risk management (i.e. from a theoretical approach, Ascui and Cojoianu, 2019) have devoted very little or no attention to wildfires.

Providing agricultural firms with the necessary sense-making and learning on physical climate change would allow them to decide how to adapt or apply transformative shifts in response to extreme weather events, reducing the probability of cessation of their operations, according to the resilience theory. With this intention, our study includes the most relevant climate change factors for the economic sector and geographical area under analysis, contending that geography determines exposure to climate-derived disasters (McKnight and Linnenluecke, 2019; Nyberg et al., 2022; Romilly, 2007) and must be considered when computing the economic impact on resources and firms' financial vulnerability (Dennis, 2022).

3. Research design

The proposed model aims to uncover the crucial financial and climatic risk factors determining a company's bankruptcy or insolvency within the following 12 months. The study’s objective is to pinpoint the drivers of company distress, considering not only individual financial ratios but also climate-related variables, particularly those concerning physical risks.

The choice of companies, countries, and years analyzed is meticulously considered. This study primarily targets companies operating in the agricultural sector, including crop and livestock production, where the effects of climate change are particularly pronounced. Agricultural businesses are susceptible to temperature, precipitation, and other climatic fluctuations because they are highly dependent on natural capital (Ascui and Cojoianu, 2019).

3.1. Sample

The present study's financial data are sourced from the ORBIS dataset provided by Bureau van Dijk (BvD). Firms with available financial data from 2016 to 2018 are meticulously selected. These selection criteria ensure the use of the most recent available financial data until 2019 for any firm under consideration.

The years selected for this analysis are particularly significant, as they represent economically stable periods in Europe from a macroeconomic perspective. This choice mitigates the influence of bankruptcy that may arise from a more significant economic downturn. For example, although data from 2020 and 2021 may technically be incorporated, these years are predominantly overshadowed by the global implications of the COVID-19 pandemic. As such, discerning whether a firm's bankruptcy arises due to the pandemic, inherent financial vulnerabilities, or specific factors such as climate-induced risks may become fuzzier.

Furthermore, the years selected for this study strive to strike a balance between historical depth and representativeness and validity of the data. Given the recent surge in global temperatures and escalation of extreme weather events, it is paramount to consider contemporary climatic influences on businesses. Factoring data from distant years may jeopardize the study's conclusions, as the economic characteristics of firms during those periods may differ substantially from those of more recent years.

Firms in Portugal, Spain, Italy, and France are considered from a regional perspective. The selection of these countries is informed by an IPCC (2021) report, which highlights that Mediterranean countries are experiencing more extensive and prolonged agricultural and ecological droughts juxtaposed with floods resulting from extreme rainfall. Consequently, these countries encounter pronounced extreme weather events and wildfires within the timeframe of this study. Notably, Greece was initially considered in this selection; however, it was ultimately excluded due to the low quality of the available data.

The sample comprises 15,036 companies. These firms are categorized as either ”distressed” or ”healthy.” A company is deemed a ”failed” if its financial statements for the year are accessible and one of the following statuses is observed within the next 12 months: rescue plan, insolvency proceedings, payment suspension, dissolved, or bankruptcy. This selection criterion ensures the use of the most recent available financial data until 2019 for any firm under consideration. Notably, this approach mirrors the strategies employed by financial institutions in their efforts to predict default. Such strategies allow them a margin of maneuverability to pre-empt potential bankruptcy or non-payment issues. This approach also aligns with the Basel IV regulations emphasizing banking stability. Based on this criterion, 458 firms are considered to have failed. This study considers pertinent accounting-based variables extensively employed in the literature.

Climatic data are sourced from the European Climate Assessment and Dataset Project (ECA&P). ECA&P aggregates observations from an extensive network of stations across Europe and the Mediterranean region. It boasts records from over 2,500 sites detailing daily precipitation patterns and over 1,300 sites documenting daily minimum and maximum temperatures. This dataset is one of the most reliable public repositories for daily European weather data. This study also integrates historical data on European wildfires. Wildfire information is derived using Fire Event Delineation for Python (FIREDpy) open-source software. FIREDpy autonomously fetches and refines fire-related data for designated areas and captures metrics, such as the number of fires, expansion of the burned area, duration, and other pertinent parameters. It is worth mentioning that although financial information is limited to the years 2016 to 2018, climate-related metrics consider data from the last 10 years; therefore, the period covered is quite extensive.

3.2. Models and variables

In the proposed model, the dependent variable is a dummy variable that equals one if the company is considered failed, and zero otherwise. This model incorporates various established variables as proxies for a firm's financial health (Du Jardin, 2010; Crutzen and Van Caillie, 2010; Tian et al., 2015; Charalambakis and Garrett 2019; Atif and Ali, 2021). The seven selected variables are profitability, long-term debt, short-term liabilities, liquidity, tangibility, size, and activity. Return on assets (*ROA*) is calculated as the ratio of net income to total assets. Long-term debt (*LONG_DEBT*) is expressed as the ratio of long-term financial debt to total assets. Short-term liabilities (*SHORT_LIAB*) are calculated as the ratio of short-term liabilities to total assets. Liquidity (*LIQ*) represents the ratio of current assets to current liabilities. Tangibility (*TANG*) is the ratio of fixed assets to total assets. Size (*SIZE*) is computed as the logarithm of total assets, and the activity variable (*ACTIVITY*) is calculated as sales growth with respect to the previous year.

In addition to these financial variables, for each firm-year, three climate variables are incorporated into the model: maximum temperature (*MAX_TEMP*), precipitation (*PRECIPI*), and number of fires (*FIRES*). *MAX_TEMP* is the anomaly in the maximum temperature observed in the last 3,650 days compared to the historically available data. *PRECIPI* is determined as the anomaly in the maximum precipitation value observed in the previous 365 days compared with historically available data. *FIRES* measures the number of fires in the last 1,865 days within a 100 km radius of the firm's location.

Linking climate variables to individual companies is considerably more challenging, especially compared with the more straightforward process of assigning financial metrics. This difficulty is primarily due to the need to accurately identify the operational locations of these companies. For larger corporations, gathering detailed information on their main production sites and key assets may not always be feasible. In addition, the available data may not always be reliable. The current study focuses on small to medium-sized enterprises (SMEs) in response to this issue. The location of an SME's headquarters is often easy to find and usually provides a good indication of its primary asset location, as supported by Griffin et al. (2019). This concept is based on the view that smaller companies tend to operate in specific areas. When adding climatic factors for each company, considering the company's distance from relevant data sources, such as weather stations, is essential. For example, if a company is close to several weather stations that record temperature data, the readings from the nearest station are assigned to that company. The abovementioned variables are identified in the equation as CRP, a climate risk variable proxy that includes *MAX_TEMP*, *PRECIPI*, and *FIRES*.

In addition, a Climate Index is calculated by extracting the first principal component of the three most influential variables in the initiation and propagation of fires (*CLIMATE_INDEX*) using maximum temperature, drought, and wind (IPPC, 2021; McKnight and Linnenluecke, 2019; Turco et al., 2014). Drought is assigned a value of one if the mean rainfall value for April, May, June, July, August, and September is below the first tercile of the average annual rainfall, and zero otherwise. The wind is calculated as the anomaly in the mean wind speed observed in the last 1,825 days compared to the historically available data.

The model used to test the hypothesis is as follows:

$$Bankruptcy = a_0 + a_1 ROA_{it} + a_2 LONG\_DEBT_{it} + a_3 SHORT\_LIAB_{it} + a_4 LIQ_{it} + a_5 TANG_{it} + a_6 SIZE_{it} + a_7 ACTIVITY_{it} + \varepsilon_{it} \tag{1}$$

$$Bankruptcy = a_0 + a_1 ROA_{it} + a_2 LONG\_DEBT_{it} + a_3 SHORT\_LIAB_{it} + a_4 LIQ_{i16-19} + a_5 TANG_{it} + a_6 SIZE_{it} + a_7 ACTIVITY_{it} + a_8 CRP_{it} + \varepsilon_{it} \tag{2}$$

$$Bankruptcy = a_0 + a_1 ROA_{it} + a_2 LONG\_DEBT_{it} + a_3 SHORT\_LIAB_{it} + a_4 LIQ_{i16-19} + a_5 TANG_{it} + a_6 SIZE_{it} + a_7 ACTIVITY_{it} + a_8 MAX\_TEMP_{it} + a_9 PRECIPI_{it} + a_{10} FIRES_{it} + \varepsilon_{it} \tag{3}$$

$$Bankruptcy = a_0 + a_1 ROA_{it} + a_2 LONG\_DEBT_{it} + a_3 SHORT\_LIAB_{it} + a_4 LIQ_{i16-19} + a_5 TANG_{it} + a_6 SIZE_{it} + a_7 ACTIVITY_{it} + a_8 FIRES_{it} + a_9 CLIMATE\_INDEX_{it} + a_{10} FIRES\ x\ CLIMATE\_INDEX_{it} + \varepsilon_{it} \tag{4}$$

The proposed models are estimated using logit regressions for the panel data. We check the validity of our results by considering different tests, such as the Wald test, Lagrange multiplier (LM test score), receiver operating characteristics (ROC), and likelihood ratio test (LR test).

4. Results and discussion

4.1. Descriptive statistics

Table 1 presents the summary statistics of the variables included in the model for the full sample (Panel A), healthy firms (Panel B), and failed firms (Panel C). Panel A reports that, on average, the overall failure rate is 1.1%, *ROA* is 2.12%, and leverage shows a high rate of short-term liabilities (35.87%) in contrast to long-term financial debt (16.78%). Comparing Panels B and C, failed firms show negative *ROA* and lower liquidity and tangibility. The higher proportion of short-term liabilities is consistent with this faster way of obtaining funds when a decrease in profitability limits the available liquidity.

Table 1. Descriptive statistics

Panel A. Full sample

	Mean	SD	Min	p25	p50	p75	Max
Failure	0.011	0.104	0.000	0.000	0.000	0.000	1.000
ROA	0.0212	0.0778	-0.3164	-0.0013	0.0085	0.0419	0.3640
LONG_DEBT	0.1678	0.2229	0.0000	0.0000	0.0673	0.2629	0.9716
SHORT_LIAB	0.3587	0.2986	0.0010	0.1016	0.2814	0.5643	1.1585
LIQ	2.3102	7.4945	0.0205	0.4377	0.9027	1.5152	80.8130
TANG	0.5582	0.3042	0.0000	0.2991	0.6013	0.8347	0.9936
SIZE	14.6752	0.9891	10.6489	14.1111	14.7623	15.3426	16.6063
ACTIVITY	0.4295	1.9992	-0.8873	-0.0747	0.0568	0.2593	16.8584
MAX_TEMP	0.6847	1.0645	-1.1713	0.2327	0.5304	0.9291	6.3055
PRECIPI	-6.0202	7.9927	-60.2500	-7.5496	-4.1157	-1.8492	9.7000
FIRES	47.6449	64.3899	0.0000	8.0000	26.0000	60.0000	380.0000

Panel B. Healthy firms

	Mean	SD	Min	p25	p50	p75	Max
ROA	0.0216	0.0769	-0.3164	-0.0011	0.0087	0.0421	0.3640
LONG_DEBT	0.1678	0.2226	0.0000	0.0000	0.0678	0.2629	0.9716
SHORT_LIAB	0.3562	0.2969	0.0010	0.1007	0.2788	0.5607	1.1585
LIQ	2.3215	7.5300	0.0205	0.4388	0.9035	1.5210	80.8130
TANG	0.5596	0.3034	0.0000	0.3016	0.6029	0.8349	0.9936
SIZE	14.6766	0.9865	10.6489	14.1135	14.7622	15.3421	16.6063
ACTIVITY	0.4278	1.9888	-0.8873	-0.0733	0.0578	0.2596	16.8584
MAX_TEMP	0.6827	1.0633	-1.1713	0.2327	0.5299	0.9291	6.3055
PRECIPI	-6.0400	8.0090	-60.2500	-7.5496	-4.1157	-1.8492	9.7000
FIRES	47.5267	64.1762	0.0000	8.0000	26.0000	60.0000	380.0000

Panel C. Failed firms

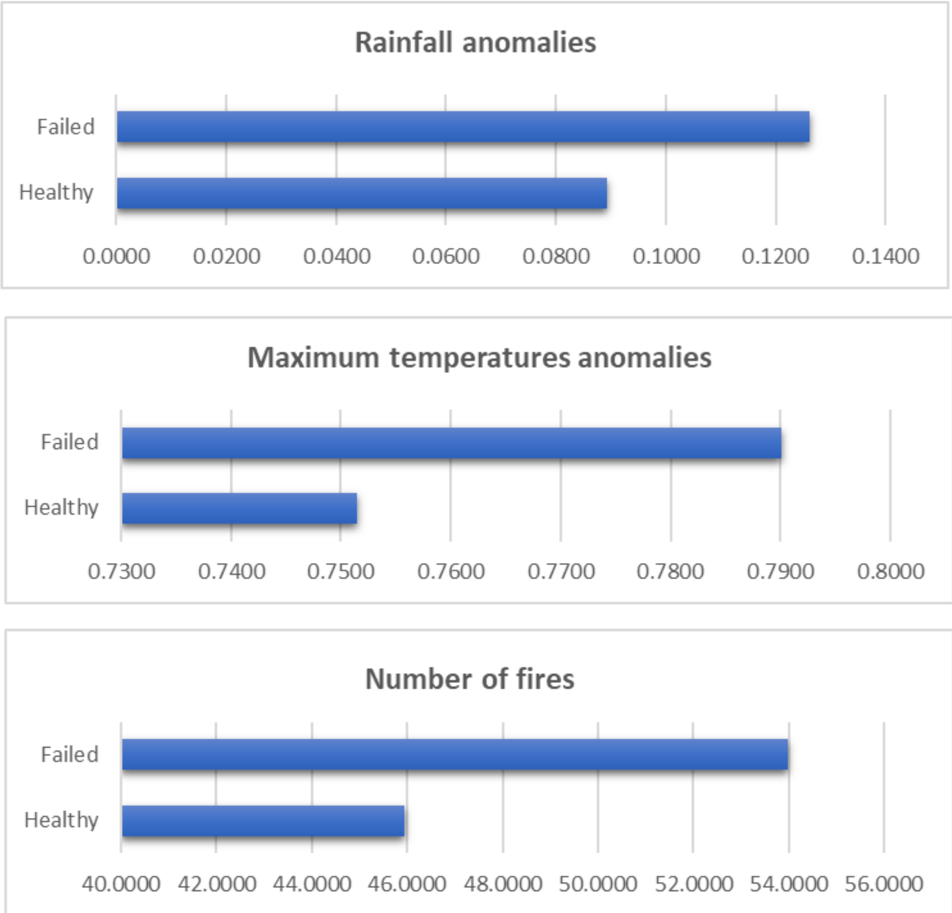
	Mean	SD	Min	p25	p50	p75	Max
ROA	-0.0210	0.1331	-0.3164	-0.0498	0.0000	0.0165	0.3640
LONG_DEBT	0.1638	0.2510	0.0000	0.0000	0.0138	0.2569	0.9716
SHORT_LIAB	0.5850	0.3567	0.0010	0.2717	0.5883	0.8839	1.1585
LIQ	1.2852	2.6463	0.0205	0.3143	0.8160	1.1229	27.3173
TANG	0.4309	0.3486	0.0000	0.0921	0.3524	0.7789	0.9936
SIZE	14.5524	1.1924	10.6489	13.8580	14.7861	15.4020	16.6063

ACTIVITY	0.5810	2.7830	-0.8873	-0.2233	-0.0084	0.2367	16.8584
MAX_TEMP	0.8627	1.1535	-1.1713	0.3407	0.6346	1.1944	6.3055
PRECIPI	-4.2346	6.1069	-60.2500	-5.2185	-3.2000	-1.3226	9.7000
FIRES	58.3079	80.8164	0.0000	7.5000	29.0000	63.0000	380.0000

Notes. The variables' definitions are reported in the Appendix.

Figure 1 reports the mean values of the climate factors used by the firm's category of financial health. In all cases, failed firms are located in areas that suffered severe climate conditions, indicating a negative effect of these extreme climate events (rainfall anomalies, anomalies in maximum temperatures, and the number of fires around the firm) on the firm's financial health.

Figure 1. Climate variables by firm's financial health



Notes. The variables' definitions are reported in the Appendix.

Table 2 presents a correlation analysis considering the full sample, healthy firms, and failed firms (Panels A, B, and C, respectively).[4] All four extreme climatic events show a significant correlation with failure (in the full sample), and the positive signs for temperature, precipitation, and fire support the results shown in Figure 1. The negative correlations between extreme precipitation and fire with tangibility and size are consistent with the deterioration/destruction of firm resources.

[4] In untabulated results we obtain values lower than two for the Variance Inflation Factor (VIF) in all models, indicating the absence of multicollinearity between the studied variables.

Table 2. Correlation analysis

Panel A. Full sample

	Failure	ROA	LONG_DEBT	SHORT_LIAB	LIQ	TANG	SIZE	ACTIVITY	MAX_TEMP	PRECIPI	WIND	FIRES
Failure	1											
ROA	-0.0570*	1										
LONG_DEBT	-0.0018	-0.0783*	1									
SHORT_LIAB	0.0798*	-0.1151*	-0.2590*	1								
LIQ	-0.0144*	0.0130*	-0.1719*	-0.2192*	1							
TANG	-0.0440*	-0.1811*	0.2034*	-0.4813*	-0.0668*	1						
SIZE	-0.0131*	-0.1415*	0.0541*	-0.3182*	0.0597*	0.4106*	1					
ACTIVITY	0.0080	0.0300*	0.0216*	0.0154*	0.0195*	0.0328*	-0.0546*	1				
MAX_TEMP	0.0176*	-0.0284*	-0.1221*	0.0687*	0.0115*	-0.0080	0.0389*	0.0005	1			
PRECIPI	0.0235*	-0.0145*	-0.1184*	0.0955*	0.0158*	-0.0762*	-0.0172*	-0.0059	0.2191*	1		
WIND	-0.0139*	0.0156*	0.1098*	-0.0636*	-0.0060	0.0589*	0.0066	0.0068	-0.1399*	-0.0710*	1	
FIRES	0.0174*	-0.0018	0.0012	0.0740*	-0.0133*	-0.0785*	-0.0902*	0.0106	-0.1059*	-0.1052*	-0.0561*	1

Panel B. Healthy firms

	ROA	LONG_DEBT	SHORT_DEBT	LIQ	TANG	SIZE	ACTIVITY	MAX_TEMP	PRECIPI	WIND	FIRES
ROA	1										
LONG_DEBT	-0.0781*	1									
SHORT_LIAB	-0.1053*	-0.2585*	1								
LIQ	0.0107	-0.1725*	-0.2193*	1							
TANG	-0.1858*	0.2032*	-0.4819*	-0.0670*	1						
SIZE	-0.1436*	0.0519*	-0.3192*	0.0603*	0.4093*	1					
ACTIVITY	0.0294*	0.0232*	0.0155*	0.0188*	0.0354*	-0.0528*	1				
MAX_TEMP	-0.0268*	-0.1213*	0.0675*	0.0117*	-0.0078	0.0398*	0.0007	1			
PRECIPI	-0.0136*	-0.1183*	0.0943*	0.0162*	-0.0760*	-0.0168*	-0.0061	0.2192*	1		
WIND	0.0174*	0.1111*	-0.0628*	-0.0062	0.0580*	0.0055	0.0076	-0.1407*	-0.0701*	1	
FIRES	-0.0003	0.0010	0.0731*	-0.0132*	-0.0785*	-0.0895*	0.0081	-0.1072*	-0.1068*	-0.0558*	1

Panel C. Failed firms

	ROA	LONG_DEBT	SHORT_LIAB	LIQ	TANG	SIZE	ACTIVITY	MAX_TEMP	PRECIPI	WIND	FIRES
ROA	1										
LONG_DEBT	-0.1071	1									
SHORT_LIAB	-0.3696*	-0.3384*	1								
LIQ	0.2561*	-0.1901*	-0.3031*	1							
TANG	-0.1233*	0.2209*	-0.3437*	-0.2453*	1						
SIZE	-0.1035	0.1987*	-0.2550*	-0.0672	0.4825*	1					
ACTIVITY	0.0755	-0.0643	-0.0219	0.1881*	-0.0895	-0.1464*	1				
MAX_TEMP	-0.0595	-0.1774*	0.0733	0.0278	0.0310	-0.0006	-0.0198	1			
PRECIPI	0.0120	-0.1355*	0.0716	0.0054	-0.0124	-0.0334	-0.0077	0.1891*	1		
WIND	-0.1466*	-0.0110	-0.0654	-0.0054	0.0949	0.0922	-0.0446	-0.0408	-0.1612*	1	
FIRES	-0.0219	0.0173	0.0592	-0.0023	-0.0363	-0.1191*	0.1327*	-0.0434	-0.0109	-0.0676	1

Notes. The variables' definitions are reported in the Appendix.

4.2. Empirical results

Table 3 presents the results of the logit regressions used to derive the probability of agricultural firm bankruptcy or insolvency based on firm-specific financial variables and geography-specific climate risk factors. The first column shows the results for the baseline model, which only includes well-known financial inductors with effects on firm bankruptcy that have been contrasted in the literature. The next five columns show the results after adding climate risk factors. Extremely high temperatures are added in column 2, extreme precipitation in column 3, and fires in column 4; all four positively and significantly affect the probability of firm bankruptcy. These results align with the damage/destruction of relevant resources from extreme climate events (resource-based theory) and with scarce previous findings on the adverse effects of high temperatures and fire danger on European agriculture (Lavalle et al., 2009).

Table 3. The effects of climate change on business failure

	(1)	(2)	(3)	(4)	(5)	(6)
ROA	-4.614***	-4.606***	-4.606***	-4.632***	-4.631***	-4.389***
	[0.637]	[0.638]	[0.639]	[0.639]	[0.641]	[0.657]
LONG_DEBT	1.010***	1.073***	1.121***	1.003***	1.163***	1.065***
	[0.281]	[0.282]	[0.282]	[0.281]	[0.282]	[0.290]
SHORT_LIAB	1.887***	1.875***	1.854***	1.873***	1.823***	1.818***
	[0.229]	[0.229]	[0.230]	[0.229]	[0.231]	[0.236]
LIQ	-0.00544	-0.00527	-0.00533	-0.00540	-0.00511	-0.00769
	[0.0140]	[0.0139]	[0.0139]	[0.0140]	[0.0138]	[0.0153]
TANG	-0.936***	-0.929***	-0.881***	-0.917***	-0.852***	-0.858***
	[0.217]	[0.217]	[0.218]	[0.218]	[0.218]	[0.222]
SIZE	0.169***	0.162***	0.165***	0.175***	0.166***	0.155***
	[0.0576]	[0.0576]	[0.0577]	[0.0577]	[0.0578]	[0.0586]
ACTIVITIY	0.0319	0.0320	0.0324	0.0311	0.0313	0.0193
	[0.0229]	[0.0229]	[0.0229]	[0.0230]	[0.0229]	[0.0249]
MAX_TEMP		0.0992**			0.0769*	
		[0.0434]			[0.0460]	
PRECIPI			0.0321***		0.0317***	
			[0.0104]		[0.0108]	
FIRES				0.00133*	0.00174**	0.00172**
				[0.000735]	[0.000735]	[0.000763]
CLIMATE_INDEX						-0.0378
						[0.0745]
FIRES*CLIMATE_ INDEX						0.00330**
						[0.00133]
Constant	-7.550***	-7.534***	-7.353***	-7.701***	-7.539***	-7.442***
	[0.856]	[0.855]	[0.861]	[0.861]	[0.863]	[0.873]
Observations	29,938	29,938	29,938	29,938	29,938	29,052
Pseudo R2	0.0691	0.0704	0.0723	0.0699	0.0743	0.0697
Wald Test (Chi sq)	269.3	5.218	9.539	3.258	17.40	18.21
Wald p-value	0.000	0.0224	0.00201	0.0711	0.000584	0.000398
Lagrange-multiplier (Score) Test	285.9	5.253	9.168	3.272	17.08	18.65
LM (Score) p-value	0.000	0.0219	0.00246	0.0705	0.000680	0.000323
ROC	0.706	0.708	0.713	0.707	0.714	0.707
LR Test		4.680	11.64	3.019	18.94	104.1

LR p-value	0.0305	0.000647	0.0823	0.000281	0.000

Notes. The variables' definitions are reported in the Appendix.

Our results for extreme rainfall are also consistent with those of Calabrese et al. (2021) for heavy rainfall events. Column 5 shows that all three factors maintain their significant effects when jointly incorporated into the model. In column 6, we test the encouraging effect of a "fire weather" index to the simple existence of fires close to firms, confirming the relevant role of weather conditions on the incidence of this catastrophe (whether ignited naturally or human-induced), the amplifying effect of combining several climatic factors (IPCC, 2021; Sutanto et al., 2020), and the importance of including wildfires (or just fires) as climate-related physical risks in the aggravating process derived from climate change in southern Europe (Lavalle et al., 2009).

5. Robustness analyses

To address reverse causality, in Table 4, we present the results obtained by estimating an instrumental variable ordinary least squares (OLS) model that resembles the conventional use of two-step least squares (2SLS). The first four columns show similar results, supporting the validity of our conclusions. However, in this approach, we also consider instrumental variables to study the effect of the number of fires on business failure (column 5). Specifically, we select anomalies in the maximum temperature, anomalies in the mean wind speed, and a proxy of droughts as instruments. The results indicate that if the number of fires is explained by climate variables that act as fire inductors, the positive effect of fires on business failures is stronger.[5]

Table 4. The effects of climate change on business failure. Two-step least squares

	(1)	(2)	(3)	(4)	(5)
ROA	-0.0690***	-0.0687***	-0.0686***	-0.0681***	-0.0632***
	[0.0082]	[0.0082]	[0.0082]	[0.0082]	[0.0083]
LONG_DEBT	0.0080***	0.0087***	0.0087***	0.0092***	0.0071**
	[0.0029]	[0.0029]	[0.0029]	[0.0029]	[0.0030]
SHORT_LIAB	0.0238***	0.0235***	0.0235***	0.0231***	0.0221***
	[0.0026]	[0.0026]	[0.0026]	[0.0026]	[0.0027]
LIQ	0.0000	0.0000	0.0000	0.0000	0.0000
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
TANG	-0.0101***	-0.0102***	-0.0099***	-0.0098***	-0.0086***
	[0.0025]	[0.0025]	[0.0025]	[0.0025]	[0.0025]
SIZE	0.0014**	0.0013*	0.0013**	0.0014**	0.0017**
	[0.0007]	[0.0007]	[0.0007]	[0.0007]	[0.0007]
ACTIVITIY	0.0005*	0.0005*	0.0005*	0.0005*	0.0003
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
MAX_TEMP		0.0013**		0.0011*	
		[0.0006]		[0.0006]	
PRECIPI			0.0002***	0.0002***	
			[0.0001]	[0.0001]	
FIRES				0.0000**	0.0001***
				[0.0000]	[0.0000]
Constant	-0.0122	-0.0120	-0.0106	-0.0129	-0.0229**
	[0.0101]	[0.0100]	[0.0101]	[0.0101]	[0.0108]
Observations	29,938	29,938	29,938	29,938	29,052
R-squared	0.0095	0.0097	0.0098	0.0101	0.0058

[5] We re-estimate the model by using probit and obtain similar results that support our main hypothesis (results available under request).

Notes. The variables' definitions are reported in the Appendix.

Finally, as a robustness test, we check the rank ordering and importance of the variables derived from our model by comparing them with the well-established gradient-boosting ensemble method (Freund and Schapire, 1996). In machine learning, utilizing an ensemble of distinct classifiers has demonstrated enhanced overall model accuracy. Boosting is a technique that initially acquires a base classifier from an original dataset, modifies the training dataset distribution based on the performance of the base classifier, and subsequently trains the next base classifier using an altered sample distribution. This method allocates weights to each training set, which can be employed to create a collection of bootstrap samples from the initial data.

Boosting is selected as a benchmark because several studies in the bankruptcy literature use ensemble strategies, including boosting, and have corroborated their advantages (Kim and Upneja., 2014; Sun et al., 2014; Wang et al., 2012). Furthermore, boosting can give more importance to features that contribute more to the classification task and are less prone to overfitting than a single and more complex classifier. The importance of the variables in a model is measured as the loss in the model's accuracy if a variable is removed from the model, keeping the remaining variables constant. Table 5 lists the importance of the variables used in the boosting ensemble model.

Table 5. The effects of climate change on business failure. Boosting model

Variable	Proposed model	Boosting Model
SHORT_LIAB	1	2
ROA	2	1
TANG	3	5
LONG_DEBT	4	9
PRECIPI	5	6
SIZE	6	3
FIRES	7	8
MAX_TEMP	8	7
ACTIVITY	9	4
LIQ	10	11
CLIMA	11	10

Notes. The variables' definitions are reported in the Appendix.

Overall, the logit/probit and boosting models show relatively similar patterns in ranking variables. Although differences are observed in the specific rankings of individual items, the overall structure and importance assigned to financial and climatic factors are generally consistent between the two methodologies. Only two variables rank differently: long-term debt and activity. These results suggest that both model types capture similar aspects of the underlying data, and their differences can be attributed to the unique characteristics of each method.

6. Conclusions

Climate change is the origin of critical effects on natural capital, a significant part of the agricultural production process that constitutes a strong dependency on this sector. In southern Europe, extreme conditions of climatic factors, such as high temperature, heavy rainfall, or lack of it, result in compound extreme events such as droughts and floods. In addition, high temperatures, in combination with lack of air humidity, the derived desiccation of soil surface, and strong wind, are called "fire weather" as inductors of fire seriousness. The direct destruction of goods and productive tangible assets, together with the deterioration of natural capital (soil erosion and difficult access to fresh water), severely affects strategic resources for the agricultural business (resource-based theory), producing immediate losses, increased costs, and reduced income. The indirect effects come from the reduced market values of non-damaged assets (reducing collateral value in credit contracts), higher insurance premiums, reduced gross domestic product, and higher rates of unemployment in the damaged area near the agricultural firm, as other firms and citizens (potential clients) also suffer losses in physical capital and significant expenses due to climate disasters.

The risks mentioned above are often underestimated. First, the growing progression of physical climate risks under climate change makes backward-looking data a poor and optimistic proxy for real risk. Second, the low recurrence rate of climatic disasters in the same specific zones induces occasional reactive measures instead of incremental adaptation (resilience theory). However, this should not be the case for financial firms, such as banks or insurance companies, since their area of influence is considerably wider, extending to many firms and clients across one or even several countries, implying that financial firms in areas where climatic disasters become endemic (chronic risk) will suffer their economic consequences.

Given the considerations above, this study adopts a lender's perspective to consider climate-derived physical risk and estimate the probability of bankruptcy of agricultural firms in four southern European countries during 2016–2018. We do not address 2019 and 2020, as the adverse effects of the COVID-19 pandemic may bias them. Considering their geographical proximity to the firm's headquarters, we assign extreme climatic events to firms, as SMEs' assets are expected to be concentrated close to and around the head office. For a sample of 15,036 firms, including 458 officially declared bankruptcy or insolvency, our results show that abnormally high temperatures, precipitation, and the incidence of fires are significant factors contributing to bankruptcy or insolvency. Furthermore, a "fire weather" index comprising a combination of high temperatures, drought, and wind, in combination with fire occurrence, shows an intensifying effect on the bankruptcy risk of agricultural businesses.

Implications and extension of our study

Our results demonstrate that underestimated physical climate risks are material and have a measurable effect on agricultural firms' bankruptcy and/or insolvency. The main implications for managers, investors, creditors, insurers, and policymakers emanate from the need to include time and geography as relevant factors in the climate change transition (Nyberg et al., 2022). Both financial systems and public administrations are final contributors of funds to help societies and productive agents cope with the effects of climate physical disasters, thus playing a critical role in climate change adaptation (Dennis, 2022; Forino and Von Meding, 2021) but also suffering economic consequences in their accounts, compromising the financial system and the states financial stability (Klusak et al., 2021) in the most dramatic cases. In line with the UNEP FI (2002) recommendations, coordinated policies are urgently required in key climate-related zones, and our study suggests concerns for southern Europe with respect to the agricultural sector.

Financial firms, mainly banks and insurance companies, can obtain an additional tool to quantify the incidence of physical climate-derived disasters in agricultural businesses; hence, they can derive probabilities and price the potential impacts of physical climate risks on firms' performance, with substantial influence on their loans and insurance terms. Knowledge of industry-wide incidence can help design institutional policies to prompt firms to develop attributes for adapting production to climate physical impacts (Linnenluecke et al., 2013), and climate change adaptation is a relevant contribution to community resilience (McKnight and Linnenluecke, 2019)

Future extensions of this work can incorporate expectations for specific geographical areas regarding the evolution of climatic factors triggering physical climate disasters according to scientific medium- and long-term estimations.

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APPENDIX

List of variables

ROA	Net income to total assets
LONG_DEBT	Long-term financial debt to total assets
SHORT_LIAB	Short-term liabilities to total assets
LIQ	Current assets to current liabilities
TANG	Fixed assets to total assets
SIZE	Log of total assets
ACTIVITY	Sales growth
MAX_TEMP	Anomalies in the maximum value of temperature observed in the last 3650 days compared with historical available data
PRECI	Anomalies in the maximum value of precipitations observed in the last 365 days compared with historical available data
FIRES	Number of fires in the last 1865 days in less than 100 km of the firm location
DROUGHT	Equals one if the mean value of the rain for April, May, June, July, August, and September is below the first tercile of the average rainfall for the year and zero otherwise
WIND	Anomalies in the mean speed of wind observed in the last 1825 days compared with historically available data