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Doctoral Thesis in Management of Innovation in the Agricultural and Food Systems of the Mediterranean Region

– XXXVI cycle –

Innovative and integrated risk management in the agri-food chains

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Abstract

Agricultural production is closely related to the weather conditions and farmers are exposed to natural hazards such as excess flood, drought, and frost. The increase of the magnitude and frequency of extreme weather events requires the implementation of several risk management tools that may enhance the resilience of farming systems to climate change. In the last years, the interest on insurance market against extreme weather events has grown and crop insurance schemes may play a key role to manage systemic weather risks, mitigating production losses and stabilizing farmers' incomes. More specifically, the weather index-based insurance represents a promising tool which may overcome some problems associated with traditional indemnity-based insurances (e.g., asymmetric information, high transaction costs, moral hazard, and adverse selection). However, the weather index-based insurance presents a major limitation, namely *basis risk*: farmers may experience severe yield losses without any reimbursement or, on the contrary, they may obtain a compensation without any yield loss mainly due to the discrepancy between the pay-out triggered by the weather index and actual losses. Clearly, this main threat limits the spread of this innovative risk management tool. Our studies aim to assess the dynamics between the weather variable and crop yield, i.e., the working principle of the weather index-based insurances, and crop insurance demand. First, we conducted a case study to deepen the knowledge on the linkages between durum wheat yields and weather events occurring in susceptible phenological phases; second, we studied how different approaches for the phenological stages identification and how different weather variables (and combination of thereof) within the econometric model may catch further relationships between durum wheat yields and weather conditions otherwise not caught; third, we assessed whether the relationship yield-temperature control for three categories of durum wheat earliness. We found several connections among yields and weather variables, highly related to both phenological stages, different temporal and design specifications within the econometric model, and earliness. We contributed to discuss on the feasibility of the weather index-based insurance at farm-level, also animating the debate on how policymakers may improve the attractiveness of these risk management tools using publicly available data.

Keywords: *climate change; farming system; crop insurance; risk management; weather index*.

Chapter 1

General introduction

1.1 Background

Agriculture is the most vulnerable sector to climate change, e.g., temperatures or rainfall may significantly affect the crop yields, also leading the proliferation of pathogens and hence pests and diseases (Malhi et al., 2021). The total economic losses from weather- and climate-related have caused damages reaching nearly 487 billion of euros in EEA member countries since 1980, and just 3% of all events are responsible for 60% of economic losses (EEA, 2022a). Extreme weather events such as heavy precipitation, flood, drought, frost, heat, and strong wind are more and more frequent, intense, long-lasting, and they are the major drivers of agricultural losses (Walsh et al., 2020; Bucheli et al., 2023). Heavy precipitation may reduce photosynthetically active radiation up to irreversible tissue damages, setting the conditions for diseases due to the proliferation of pathogens, nutrient leaching, soil erosion, and oxygen deficit (Makinen et al., 2018; Zampieri et al., 2019), also inducing flash flood events, in combination with other factors as the antecedent soil moisture (Diakakis, 2012; Kaiser et al., 2020). Drought and water shortage may affect the metabolism of plants with changes in root growth and architecture, and other tissue-specific responses that modify the flux of cellular signals (Gupta et al., 2020). The stress due to drought events is the main factor limiting the development of crop and its productivity (Iqbal et al., 2020). Cold may damage the leaf and seedling survival, also leading to the sterility and the abortion of formed grains, especially for the cereal crops (Barlow et al., 2015). Heat directly affects the crop physiology, reducing photosynthesis rates, leading the acceleration of leaf senescence processes, oxidative damages, and pollen sterility (Rezaei et al., 2015). On-farm and risk-sharing strategies are available to improve the resilience of farming systems to weather risks. The former includes risk control (i.e., risk prevention such as irrigation, shading, pest control, improved planning and monitoring activities), reserves (i.e., stocking, financial savings, additional labour input), and diversification (i.e., agricultural and structural diversification as nature conservation or agrotourism, off-farm allocation of resources); the latter includes risk pooling (i.e., mutual funds, agricultural insurance, membership in cooperatives, credit unions, producer organizations), and risk transfer (i.e., forwards, futures contracts) (Vroege and Finger, 2020). Member States may grant support for risk management tools (e.g., financial contribution to insurance premiums and to mutual funds) which can help farmers to manage production and income risks related to their agricultural activity and over which they have no control (Devot et al., 2023). The new Common Agricultural Policy (CAP) reform is putting increasing emphasis on instrument supporting proactive management of the effects of extreme weather events due to climate change (Devot et al., 2023). Among the risk management tools, the weather index-based insurance may play a key role protecting farmers against weather-related risks. Unlike traditional indemnity crop insurances which rely on yield losses and physical damage observations, weather index-based insurances indemnify the farmers based on predefined weather parameters (or indexes) as triggers, e.g., excess rainfall or extremely hot temperatures, easily measurable and directly related with production yields (Barnett and Mahul, 2007; Shirsath et al., 2019; Vroege and Finger, 2020). Therefore, the indemnification is triggered whenever the value of the index exceeds or falls short the threshold (Belissa et al., 2019; Tappi et al., 2023). The index, recorded by weather stations or provided by other data sources, is independent, objective, transparent, and free from manipulations (Conradt et al., 2015; Shirsath et al., 2019 Bucheli et al., 2021). These characteristics represent the strengths of weather index-based insurances when compared with the traditional indemnity insurances. Sure enough, the latter show some issues as the asymmetric information, high transaction costs, moral hazard, and adverse selection (Ceballos et al., 2019; Abdi et al., 2022). However, the weather index-based insurances present the limit of basis risk, i.e., the discrepancy between insurance payouts and agricultural output (Dalhaus et al., 2018; Leblois et al., 2020). More specifically, the insured farmers may experience yield losses, while the weather index does not trigger a payment, or may obtain a compensation without having any yield losses because the index trigger the reimbursement, in other words, the index is not perfectly correlated with the actual losses which affected insurance policyholders (Heimfarth and Musshoff, 2011; Clement et al., 2018). Furthermore, following the previous reasoning, the insured farmers may not be adequately compensated as result of production losses (Dalhaus et al., 2018). Basis risk can be separated into three categories depending on the causes: (i) spatial (or geographical) basis risk due to the distance of weather station from the location covered by insurance contract; (ii) design basis risk due to the imperfect correlation between weather index and crop yields; (iii) temporal basis risk due to imperfect time period selection for deriving the index, e.g., the weather index does not capture the phenological stage more susceptible to a specific weather event (Dalhaus et al., 2018; Abdi et al., 2022; Shmidt et al., 2022). Although premium cost represents the major limitation for the weather index-based insurance widespread (Lichtenberg and Iglesias, 2022), basis risk hampers the functioning of index insurance products and lowers insurance demand (Clement et al., 2019). The challenge is to identify both an effective weather index and the damage thresholds depending on availability of data and models, as well as on the deepening of the critical aspects driving the weather-yields relationships, a major driver of distrust in currently offered index-based insurance schemes (Ceballos et al., 2019). Weather index insurance allows farmers to diversify their risk portfolio, also playing a crucial role in enhancing farmers' access to credit and investment (Tadesse et al., 2015).

1.2 Objective of the thesis

The objectives of the thesis are at least twofold: first, it provides empirical evidence on how yields and weather variables are correlated, i.e., the working principle of the weather index-based insurances; second, it animates the debate on how policymakers may make use of publicly available data to calibrate an effective weather index-based insurance. More specifically, the thesis tries to replay to the following research questions:

1. How durum wheat yields and weather events occurring in susceptible phenological stages are correlated?
2. How different weather variables (and combinations of thereof) and different approaches identifying phenological stages (i.e., Growing Degree Days vs fixed time period) may lead to different results on the relationships between durum wheat yields and weather variables?
3. How different durum wheat earliness (i.e., early-maturing, middle-maturing, and late-maturing) may affect the yield-temperatures relationship across different phenological stages?

Apart from the new knowledge to the scientific community, the thesis has direct implications for farmers aiming to adopt ex-ante risk management strategies (e.g., choice of earliness), and for policymakers planning ex-post risk management strategies (e.g., incentive to crop insurance uptake).

1.3 Structure of the thesis

The remainder of the thesis is composed of three research chapters, with each chapter aimed at achieving the research objectives discussed above (Chapter 2-4), and a last chapter with a general conclusion.

Chapter 2 analyses the first objective deepening the connections between weather conditions and durum wheat yields.

Chapter 3 focuses on the second objective emphasizing the importance of crop phenology and the combination of weather variables within the econometric model to catch further yield-weather relationships.

Chapter 4 investigates the third objective, deepening how minimum and maximum temperatures may affect durum wheat yields across different phenological stages and earliness.

Chapter 5 presents the general conclusion of this research work, also synthetizing the main findings of the thesis, highlighting limitations and future research directions.

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Chapter 2

On the relationships among durum wheat yields and weather conditions: evidence from Apulia region, Southern Italy

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On the relationships among durum wheat yields and weather conditions: evidence from Apulia region, Southern Italy

Abstract

The weather index-based insurances may help farmers to cope with climate risks overcoming the most common issues of traditional insurances. However, the weather index-based insurances present the limit of the basis risk: a significant yield loss may occur although the weather index does not trigger the indemnification, or a compensation may be granted even if there has not been a yield loss. Our investigation, conducted on Apulia region (Southern Italy), aimed at deepening the knowledge on the linkages between durum wheat yields and weather events, i.e., the working principles of weather index-based insurances, occurring in susceptible phenological phases. We found several connections among weather and yields and highlight the need to collect more refined data to catch further relationships. We conclude opening a reflection on how the stakeholders may make use of publicly available data to design effective weather crop insurances.

Keywords: climate change, farming system, phenological phase, risk, weather insurance.

1. Introduction

Farming activities are exposed and vulnerable to several risks, among which the weather risks are increasingly frequent and impactful due to cli mate change (Conradt et al., 2015). Among the several strategies available to reduce the weather impacts on farming systems, e.g., pest control, financial saving, agricultural and structural diversification (Vroege and Finger, 2020), the crop insurance programs can play an important role (Di Falco et al., 2014). In recent years, the attention for the weather index-based insurances (WIBIs) has been growing mainly because these tools may help to overcome some of the challenges associated with traditional indemnity-based insurances, e.g., asymmetric information, high transaction costs, moral hazard, and adverse selection (Norton et al., 2013; Dalhaus and Finger, 2016; Belissa et al., 2019; Ceballos et al., 2019). Differently from the traditional insuranc es, which provide pay-outs depending on actual yield losses, WIBIs indemnify the farmers when an index, computed on rainfall or temperature and highly correlated with farms performance (e.g., yields), is triggered (Conradt et al., 2015; Dalhaus and Finger, 2016). Therefore, farmers will be indemnified when the index exceeds a pre-determined threshold (Belissa et al., 2019). Moreover, WIBIs can be manipulated neither by the insurers or the insured because they are collected from historical and current dataset provided by recognized bodies (Belissa et al., 2020; Vroege et al., 2021). However, WIBIs present a limit, namely basis risk: a significant yield loss may occur even if the weather index does not trigger the payment (Conradt et al., 2015; Dalhaus et al., 2018) or a compensation may be granted even if there has not been a yield loss (Heimfarth and Musshoff, 2011). The contribution of our study is at least twofold: first, we provide empirical evidence on how yields and weather conditions are correlated, more specifically, we deepen the knowledge on the linkages between durum wheat yields and weather events occurring in susceptible phenological stages; second, we start a reflection on how stakeholders may make use of publicly available data to design an effective crop insurance scheme. We focused on the Apulia region (Southern Italy) which is the main national producer of durum wheat: almost a thousand of tons of production, i.e., accounting for 25% of the Italian durum wheat production, and about 344 thousand cultivated hectares, i.e., accounting for 28% of the Italian area utilized to grow durum wheat (ISMEA, 2020).

2. The Italian crop insurance system

The Italy boasts a long tradition of public subsidies for agricultural risk management. The “Fondo di Solidarietà Nazionale” (FSN) was instituted in 1974 to finance both insurance policies and ex-post payments (Enjolras et al., 2012). Moreover, the EU Common Agricultural Policy allocated funds for agricultural insurances (art. 37 of EU Reg. 1305/2013) to cope economic losses due to adverse weather conditions, plant diseases, epizooties, and parasitic infestations (Santeramo et al., 2016; Rogna et al., 2021). Despite the public interventions, the participation level to insurance programs remains low (i.e., around 15 percent) mainly due to high costs of bureaucracy (i.e., complexity of procedures), delays in payments, lack of experience with crop insurance contracts or lack of high-quality information on existing insurance tools (Santeramo, 2019). The role of Defense Consortia, introduced both to facilitate the match of insurers and farmers in the subsidized crop insurance market and to reduce the asymmetric information, is not negligible. It emerges a North-South territorial dualism that affects farmers participation: Defence Consortia are more effective in Northern Italy than in the Southern Italy and, also, the strong presence of producer organizations and cooperatives aggregates the crop insurance’s demand in the Northern Italy (Santeramo et al., 2016). Moreover, farmers who trust more in the intermediaries assisting them are inclined to adopt insurance tools to cope the risk of production loss, while risk averse farmers tend to implement other risk management strategies as crop or financial diversification (Trestini et al., 2018). In Italy, only the 9.9 percent of Utilised Agricultural Area is covered by insurance contracts and 20.9 percent of production value is insured (ISMEA, 2021). According to a survey conducted by ISMEA in 2018 on low participation to the subsidized agricultural insurance systems, most Italian farmers renounce to subscribe insurance contracts due to economic reasons, highlighting the high costs of policies. The share of farmers who believe that their farms are not exposed to specific risks or who have had negative experiences when receiving compensation, losing trust on insurance market systems, is also not negligible. Indeed, Giampietri et al., 2020 found that the trust affects the decision-making process: under uncertainty, the trust may substitute the knowledge also overcoming the lack of experience, therefore, strong communication campaigns to improve farmers' participation are recommended. Moreover, focusing on the WIBIs, also subsidized by the Measure 17 of National Rural Development Program 2014-2020, a lack of knowledge emerged among big insured farmers, i.e., WIBIs were unknown to 93 percent of them (ISMEA, 2020). Furthermore, some farmers believe that index-based insurances are inadequate to manage the weather risks due to the distrust of the objectivity of the indexes and parameters used, also showing an aversion to any future subscriptions. Clearly, it is necessary to improve the appeal and communication of these innovative risk management tools, also considering that any intervention aimed at promoting farmer participation should improve the competition among insurance providers, also reducing at the same time the asymmetric information and opportunistic behaviour (Menapace et al., 2016; Rogna et al., 2021; Santeramo and Russo, 2021). In this complex scenario, we estimate the yield response equation to investigate the responsiveness of yield to climate, deepening the working principles of weather index-based insurance, through a case study on durum wheat crop in the Apulia region, also animating the debate on the use of publicly available data to the development of an effective and attractive tool to manage climatic risk in agriculture.

3. Data and research methodology

An agronomic review on durum wheat allowed us to identify sensitive phenological stages of durum wheat in Apulia region and those critical weather events occur ring in certain phenological stages that may cause significant production losses (Table 1). Cold sensitivity is higher during the germination phase that occurs 10-15 days after sowing in which temperatures of few degrees centigrade below zero may cause considerable damages (Baldoni and Giardini, 2000, Angelini, 2007; Disciplinare di Produzione Inte grata della Regione Puglia, 2021). Likewise, temperatures of few degrees centigrade below zero during the stem elongation phase may cause stems death and serious damages to the tissue of the internodes (Baldoni and Giardini, 2000; Angelini, 2007; Disciplinare di Produzione Integrata della Regione Puglia, 2021). Flowering stage occurs in late May and lasts about 10 days in which wheat crop is highly sensitive to cold stress that may cause death of flowers (Angelini, 2007; Baldoni and Giardini, 2000; Disciplinare di Produzione Integra ta della Regione Puglia, 2021). Heat and drought stress during susceptible flowering and grain filling stages (i.e., after flowering, until the first decade of July) may cause considerable reductions in wheat yield and quality, lead ing the acceleration of leaf senescence process, reducing photosynthesis, causing oxidative damage, pollen sterility, also reducing physiological and metabolic imbalances, photosynthesis, grain numbers and weight (Angelini, 2007; Asseng et al., 2011; Li et al., 2013; Farooq et al., 2014; Rezaei et al., 2015; Zampieri et al., 2017; Makinen et al., 2018). Heavy rainfall during the entire crop cycle may cause significant production losses due to the proliferation of pathogens, nutrient leaching, soil erosion, inhibition of oxygen uptake by roots (i.e., hypoxia or anoxia), waterlogging and lodging (Zampieri et al., 2017; Makinen et al., 2018). Furthermore, we collected yearly total production (tons) and area harvested (hectares) data for durum wheat crop from the National Institute of Statistics (ISTAT), from 2006 to 2019, for each province of Apulia region, also calculating the respective yields (tons/ hectare). Then, for the same time-period, we collected 10-days frequency weather data from six synoptic weather stations of the Institute for Environmental Protection and Research (ISPRA), one for each province of Apulia region: Bari (BA), Barletta-Andria-Trani (BT), Brindisi (BR), Foggia (FG), Lecce (LE), Taranto (TA). Weather data include 10-days average minimum temperature (°C), i.e., the average of daily minimum temperatures, 10 days average maximum temperature (°C), i.e., the average of daily maximum temperatures, and 10-days cumulative precipitation (mm), i.e., the average of daily precipitation. Details on collected variables are shown in Table 2. Our empirical approach is based on a panel data model that includes fixed effect (i.e., it is a major advantage of the panel rather than cross-sectional regression) both to control for unobservable variables such as seed varieties or soil quality that may vary across the space, i.e., provinces, and to catch the variation across the time within the Apulian provinces (Tack et al., 2015; Blanc and Schlenker, 2017; Kolstad and Moore, 2020).

Table 1. Phenological stages, weather events and critical limits of durum wheat in Apulia region.

Phenological stage	Weather event	Time interval	Critical limit	Reference
Sowing	Cold	From the first decade of November to the first decade of December	Temperature < 0 °C	Baldoni and Giardini, 2000; Angelini, 2007; Disciplinare di produzione integrata della Regione Puglia, 2021
Germination	Cold	From the second decade of November to the second decade of December	Temperature < 0 °C	
Stem elongation	Cold	From the second decade of March to the third decade of April	Temperature < 0 °C	Baldoni and Giardini, 2000; Angelini, 2007

Flowering	Cold	From the second decade of May to the first decade of June	Temperature < 0 °C	Angelini, 2007; Disciplinare di produzione integrata della Regione Puglia, 2021
	Heat, drought		Temperature > 30-31 °C	Angelini, 2007; Rezaei et al., 2015
Grain filling	Heat, drought	From the second decade of June to the first decade of July	Temperature > 34 °C	Angelini, 2007; Asseng et al., 2011; Rezaei et al., 2015; Zampieri et al., 2017; Makinen et al., 2018
All phases	Excessive rainfall	From first decade of November to the first decade of July	Rainfall > 40 mm/day	Makinen et al., 2018

Table 2. Details on collected variables.

Variable (unit)	Frequency	Time-period	Province	Weather station - province (no. of obs, SR in km^2)	Source
durum wheat yield (tons/hectares)	Yearly			-	ISTAT
average minimum temperature (°C) average maximum temperature (°C) cumulative precipitation (mm)	10-days	2006-2019	Bari (BA) Barletta-Andria-Trani (BAT) Brindisi (BR) Foggia (FG) Lecce (LE) Taranto (TA)	Bari - BA (501, 5.138) Trani - BT (144, 1.543) Brindisi - BR (471, 1.839) Monte Sant'Angelo - FG (504, 7.008) Lecce - LE (471, 2.799) Marina di Ginosa – TA (471, 2.437)	ISPRA, UCEA, ARPA

Note: missing data have been integrated including Research Unit for Climatology and Meteorology (UCEA) and Regional Agency for the Protection of the Environment (ARPA) datasets. Table includes no. of observations and spatial resolution (SR) of weather stations.

The relationship between durum wheat yields and weather events is synthesized as follows:

$$y_{it} = f(w_{it}) + \mu_i + \theta_t + \epsilon_{it}$$

where $y_{it}$is the yield over the space (i) and time (t) as function (f) of weather (w_{it}), also including fixed effects over space (μ_i) and time (θ_t), error term and "controls" refers to other relevant exogenous variables (ϵ_{it}) (Kolstad and Moore, 2020). More specifically, we conducted temporal and spatial autocorrelation identifying those con tiguous provinces having a larger shared borders for a twofold check: (i) verify if the weather events occurring in a province may affect durum wheat yields in the con tiguous province; (ii) control if the yields may be affected by weather events occurring at time t-1. Undoubtedly, both environmental and agronomic factors may justify the extreme variability of the durum wheat yield across the Apulian provinces: Foggia shows the highest average durum wheat yields while Lecce shows the lowest average yields, although it is characterized by lower yield variability than other provinces as Brindisi that, on the contrary, is more affected by environmental and agronomic factors, reason why it may benefit of crop insur ance programs more than other provinces to cope yields fluctuations (Table 3).

Table 3. Durum wheat yields (tons/hectare) among Apulian provinces

	Average	Minimum	Maximum	Standard deviation
Bari	0.234	0.170	0.306	0.045
BAT	0.224	0.200	0.260	0.020
Brindisi	0.285	0.180	0.420	0.071
Foggia	0.314	0.200	0.420	0.047
Lecce	0.189	0.160	0.220	0.018
Taranto	0.244	0.100	0.350	0.057

Note: data include yearly durum wheat yield from 2006 to 2020. Source: ISTAT, 2020.

4. Results

Our results clearly show that a relationship links weather conditions and production yields in the Apulia region. More specifically, precipitation seem to have a negative effect on durum wheat yields (Table 4).

Table 4. Effects of weather variables on durum wheat yield

VARIABLES	Panel prov FE time trend	Panel temporal correlation prov FE time trend	Panel spatial correlation prov FE time trend	Panel temporal correlation spatial correlation prov FE time trend
Temperature (min)	-0.00764	-0.00124	-0.46909***	-0.45553**
	(0.10641)	(0.11715)	(0.17058)	(0.18731)
Temperature (min) sq.	0.00049	-0.00023	0.00892*	0.01384**
	(0.00296)	(0.00320)	(0.00490)	(0.00544)
Temperature (max)	0.22572	0.28286*	0.61165**	0.66801**
	(0.14125)	(0.15378)	(0.25587)	(0.27703)
Temperature (max) sq.	-0.00523*	-0.00612**	-0.01530***	-0.02022***
	(0.00278)	(0.00299)	(0.00515)	(0.00568)
Precipitation	-0.01646**	-0.01625*	-0.03939**	-0.04670**
	(0.00799)	(0.00844)	(0.01819)	(0.01954)
Precipitation sq.	0.00008	0.00007	0.00019	0.00024
	(0.00006)	(0.00006)	(0.00017)	(0.00018)
Yield (lag)	-	0.10464***	-	-0.09290***
		(0.02153)		(0.03579)
Temperature (min) contig.	-	-	0.23065***	0.18642***
			(0.06565)	(0.07019)
Temperature (max) contig.	-	-	0.00822	0.04557
			(0.10765)	(0.11545)
Precipitation contig.	-	-	0.00537	0.00771
			(0.00704)	(0.00837)
Observations	1,837	1,638	914	833
Number of id	6	6	4	4

Note: panel regression model was processed in STATA software. It includes provincial fixed effect, time trend, temporal (i.e., yield lag) and spatial (contiguous variables) autocorrelation. Standard errors in parentheses:
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

However, controlling by spatial and temporal autocorrelation, the effects of temperatures have been caught. Minimum temperatures negatively affect durum wheat yields, while maximum temperatures positive ly affect the yields, both in a non-linear way. Indeed, we included the squares of weather variables to catch the nonlinearity, in other terms, the trade-off between weather and yields (Blanc and Schlenker, 2017). Our results clearly highlight that the weather affects the yields in a nonlinear way, therefore, variables have a statistically significant inverted-U shape relationship (Schlenker and Roberts, 2009; Lobell et al., 2011). Last but not least, minimum temperatures may affect the contiguous provinces. According to the scientific literature, any excess (or deficit) of temperature and precipitation (or their combinations) may cause severe yield losses on durum wheat (Baldoni and Giardini, 2000; Angelini, 2007; Asseng et al., 2011; Li et al., 2013; Farooq et al., 2014; Rezaei et al., 2015; Zampieri et al., 2017; Makinen et al., 2018). Furthermore, we estimated the model for each phenological phase of durum wheat to capture the potential heterogeneity in the effect of weather variables, also controlling by spatial and temporal autocorrelation. Our results show that the relationship between weather variables and yields is valid only for some weather variables in certain phenological phases. More specifically, the maximum temperatures and precipitation positively affect durum wheat yield in a nonlinear way when occur in the germination and grain filling stages, respectively (Table 5).

Table 5. Effects of weather variables on yield by phase

VARIABLES	sowing	germination	stem elongation	flowering	grain filling
Yield (lag)	-0.11883	0.05952	0.17798*	-0.04474	0.09403
	(0.20660)	(0.20523)	(0.09219)	(0.18593)	(0.14041)
Temperature (min)	0.95845	-0.00051	0.50020	-1.32087	-0.65587
	(2.53724)	(1.74362)	(1.26379)	(4.06620)	(3.83238)
Temperature (min) sq.	-0.01783	0.01530	-0.01201	0.03550	0.02171
	(0.11363)	(0.08655)	(0.05223)	(0.10882)	(0.08353)
Temperature (max)	3.15220	23.00804**	-2.73726	7.62398	-1.65011
	(12.35641)	(10.88917)	(2.21349)	(8.51643)	(6.74553)
Temperature (max) sq.	-0.15964	-0.76330**	0.06023	-0.15868	0.01396
	(0.35336)	(0.33477)	(0.05582)	(0.15987)	(0.11320)
Precipitation	0.04601	-0.07450	-0.03735	-0.43463	0.42332*
	(0.12015)	(0.11228)	(0.07473)	(0.42173)	(0.24351)
Precipitation sq.	-0.00034	0.00054	0.00049	0.01188	-0.00826*
	(0.00088)	(0.00084)	(0.00101)	(0.01680)	(0.00463)
Temperature (min) contig.	1.05294**	0.86957**	0.62187***	0.52210	0.55304**
	(0.41397)	(0.35021)	(0.17188)	(0.35845)	(0.23765)
Temperature (max) contig.	0.38942	0.17524	-0.06474	0.22627	0.00512
	(1.25128)	(1.33537)	(0.34861)	(0.52741)	(0.37530)

Precipitation contig.	-0.05370	0.01278	-0.01394	-0.10017	-0.05635
	(0.05168)	(0.04199)	(0.03275)	(0.11446)	(0.04998)
Observations	42	44	125	43	67
Number of id	4	4	4	4	4

Note: panel regression model was processed in STATA software. It includes provincial fixed effect, time trend, temporal (i.e., yield lag) and spatial (contiguous variables) autocorrelation. Standard errors in parentheses:

*** Significant at the 1 percent level

** Significant at the 5 percent level

* Significant at the 10 percent level

Moreover, minimum temperatures may affect the contiguous provinces. Clearly, ten-days data we have collected does not highlight the dynamics between weather events occurring in certain phenological stages and durum wheat yields mainly because the impacts of daily weather are not captured. Moreover, most variables are not statistically significant: this limit opens a reflection on data disaggregation level and on the need to collect more spatially and temporally refined data, also laying the foundations for the development of an effective index that reflects the responsiveness of the yields to climatic conditions to be implemented in the WIBIs. The evidence resulting from our econometric model on phenological stages is also in contrast with the literature: germination stage is highly sensitive to cold stress (Baldoni and Giardini, 2000, Angelini, 2007; Disciplinare di Produzione Integrata della Regione Puglia, 2021), while there are not evidences on heat stress during this stage. However, our study may help the debate suggesting precise directions for the future research.

5. Conclusions

Participating in index-based crop insurance schemes is a key challenge to improve the resilience of farming systems and adopting effective subsidies to enhance participation in the schemes is a pressing goal for policymakers. In this complex scenario, we investigated how temperatures and precipitation are correlated with yields data to reflect on potential designs for the index-based insurance schemes. While not novel (e.g., Chen et al., 2014), we found that weather changes affect durum wheat yields in a nonlinear way and some weather events occurring in certain phenological phases may have an impact on the yields. Our results are important to show that even with aggregated data the evidence is striking. However, focusing on phenological stages, our findings are in contrast with the literature highlighting the complexity of the phenomenon and the need to rely on more temporally and spatially disaggregated data. Although we provided clear evidence on the weather yield relationship, it is impossible to design a WIBI using 10-days weather data. Therefore, our contribution may help the debate suggesting precise directions for the future research: first, a major effort should be devoted to the collection of weekly or daily weather observations, also identifying empirical damage thresholds that can be verified at farm-level, as well as the collection of production area or municipal data; a promising approach could be the Growing Degree Days tool so as to calibrate the more precisely the growing stages in a view to a better explanation of weather risks on crop performances (Conradt et al., 2015; Dalhaus et al., 2018; Lollato et al., 2020); last but not least, the design of the index based insurance schemes needs of further investigation because establishing a triggering index is a major challenge for the stakeholders involved in the implementation of the insurance schemes. The debate on crop insurance schemes is still vivid, and it will be so also in the next decade due to the central role that the risk management (old and novel) tools will have in the new CAP (Meuwissen et al., 2018; Severini et al., 2019; Cordier and Santeramo, 2020).

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Chapter 3

Temporal and design approaches and yield-weather relationship

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Temporal and design approaches and yield-weather relationship

Abstract

The climate changes and the weather events affect agricultural production and farmers' income. Several strategies may help improving the resilience of farms to climate change, and particular mention should be done to the weather index-based crop insurance schemes, as they rely on the yield-weather relationship. A vast majority of studies investigate the limitation of the weather index insurance, due to the complex relationships linking weather events and yields and the difficulty to capture them with an index (i.e., the basis risk). The literature has not devoted sufficient attention to compare different specifications within the same statistical model in yield-weather estimation. Our study, conducted on durum wheat in Italy, shows how the identification (and design) of the phenological stages (i.e., temporal specifications) may help capturing or depicting the yield-weather relationships. The negative effects of the low temperatures, especially during the early stages of durum wheat, is remarkable. Our findings contribute to the debate on the design of triggers in weather indexes (e.g., for minimum temperatures), stimulating new research directions to assist stakeholders interested in planning agricultural risk management interventions.

Keywords: basis risk, crop, climate, phenological stage, insurance, risk management

1. Introduction

Climate and extreme weather events such as drought, heat, and excess rainfall heavily affect agricultural production hampering the smallholder farmers on productivity-enhancing or technologies investments (Ceballos et al., 2019; Anghileri et al., 2022). Farmers may improve their resilience to climate change by implementing several agroecological practices, e.g., crop diversification, maintaining local genetic diversity, soil organic management and water conservation (Altieri et al., 2015). Vroege and Finger (2020) provided an overview of risk management strategies to cope with climate risks, namely: on-farm strategies (e.g., risk prevention as irrigation, shading, pest control, financial savings, agricultural and structural diversification) and risk-sharing strategies (e.g., mutual funds, agricultural insurance, membership in cooperatives and producer organizations). Among these, crop insurance schemes may represent a suitable tool to mitigate unexpected losses and to stabilize farmers' incomes (Shirsath et al., 2019; Vroege and Finger, 2020). In the past years, the focus on the weather index-based insurances (WIBIs) to manage climate and extreme weather-induced damage to crop has increased (Barnett and Mahul, 2007; Anghileri et al., 2022). In contrast to traditional insurance products which provide pay-outs based on yield losses experienced by farmers and on physical damage observations, WIBIs are based on an independent, objective, transparent, and manipulation free weather index that is heavily related to crop yields, rainfall or temperatures, recorded by specific weather stations (or other data sources)) during a certain time window. Indemnity is triggered whenever the value of the index exceeds or falls short of a predetermined threshold, e.g., deficit or excess rainfall, drought or extreme temperatures that may have a significative impact on crop yields (Barnett and Mahul, 2007; Conradt et al., 2015a, 2015b; Dalhaus and Finger, 2016; Dalhaus et al., 2018; Shirsath et al., 2019; Bucheli et al., 2021; Tappi et al., 2022). WIBIs may play a crucial role in overcoming some of the issues related to the traditional indemnity-based insurances, such as adverse selection[1], asymmetric information[2], and moral hazard[3] (Conradt et al., 2015a, 2015b; Belissa et al., 2019, Bucheli et al., 2022). However, they present a major limit, namely *basis risk*: farmers may experience severe yield losses without any reimbursement (Conradt et al., 2015a, 2015b) or, on the contrary, they may obtain a compensation without any yield loss (Heimfarth and Musshoff, 2011) mainly due to the discrepancy between the pay-outs triggered by the weather index and actual losses. More specifically, basis risk can be decomposed in three parts: (i) spatial (or geographical) basis risk, due to the distance of weather stations from farms; (ii) design basis risk, due to the inadequate choice of index to predict the yield losses; (iii) temporal basis risk due to the inaccurate choice of the time-period for index determination. Some authors proposed solutions to reduce basis risk. Focusing on spatial basis risk, Norton et al. (2013) suggested to ensure multiple weather stations in a single contract as “risk portfolio”, while Boyd et al. (2019) and Leppert et al. (2021) showed the advantages of using an interpolation approach that includes multiple weather stations into the estimate, rather than relying only on the closest available station to farms. Focusing on design basis risk, Abdi et al. (2022), conducted a systematic review of the last 20 years on weather index insurance design finding that rainfall and temperature indices were prevalent compared them to those based on droughts and floods, vegetation, soil moisture, humidity, and sunshine hours. Regarding the temporal basis risk, Dalhaus et al. (2018), highlighted the importance to consider the phenological observations provided by public bodies to catch the vulnerability of specific crop stages to weather events. Conradt et al. (2015a, 2015b), proposed a more accurately flexible approach to identify crop growing stages rather than fixed calendar dates. Afshar et al. (2021) improved the performance of index insurance integrating biophysical process-based crop model, phenological monitoring through satellite remote

[1] Adverse selection occurs when risk exposed farms tend to subscribe insurances more often (Vroege et al., 2021).
[2] Asymmetric information occurs when farmers and insurers do not have the same information (Santeramo, 2018).
[3] Moral hazard occurs when farms purchasing insurance products are inclined to adopt riskier behaviours (Santeramo and Ford Ramsey, 2017).

sensing, and machine learning techniques). Other studies included simple indexes (e.g., rainfall or temperatures) by summing up the weather information within the crop stages in a specific territory (Turvey, 2001; Kellner and Musshoff, 2011). Black et al. (2015), investigated the role of temporal aggregation satellite-based weather data as crop yields are linked more closely to cumulative weather events than to instantaneous, e.g., soil moisture is affected by the accumulation of rainfall over weeks or months. Moreover, several authors synthetized different approaches in yield-weather relationships[4]: Auffhammer et al. (2020), identified five pitfalls that may lead to measurement errors in the econometric analyses of climate change, also deepening the issues on the disaggregation level of weather data (across space and time) and on climate models as global climate models that provide long-run predictions of climate; Carter et al. (2018), compared the most used methods (i.e., cross-sectional and panel regression analysis) to assess the climate impacts on agricultural outcomes; Webber et al. (2020), used a novel combination of dynamic, process-based crop model and data-driven machine learning approach to investigate the relationship between yield and weather, also considering the crop phenology based on a database. Conradt et al. (2015a, 2015b), showed the advantages of quantile regression to design an effective insurance contract. However, the literature still neglects the role of the temporal and design specifications within the same econometric model that may lead to different results in yield-weather assessment, i.e., the working principle of index-based insurances. Our study aims to assess how different approaches for the phenological stages identifications (i.e., temporal specifications) and how different weather variables and combination of thereof (i.e., design specifications) within the econometric model may catch further relationships between yields and weather conditions otherwise not caught. We focused on durum wheat in Italy, the first world producer of pasta from durum and territory highly suited to produce of wheat (De Vita et al., 2007). Crop phenology is very important to evaluate the impacts of extreme weather events, e.g., drought and heat during flowering and grain filling stages may lead to heavily yield losses (Farooq et al., 2014; Zampieri et al., 2017). Therefore, we identified five phenological stages of durum wheat (i.e., starting, development, flowering, maturity, end) using two approaches, i.e., fixed time windows and Growing Degree Days (GDD), also including different sowing dates and varieties (i.e., early, middle, and late). This is because the timing of a crop's susceptibility to weather events may differ across farms due to the differences in management practices leading to an inaccurate estimation of yield losses (Afshar et al., 2021). Furthermore, we included daily weather variables and combination of thereof in the econometric model to assess and compare their effects on yearly durum

[4] We gratefully acknowledge the comment raised by the reviewer. Although our paper shows similarities with cited studies on yield-weather relationships which deepened the issues on estimation models (e.g., global climate models, cross-sectional and panel regression analysis, quantile regression, long differences, etc.) and on some aspects such as nonlinearities, displacement, uncertainty, adaptation, and cross-study comparison, we used the same statistical method (i.e., panel regression) to assess how different specifications that also consider different phenological stages may show different results on yield-weather assessment.

wheat yields: temperatures, precipitation, crop evapotranspiration, crop water deficit, and temperature range as difference of daily maximum and minimum temperature. In particular, crop evapotranspiration and crop water deficit, phenological phases-related and crop-specific variables, are very important components to evaluate possible drought stress conditions occurring during growth stages, which are the main limiting factors in durum wheat grain yield (Djaman et al., 2018; Zhang et al., 2021). Often, the policymakers encourage the participation in crop insurance schemes providing large subsidies recognising the gravity of climate changes impacts and investment in adaptation strategies (Collier et al., 2009; Santeramo et al., 2016; Santeramo, 2018, 2019). However, according to a survey conducted in 2018 by the Institute of Services for the Agricultural Food Market (ISMEA) on risk management perceptions of Italian big insured farms, it emerged a low propensity to underwrite weather index contracts exists due to the distrust of the objectivity of the indices and parameters used. The deepening of the dynamics yield-weather is a key concept in improving the underwriting of insurance contracts, therefore, our contribution is at least twofold: first, we emphasize on how differences in design and temporal specifications, i.e., comparing different combinations of weather variables (design specifications) occurring in susceptible phenological stages of durum wheat (temporal specifications) may influence the yields-weather relationships, also highlighting further relationships otherwise not caught; second, we animate the debate on how policymakers may make use of publicly available data to calibrate an effective weather index-based insurance.

2. Data and method

2.1 Empirical yield model

Our regression model is based on a panel data as a suitable method to assess the impact of climate change on agriculture as includes fixed effects to control for unobservable heterogeneity (e.g., soil quality or management practices) across the space and time (Tack et al., 2015). This approach gives an estimate of the short-run response to weather variation (Kolstad and Moore, 2020). Mérel and Gammans (2021) highlighted that the panel approaches with fixed effects widely used in short-run weather impacts estimation may also capture long-run climatic response. Our econometric regression is shown below:

$$y_{it} = f(w_{it}) + \theta_{it} + \varepsilon_{it}$$

where y_{it} is the yield over the province (*i*) and year (*t*) as function (*f*) of daily weather variables (w_{it}), θ_{it} capture the fixed effects over the space (*i*) and time (*t*), and (ε_{it}) is the error term. Furthermore, we designed our econometric model identifying three specifications that include different weather variables and combinations of thereof: (i) specification A (*baseline*), in which the durum wheat yield is function of temperatures, precipitation, and their squares; (ii) specification B, in which the durum wheat yield is function of temperatures, precipitation, and their squares, crop evapotranspiration, and crop water deficit; (iii) specification C, in which the durum wheat yield is function of precipitation and its square, crop evapotranspiration, crop water deficit, daily temperature range and its square. We included the squares of weather variables to capture the nonlinearity, i.e., the trade-off between weather and yields (Blanc and Schlenker, 2020). For each temporal and design specification, we adopted the same econometric regression, i.e., multiple panel regression. Generally, multiple regression is used to assess the relationship between several independent variables (e.g., weather variables) and a dependent variable (e.g., yield). This approach may lead to a more accurate and precise understanding of the connections between variables, more specifically, multiple panel regression may capture the influence of all the independent variables together as well as separately on dependent variable examined rather than simple panel regression (Nageswara Rao, 1983). Although gridded datasets provide highly disaggregated weather observations, discrepancy with what really occur on the farms may emerge, e. g., adding or removing weather stations, missing values, and the spatial correlation introduced by extrapolation algorithms may create potential biases in the econometric analysis (Auffhammer et al., 2020).

2.2 Study area and collected data

Durum wheat is the main cereal crop in Italy with a production of 4 million of tons cultivated in 1.2 million of hectares. Production is concentrated in Southern and Central Italy, while Northern Italy produces slightly more than 10 percent of national production. Province of Foggia (Southern Italy) is the main durum wheat producer of Italy with 750,000 tons (Fig. 1).

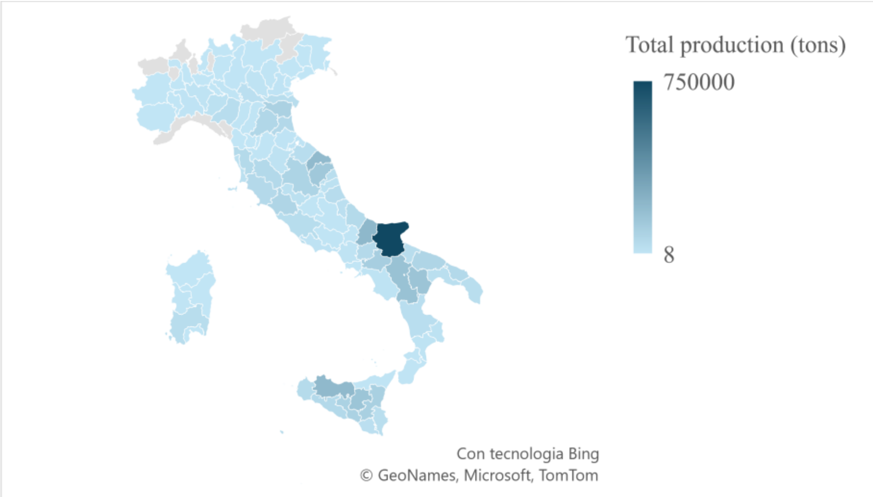

Fig. 1: Durum wheat Italian production by province. Source: ISTAT, 2020.

We collected yearly durum wheat yields data (i.e., total production over area harvested) of 30 main durum wheat-producing Italian provinces[5] from the National Institute of Statistics (ISTAT), from 2006 to 2020. Moreover, for the same time-period, we collected daily weather data from Joint Research Centre - Agri4Cast Meteorological database of European Commission that includes daily weather observations (i.e., temperatures, precipitation, wind speed, vapour pressure, potential evapotranspiration, global radiation) from stations interpolated on a 25 × 25 km grid. We aggregated the weather variables by average for the 30 main durum wheat-producing provinces selecting those most impactful on the yields (Guasconi et al., 2011): maximum air temperature (T max), minimum air temperature (T min), diurnal temperature range (DTR)[6], and precipitation (Prec). Moreover, wind speed, vapour pressure and potential evapotranspiration variables have been included to calculate further variables that may affect the yields: crop evapotranspiration (ETc)[7] and crop water deficit (CWD)[8]. Descriptive statistics of collected variables are shown in the Table 1:

[5] The main durum wheat-producing Italian provinces in decreasing order are: Foggia, Campobasso, Palermo, Ancona, Potenza, Matera, Enna, Macerata, Avellino, Catania, Ferrara, Caltanissetta, Perugia, Bari, Viterbo, Bologna, Ravenna, Brindisi, Siena, Agrigento. Benevento, Grosseto, Pisa, Chieti, Trapani, Teramo, Roma, Barletta-Andria-Trani, Rovigo, Pesaro-Urbino.

[6] Lobell (2007) showed that increasing in diurnal temperature range (i.e., the difference between maximum and minimum temperature) may negatively affect rice and maize yields.

[7] The Food and Agriculture Organization (FAO) defines the crop evapotranspiration as “the rate of evapotranspiration from an extensive surface of 8 to 15 cm tall, green grass cover of uniform height, actively growing, completely shading the ground and not short of water” (Xiang et al., 2020).

[8] Crop water deficit is defined as “consequence of water loss from the leaf as the stomata open to allow the uptake of carbon dioxide from the atmosphere for photosynthesis” (Turner, 1986).

Table 1. Descriptive statistics of collected variables.

Variables	Obs.	Mean	Std. Dev.	Min	Max
Durum wheat yield (tons/ha)	162,909	35.990	12.603	17	81.424
T min (°C)	164,370	11.285	6.410	-11.650	29.938
T max (°C)	164,370	20.123	7.829	-5.336	43.675
Prec (mm)	164,370	1.686	4.080	0	86.938
ET_c (mm) BGA	54,960	-3.128	2.222	-11.240	7.312
ET_c (mm) FAO 56	108,120	-2.349	2.186	-11.240	7.312
ET_c (mm) GDD 15	68,832	-1.376	1.013	-8.797	1.909
ET_c (mm) GDD 25	67,784	-1.447	1.086	-9.248	1.909
ET_c (mm) GDD EU	54,833	-1.305	1.011	-8.589	1.909
CWD BGA	54,960	-0.930	9.441	-2046.190	360.241
CWD FAO 56	108,120	-1.522	7.706	-2046.190	360.241
CWD GDD 15	68,832	-1.920	5.686	-131.135	600.759
CWD GDD 25	67,784	-1.882	9.349	-2046.190	309.273
CWD GDD EU	54,833	-1.984	6.124	-285.070	600.759
DTR (°C)	164,370	8.838	3.244	0.099	22

Note: ETc and CWD variables are phenological stage specific. BGA identifies the stages provided by Baldoni and Giardini (2000), and Angelini (2007); FAO 56 identifies stages provided by FAO Paper no.56; GDD 15, GGD 25, GDD EU identify stages calculated through Growing Degree Days approach at different sowing dates, November 15, November 25, and sowing dates provided by Agri4Cast EU dataset, respectively.

For our purpose, we used data provided by recognised authorities which are available both to public bodies and private citizens[9].

2.3 Impacts of weather conditions on durum wheat yields

The durum wheat crop is more susceptible to specific weather events in certain phenological stages, more specifically, cold sensitivity is higher during the starting and development stages, in which temperatures of 0 ◦C may cause growth arrests and considerable damages, especially when the soil is moist (Baldoni and Giardini, 2000; Angelini, 2007). Tack et al., 2015, found that freezing temperature in the fall season is one of the biggest drivers of wheat yield losses until 9 percent. Although many cultivars have high levels of frost tolerance, cold stress (<0 °C) during the vegetative stage may lead to a reduction in the rate of photosynthesis or even leaf, root, and plant death, also threatening seedling

[9] We gratefully acknowledge the comment raised by the reviewer. The understanding of yield-weather relationships using spatially (i.e., NUTS 3) and temporally (i.e., daily, or yearly) refined data publicly available represents a limit. Although the analysis of yield-weather relationships using weather stations at farm-level could be a suitable solution for further empirical estimates, the limits associated with the spatial distribution still remain (i.e., private weather station are not widely distributed). Moreover, farm-level data are not available to public bodies to plan further policies on agricultural risk management.

survival (Whaley et al., 2004; Barlow et al., 2015). Moreover, the flowering stage is susceptible to frost (Baldoni and Giardini, 2000). Heat and drought occurring in the flowering and grain-filling stages (i.e., maturity-end) may lead leaf senescence, pollen sterility, oxidative damages, reduction in photosynthesis, adversely affecting the yields (Farooq et al., 2014; Rezaei et al., 2015; Zampieri et al., 2017). High temperatures during Spring season (>34 °C) concomitant with flowering and grain filling stages may reduce yields until 7.6 percent (Tack et al., 2015). Moreover, higher temperatures increase the evapotranspiration demand, reduces the crop water use efficiency, causes water stress or its scarcity, and is highly related to yield losses (Saadi et al., 2015; Zampieri et al., 2017). Additionally, heavy rainfall may cause significant production losses due to the proliferation of pathogens, nutrient leaching, soil erosion, inhibition of oxygen uptake by roots (i.e., hypoxia or anoxia), waterlogging, and lodging (Zampieri et al., 2017). However, rainfall in the Spring may partially offset negative warming effects on yields (Tack et al., 2015).

2.4. Phenological stages identification

We identified five phenological stages of durum wheat: (i) starting, from sowing to leaf development; (ii) development, from leaf development to anthesis; (iii) flowering, from anthesis to seed fill; (iv) maturity, from seed fill to dough stage; (v) end, maturity complete. Each phase has been identified through two approaches: (a) fixed time windows provided by Baldoni and Giardini, 2000, and Angelini, 2007, which indicated the time-period of crop phenology; (b) GDD, i.e., the summatory of mean daily temperatures starting from sowing dates. This is computed by assigning a heat value to each day, giving an estimate of the amount of seasonal growth of plants, and is commonly used to predict events and schedule management activities (Miller et al., 2001). The formers are reported in the Table 2, while the latter in the Table 3:

Table 2. Phenological stages of durum wheat identified by fixed time windows.

Stage	BGA (Macro-region)	FAO 56
Starting	2nd - 3rd decade of October (Northern Italy) 1st - 2nd decade of November (Center of Italy) 2nd - 3rd decade of November (Southern Italy and Islands)	November 15 – December 14
Development	2nd - 3rd decade of March – by the end of April	December 15 – May 03
Flowering	2nd - 3rd decade of May	May 04 – May 14
Maturity	3rd decade of May – by the end of June	May 15 – June 12
End	3rd decade of June –1st decade of July	June 13 – July 12

Note: BGA identifies phenological stages provided by Baldoni and Giardini (2000), and Angelini (2007). Flowering stage has been identified in FAO 56 as the first 10 days of maturity stage (Angelini, 2007).

For GDD calculation, we considered the following sowing dates: November 15 (Allen et al., 1998), November 25 (10-days shift)[10], and sowing dates of wheat provided by EU JRC Agri4Cast dataset for each province investigated, therefore, GDD 15/25/EU will identify the sowing dates for the calculation of GDD. Furthermore, we included three durum wheat varieties (i.e., early, middle, and late) based on GDD centigrade ranges to assess the responsiveness of varieties to change in weather in specific phenological stages (Table 3):

Table 3. Durum wheat varieties and phenological stages identified by GDD ranges.

Stage	Growing Degree Days (°C)		
	Early varieties	Middle varieties	Late varieties
Starting	0-169	0-189	0-208
Development	169-807	189-854	208-901
Flowering	807-1068	854-1121	901-1174
Maturity	1068-1434	1121-1495	1174-1556
End	1434-1538	1495-1602	1556-1665

Note. GDD 15/25/Agri4Cast identifies the sowing dates for the calculation of Growing Degree Days: November 15 (GDD 15); November 25 (GDD 25); sowing dates provided by Agri4Cast dataset. Source: Allen et al., 1998; Miller et al., 2021; Agri4Cast winter soft wheat phenological database for Europe.

3. Results

Our main results show irregularities in high temperatures and precipitation among different specifications: *pooled* seems to catch a nonlinear negative effect of maximum temperatures on yields, while *panels,* on the contrary, catches a nonlinear positive effect. Precipitation seems to have a nonlinear positive impact on yields both in *pooled* specification and in *panels* that include fixed effects by year, exclusively (Table 4).

[10] Nowadays, the wheat cultivation practices commonly in use postpone sowing date to response to climate change; in this way would be possible to increase the received precipitation by the crop during the early growth phase (Nouri et al., 2017).

Table 4. General regressions on yields-weather relationships.

VARIABLES	Pooled	Panel	Panel year FE	Panel time trend	Panel Year FE Prov FE	Panel Prov FE Time trend
T min	**-0.87797*** **	**-0.08726*** **	**-0.03715*** **	**-0.07950*** **	**-0.03692*** **	**-0.07926*** **
	(0.02471)	(0.01063)	(0.01008)	(0.01058)	(0.01007)	(0.01058)
$(T\ min)^2$	**-0.00182***	**0.00310*** **	**0.00103** **	**0.00215*** **	**0.00103** **	**0.00215*** **
	(0.00103)	(0.00044)	(0.00042)	(0.00044)	(0.00042)	(0.00044)
T max	**-0.47194*** **	**0.08261*** **	**0.04532*** **	**0.05839*** **	**0.04546*** **	**0.05854*** **
	(0.02922)	(0.01248)	(0.01185)	(0.01244)	(0.01184)	(0.01243)
$(T\ max)^2$	**0.02647*** **	**-0.00159*** **	**-0.00080*** **	**-0.00077** **	**-0.00081*** **	**-0.00077** **
	(0.00070)	(0.00030)	(0.00029)	(0.00030)	(0.00029)	(0.00030)
Prec	**0.44666*** **	-0.00143	**0.01133***	-0.00071	**0.01120***	-0.00085
	(0.01479)	(0.00636)	(0.00603)	(0.00633)	(0.00603)	(0.00633)
$(Prec)^2$	**-0.00810*** **	0.00004	**-0.00041***	-0.00004	**-0.00041***	-0.00004
	(0.00053)	(0.00023)	(0.00021)	(0.00022)	(0.00021)	(0.00022)
year FE			Yes		Yes	
prov FE					Yes	Yes
year				Yes		Yes
Obs.	162,909	162,909	162,909	162,909	162,909	162,909
No. of prov		30	30	30	30	30

Note: we also provided stand-alone estimations for each weather variables. Although some relationships are captured through the analyses of a single independent variable, multiple regression that includes multiple weather variables considers their combined effect on yields since it can capture the effects of temperatures (both minimum and maximum), otherwise not caught by single variable analyses, which represent the main challenge of grain producers under climate change scenarios (Barlow et al., 2015).

Focusing on nonlinear effects of temperatures in the specification which control by fixed effects and time trend, it emerged that low temperature negatively affects durum wheat yield until 19 ◦C, while high temperatures positively affect yields until 39 ◦C[11]. In general, the results highlight a strong relationship between durum wheat yields and weather variables, more specifically, low temperatures negatively affect the yields, while high temperatures seem to have a positive effect, both in a nonlinear way. According to the literature, frost during the crop cycle of wheat may cause spikelets death and limited internode extension leading to yield losses (Whaley et al., 2004), while heat stress may affect both quality and grain yields up to 50% due to rapidly senesced of leaves (Asseng et al., 2011). Changing in design (i.e., including further agrometeorological variables such as *ETc*, CWD, and DTR to assess yields-weather relationships) and in temporal specifications (i.e., using different approaches

[11] The thresholds have been calculated by turning point method.

to identify the phenological stages also related to *ETc*) of our econometric model seems to have no effect on the negative relationship low temperatures-yields and on the positive relationship *ETc*-yields. However, the positive effects of high temperatures and the negative effects of precipitation on yields are strongly related to the design of specifications as they can be captured only in FAO 56 (i.e., specification B) and in GDD EU (i.e., specifications B and C), respectively (Table 5).

Table 5. Relationship among durum wheat yields and weather conditions using different temporal and design specifications.

		BGA		FAO 56		GDD 15		GDD 25		GDD EU	
	Baseline	B	C	B	C	B	C	B	C	B	C
T min	**-0.07926*****	**-0.05365****		**-0.07592*****		**-0.05392*****		**-0.04081****		**-0.05372*****	
	(0.01058)	(0.02432)		(0.01202)		(0.01595)		(0.01602)		(0.01804)	
$(\text{T min})^2$	**0.00215*****	0.00133		**0.00219*****		0.00021		-0.00101		0.00052	
	(0.00044)	(0.00101)		(0.00062)		(0.00116)		(0.00115)		(0.00137)	
T max	**0.05854*****	0.02770		**0.03399****		0.02017		-0.01226		-0.00448	
	(0.01243)	(0.02962)		(0.01491)		(0.02326)		(0.02248)		(0.02609)	
$(\text{T max})^2$	**-0.00077****	0.00013		0.00025		0.00111		**0.00236*****		**0.00231****	
	(0.00030)	(0.00069)		(0.00042)		(0.00082)		(0.00077)		(0.00093)	
DTR			0.01593		**0.03735*****		**0.04951*****		**0.04290*****		**0.03904*****
			(0.01376)		(0.00887)		(0.01127)		(0.01139)		(0.01315)
DTR^2			**0.00044***		0.00012		0.00004		0.00042		0.00069
			(0.00026)		(0.00021)		(0.00038)		(0.00037)		(0.00044)
(Prec)	-0.00085	-0.00612	-0.00780	-0.00502	-0.00936	-0.00411	-0.00557	-0.00983	-0.01178	**-0.02373***	**-0.02580****
	(0.00633)	(0.01217)	(0.01213)	(0.00829)	(0.00825)	(0.01085)	(0.01081)	(0.01015)	(0.01013)	(0.01250)	(0.01244)
$(\text{Prec})^2$	-0.00004	-0.00039	-0.00034	-0.00020	-0.00010	-0.00008	-0.00007	0.00003	0.00006	0.00039	0.00041
	(0.00022)	(0.00044)	(0.00044)	(0.00031)	(0.00031)	(0.00035)	(0.00035)	(0.00038)	(0.00038)	(0.00040)	(0.00039)
ETc		**0.05072*****	**0.04162*****	**0.07332*****	**0.04434*****	**0.12368*****	**0.11906*****	**0.12728*****	**0.12684*****	**0.16193*****	**0.14932*****
		(0.01396)	(0.01304)	(0.01312)	(0.01165)	(0.02567)	(0.02528)	(0.02500)	(0.02434)	(0.03137)	(0.03073)
CWD		-0.00282	-0.00284	-0.00113	-0.00166	0.00020	-0.00062	-0.00106	-0.00152	0.00168	0.00058
		(0.00248)	(0.00247)	(0.00238)	(0.00237)	(0.00573)	(0.00570)	(0.00248)	(0.00248)	(0.00616)	(0.00613)
Obs.	162,909	54,472	54,472	107,159	107,159	68,299	68,299	67,271	67,271	54,300	54,300

Notes: temperatures are not shown in the specification C due to the collinearity with daily range temperature variable which seems to have a positive effect on yields. We also provided an assessment of quality of estimation through R^2 measurement. The inclusion of variables is slightly increasing the R^2, in other terms, the R^2 of the restricted specifications never exceed the R^2 of unrestricted.

In terms of phenological stages (Tables 9-13 in Appendix), our results show high susceptibility for any change in design and temporal specifications. Interesting evidence emerged, e.g., in starting stage (Table 9 in Appendix), minimum and maximum temperatures seem to have negative and positive nonlinear effects on yields, respectively, both in FAO 56 and in GDD 15 which share the same sowing date (i.e., November 15). According to Baldoni and Giardini (2000), low temperatures during the first stages, especially in conditions of high humidity, may cause major damages. The implication is that the choice of sowing date is relevant because it can capture temperature relationships regardless of the approach used to identify starting stage. To confirm this, shifting the sowing dates by 10 days using the same approach (i.e., GDD 15 and GDD 25), different evidence emerged, i.e., the effect of low temperatures is captured only in GDD 15. High temperatures seem to have no effect in development stage (Table 10 in Appendix), and irregularities emerged in BGA which captures the opposite relationship of low temperature and precipitation to the other specifications and, likewise, for DTR. Moreover, using the same temporal approach (i.e., GDD) but changing the sowing dates, the negative effect of low temperatures is always captured. The effect of *ETc* on yields is positive and it is independent of the approaches used. Again, it highlights that any change in the design or temporal approach to assess the effects of weather variables on yields may lead to different results, and that sowing dates are relevant. Precipitation seems to have no effect in the flowering stage (Table 11), while regularities emerge among design approaches, within the temporal specifications: the effects of temperatures and *ETc* on yields are the same among A-B, and B-C specifications. However, irregularities emerge among temporal approaches: high temperatures positively affect the yields except in GDD EU where, according to the literature (Farooq et al., 2014; Zampieri et al., 2017), the relationship is negative. Temporal and design approaches heavily affect the relationship yields-weather in maturity stage (Table 12): the negative effect of low temperatures and precipitation is captured only in BGA and GDD EU, respectively, while the effect of high temperature is captured both in FAO 56 and GDD 15, although there are irregularities between specification. Moreover, the negative effect of *cws* is shown only in BGA. Finally, DTR seems to have a nonlinear negative effect on yields in the end stage, while BGA specifications capture more relationships yields-weather than others (Table 13). Focusing on durum wheat varieties (Table 6), starting from the same sowing date (i.e., November 15) and approach (i.e., GDD), it emerged that the relationships yields-weather is not affected by the variety in starting, development, and flowering stages. However, maturity and end stages showed clear differences in catching relationships. More specifically, late varieties in maturity stage and early varieties in end stage may catch the negative relationship of high temperature on yields. In general, low temperatures seem to have a negative effect during the early stages (i.e., starting and development), while the negative effect of high temperatures is always caught during the flowering phase, regardless of the varieties (Farooq et al., 2014; Rezaei et al., 2015; Zampieri et al., 2017; Mäkinen et al., 2018)

Table 6. Relationships among durum wheat yields and weather conditions among durum wheat varieties during crop cycle.

	Starting			Development			Flowering			Maturity			End		
	early	middle	late	early	middle	late	early	middle	late	early	middle	late	early	middle	late
T min	**-0.15404***	**-0.16897****	**-0.17878****	**-0.07727*****	**-0.07318*****	**-0.06639*****	0.08320	0.10570	0.09917	0.07934	0.08918	0.04993	0.24944	0.04270	0.32460
	(0.08242)	(0.07602)	(0.07034)	(0.02191)	(0.02160)	(0.02144)	(0.06113)	(0.06890)	(0.07273)	(0.08097)	(0.08439)	(0.08996)	(0.21432)	(0.22877)	(0.27129)
$(T\ min)^2$	0.00685	0.00678	0.00663	-0.00117	-0.00090	-0.00067	-0.00298	-0.00565	-0.00637	-0.00749	-0.00702	-0.00529	-0.01452	-0.00608	-0.01378
	(0.00548)	(0.00511)	(0.00479)	(0.00214)	(0.00211)	(0.00209)	(0.00496)	(0.00534)	(0.00542)	(0.00497)	(0.00494)	(0.00505)	(0.01114)	(0.01147)	(0.01283)
T max	**0.31774****	**0.23426***	**0.25097***	0.06570	0.03823	0.02060	**-0.25329*****	**-0.29323*****	**-0.17960****	-0.01475	-0.05627	**-0.18812***	**-0.68208*****	-0.20209	-0.05940
	(0.14581)	(0.13782)	(0.13102)	(0.04244)	(0.04118)	(0.03986)	(0.07862)	(0.08304)	(0.08507)	(0.09672)	(0.10024)	(0.10657)	(0.23904)	(0.27092)	(0.29382)
$(T\ max)^2$	-0.00689	-0.00378	-0.00433	0.00010	0.00128	0.00178	**0.01152*****	**0.01160*****	**0.00729*****	0.00064	0.00176	**0.00684****	**0.02239*****	**0.01259***	0.00528
	(0.00525)	(0.00500)	(0.00479)	(0.00196)	(0.00187)	(0.00178)	(0.00272)	(0.00276)	(0.00275)	(0.00281)	(0.00284)	(0.00293)	(0.00621)	(0.00686)	(0.00713)
Prec	-0.04284	**-0.04768***	-0.04354	-0.01746	-0.01864	-0.01563	-0.00884	0.01779	0.00761	-0.03290	**-0.08944****	**-0.08828****	**-0.30095*****	0.07902	0.08993
	(0.02985)	(0.02861)	(0.02745)	(0.01532)	(0.01494)	(0.01474)	(0.02866)	(0.03065)	(0.03137)	(0.03349)	(0.03481)	(0.03541)	(0.08871)	(0.06774)	(0.06887)
$(Prec)^2$	0.00124	0.00142	**0.00142***	-0.00013	-0.00002	-0.00006	0.00066	-0.00025	-0.00012	0.00081	0.00194	0.00177	**0.01290*****	-0.00287	-0.00215
	(0.00091)	(0.00088)	(0.00086)	(0.00053)	(0.00052)	(0.00052)	(0.00105)	(0.00115)	(0.00117)	(0.00143)	(0.00151)	(0.00159)	(0.00482)	(0.00300)	(0.00278)
prov FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,891	5,576	6,231	27,951	28,963	29,924	8,511	8,320	8,173	9,341	9,178	9,030	2,272	2,263	2,211
No. of prov	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23

Note. Phenological stages have been identified by GDD EU.

We also provided further estimates that include spatial clusters (i.e., coastal and internal provinces, northern and southern provinces) to assess whether the location may affect the relationship between durum wheat yield and weather conditions[12]. The results remain robust among the specifications and the effects of weather variables on yields are statistically significant (Table 14, in the online appendix). More specifically, clustering for coastal provinces, the yield-weather relationships are captured only in Northern provinces. Clustering for coastal and internal provinces, the yield-weather relationships are captured only in Northern provinces. Clustering for northern and southern provinces, the effects of low temperatures on yields is captured both in coastal and internal provinces, while the effects of high temperatures is captured in the internal provinces, and the effect of precipitation is captured only in the coastal provinces. These results (showed in the Table 15, online appendix) suggest that the weather indexes could be different based on the spatial locations, in other words, some weather variables are more important in some provinces than others, despite the relationships are stable between specifications.

4. Conclusions

The weather conditions severely affect crop yields and may be coped with crop insurance schemes, which help farmers coping with unexpected yield losses (Shirsath et al., 2019; Vroege and Finger, 2020). The WIBI, whose working principle is based on the yield-weather relationships, are promising risk management tools (Barnett and Mahul, 2007; Anghileri et al., 2022) although it presents a major limitation (i.e., basis risk). Nonetheless, the design of the WIBI, and the challenges imposed by the basis risk, are at the core of a vivid debate (Norton et al., 2013; Dalhaus et al., 2018; Boyd et al., 2019; Afshar et al., 2021; Leppert et al., 2021). Numerous studies have focused on empirical evidence to model the yield-weather relationships (Carter et al., 2018; Auffhammer et al., 2020). However, literature falls short of studies that compare specifications within the same econometric model to assess yield-weather relationships. Focusing on durum wheat in Italy, we investigate how weather events that occur in phenological stages identified by different approaches (i.e., temporal specifications) and how different weather variables and combination of thereof (i.e., design specifications) of the econometric model may lead to different results in the yield-weather assessment. We found several connections among weather and yields. The evidence suggests that the number of observations is not related to the number of yields-weather relationships, e.g., comparing starting and development stages characterized by 4,520 and 22,746 observations, respectively, it emerged that the former captured more. In general, *ETc* and DTR positively affect the yields in all phenological stages,

[12] We gratefully acknowledge the comment raised by the reviewer.

and they are the only variables that do not seem to be affected by changes in temporal and design specifications. The choice of sowing dates may play a crucial role: a 10-days shift, using the same temporal and design approaches, may lead to a different estimation of yield losses due to changes in weather. Clustering for spatial dummies among provinces, it emerged that some weather variables are more important in some provinces than others. This should be considered by policymakers to plan risk management tools as weather insurances based on indexes which may be different depending on the location. Another implication is that the choice of specifications of the econometric model is very important to catch the relationships weather-yields. The negative effect of low temperatures, especially during the early stages, is always caught, regardless of specifications. GDD EU provided by Agri4Cast dataset seems to be the best model that is likely closest to what could happen on farms supported by the agronomic literature: minimum temperatures negatively affect the yields when they occur in the starting and development stages (Baldoni and Giardini, 2000; Whaley et al., 2004; Angelini, 2007; Barlow et al., 2015), maximum temperatures negatively affect the yields when they occur in the flowering stage (Farooq et al., 2014; Rezaei et al., 2015; Zampieri et al., 2017; Mäkinen et al., 2018), heavily precipitation negatively affect the yields when it occurs in the maturity stage (Zampieri et al., 2017; Mäkinen et al., 2018). Changes in design and temporal specifications seem to have no effect on the negative relationship low temperatures-yields and on the positive relationship *ETc*-yields. This result may contribute to establish a triggering index (i.e., for minimum temperatures) that represent a main challenge for agricultural policy focused on agricultural risk management. Given the importance of weather conditions on crop yields, financial insurance for extreme weather events is a key challenge to manage the risks threatening smallholder farmers. Therefore, understanding the dynamics of yields-weather relationship is essential to calibrate the WIBIs, and increased both its effectiveness and attractiveness. Policymakers, who already provide large subsidies to improve crop insurance participation, may make use of publicly available data (i. e., Agri4Cast datasets) to develop an effective tool for agricultural risk management. Unfortunately, farm-level weather data are not available to public bodies. Although the analyses of more refined data (i.e., at farm level) could be a suitable solution for further empirical estimates also representing a next step of our approach, the limits related to the spatial distribution of the weather station still remain (i.e., private weather stations are not widely distributed).

5. References

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6. Appendix

Below the method for ET_c identification:

ET_c is highly crop- and phenological stage-specific and it is one of the main factors determining how much precipitation remains in the soil available for the crops (Enenkel et al., 2019). ET_c has been identified by the following formula:

$$ET_c = k_c * ET_0$$

where, k_c is the crop coefficient specific (i.e., property of plant used in predicting evapotranspiration) for durum wheat and ET_0 is the daily potential evapotranspiration (i.e., amount of water that would be evaporated and transpired by a specific crop) included into Agri4Cast dataset.
We identified k_c variable through the following formula proposed by Allen et al., 1998 for the correction of climatic factors:

$$k_c = k_{c(Tab)} + [0.04\,(u_2 - 2) - 0.004\,(RH_{min} - 45)]\left(\frac{h}{3}\right)^{0.3}$$

where $K_{c(Tab)}$ is a table crop coefficient highly related to each phenological stages (Table 7), u_2 is wind speed at 2 meters high, RH_{min} is mean value of minimum daily relative humidity, and h is plant height.

Table 7. Crop coefficient values ($K_{c(Tab)}$) by phenological stage of durum wheat

	Starting	Development	Flowering	Maturity	End
$K_{c(Tab)}$	0.7	0.7	1.15	1.15	0.30

Source: Allen et al., 1998. Flowering is identified as the first 10-days of maturity stage (Angelini, 2007).

Since Agri4Cast dataset includes wind speed variable at 10 meters high (u_{10}), we used the following formula to convert u_{10} in u_2:

$$u_2 = u_{10} * \frac{4.87}{\ln[67.8 * (10 - 5.42)]}$$

Moreover, since Agri4Cast dataset includes vapour pressure (vp) variable, we used the following formulas (Wang et al., 2007; Suzuki et al., 2012) to calculate saturated vapour pressure (formula 1) and thus to identify the relative humidity variable (formula 2).

Formula 1. Saturated vapour pressure (svp) calculation

$$svp = 0.6108 * Exp \frac{17.27 * avg\ temperature}{avg\ temperature + 237.3}$$

Formula 2. Relative humidity (RH) calculation

$$RH = \frac{vp}{svp} * 100$$

The heights for the growing stages of durum wheat are shown below (Table 8):

Table 8. Wheat height by phenological stage

	Starting	Development	Flowering	Maturity	End
Plant heights (meters)	0.2	0.5	1.00	1.00	1.00

Source: Song et al., 2019

Table 9. Relationship among durum wheat yields and weather conditions using different temporal and design specifications in starting stage.

	BGA			FAO 56			GDD 15			GDD 25			GDD EU		
	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
T min	-0.07707	-0.03676		**-0.14455*** **	**-0.12045*** **		**-0.18915*** **	**-0.17006*** **		0.00047	0.03226		**-0.16897** **	**-0.13179* **	
	(0.09958)	(0.10202)		(0.04170)	(0.04260)		(0.05257)	(0.05399)		(0.03756)	(0.03948)		(0.07602)	(0.07763)	
(T min)^2	-0.00455	-0.00614		**0.00597** **	**0.00498* **		**0.01298*** **	**0.01191*** **		**-0.00735** **	**-0.00895*** **		0.00678	0.00596	
	(0.00565)	(0.00575)		(0.00288)	(0.00291)		(0.00364)	(0.00368)		(0.00317)	(0.00322)		(0.00511)	(0.00514)	
T max	-0.10743	-0.12262		**0.18507** **	**0.15493* **		**0.33811*** **	**0.31198*** **		**0.16984** **	0.11281		**0.23426* **	0.20127	
	(0.17007)	(0.17425)		(0.07913)	(0.08040)		(0.09905)	(0.10026)		(0.07360)	(0.07605)		(0.13782)	(0.13915)	
(T max)^2	0.00706	0.00826		**-0.00596** **	-0.00449		**-0.01237*** **	**-0.01125*** **		**-0.00562* **	-0.00266		-0.00378	-0.00166	
	(0.00561)	(0.00574)		(0.00296)	(0.00301)		(0.00375)	(0.00379)		(0.00339)	(0.00352)		(0.00500)	(0.00509)	
DTR			**0.11978** **			**0.09014*** **			**0.07863* **			0.02376			-0.00044
			(0.06052)			(0.03088)			(0.04162)			(0.03477)			(0.05367)
DTR^2			0.00063			**-0.00222* **			**-0.00306* **			0.00224			**0.00495** **
			(0.00237)			(0.00132)			(0.00174)			(0.00170)			(0.00229)
Prec	**0.05852** **	0.08664	0.06849	0.02213	**0.08883** **	**0.09531*** **	0.00823	**0.07888* **	**0.09914** **	0.03043	**0.14545*** **	**0.15287*** **	**-0.04768* **	-0.01368	0.00543
	(0.02814)	(0.06061)	(0.05951)	(0.01870)	(0.03449)	(0.03398)	(0.02496)	(0.04493)	(0.04444)	(0.02651)	(0.05115)	(0.04975)	(0.02861)	(0.06048)	(0.05992)
(Prec)^2	**-0.00148* **	**-0.00171** **	**-0.00173** **	-0.00073	-0.00101	-0.00103	-0.00034	-0.00053	-0.00062	-0.00107	**-0.00157* **	**-0.00164* **	0.00142	0.00114	0.00108
	(0.00077)	(0.00078)	(0.00078)	(0.00062)	(0.00063)	(0.00063)	(0.00079)	(0.00080)	(0.00080)	(0.00092)	(0.00093)	(0.00093)	(0.00088)	(0.00089)	(0.00089)
ETc		**1.60408** **	**1.68510** **		**0.95394** **	**0.85173** **		0.64023	0.18005		**1.47130** **	**1.94526*** **		**1.81301** **	**1.45603** **
		(0.71628)	(0.71445)		(0.41759)	(0.40811)		(0.63563)	(0.61859)		(0.61330)	(0.59757)		(0.74246)	(0.72742)
CWD		0.01058	-0.00349		**0.03380** **	**0.03738** **		**0.03800* **	**0.04891** **		**0.05105** **	**0.05375** **		0.01203	0.02275
		(0.03751)	(0.03643)		(0.01674)	(0.01642)		(0.02099)	(0.02071)		(0.02174)	(0.02115)		(0.03341)	(0.03309)
Obs.	4,520	4,520	4,520	13,380	13,380	13,380	7,472	7,472	7,472	9,342	9,342	9,342	5,576	5,576	5,576

Focusing on the starting stage, FAO 56 and GDD 15 are the specifications which capture more relationships. In general, minimum temperatures have a nonlinear negative effect on yields, while maximum temperatures showed irregularities: their impact on yields seems to be positive in FAO 56 and GDD 15 specifications and negative in GDD 25 specifications. Precipitation, evapotranspiration crop water deficit and temperature range seem to have positive effects on yields among specifications. The interesting evidence is that choice of sowing date is relevant because it can capture temperature relationships regardless of the approach used to identify the starting stage: shifting the sowing dates by 10 days using the same temporal approach (i.e., GDD 15 and GDD 25), different evidence emerged, i.e., the effect of low temperatures is captured only in GDD 15.

Table 10. Relationship among durum wheat yields and weather conditions using different temporal and design specifications in development stage.

	BGA			FAO 56			GDD 15			GDD 25			GDD EU		
	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
T min	0.04932	**0.09701****		**-0.05969*****	**-0.04633*****		**-0.05224*****	**-0.04028****		**-0.07089*****	**-0.05924*****		**-0.07318*****	**-0.06211*****	
	(0.04598)	(0.04692)		(0.01581)	(0.01596)		(0.01929)	(0.01954)		(0.02069)	(0.02097)		(0.02160)	(0.02186)	
$(T\ min)^2$	-0.00270	**-0.00498***		0.00136	0.00061		**-0.00413****	**-0.00511*****		0.00011	-0.00068		-0.00090	-0.00210	
	(0.00277)	(0.00281)		(0.00116)	(0.00117)		(0.00171)	(0.00173)		(0.00185)	(0.00188)		(0.00211)	(0.00214)	
T max	0.00010	0.07379		0.02729	0.01204		0.00387	-0.01970		-0.01202	-0.02930		0.03823	0.00814	
	(0.06146)	(0.06569)		(0.02270)	(0.02360)		(0.03472)	(0.03566)		(0.03492)	(0.03587)		(0.04118)	(0.04219)	
$(T\ max)^2$	0.00060	-0.00081		0.00015	**0.00151***		**0.00269***	**0.00440*****		**0.00259***	**0.00403*****		0.00128	**0.00327***	
	(0.00178)	(0.00187)		(0.00078)	(0.00082)		(0.00150)	(0.00157)		(0.00144)	(0.00150)		(0.00187)	(0.00196)	
DTR			**-0.06203*****			**0.02928****			**0.06807*****			**0.05656*****			**0.07059*****
			(0.02286)			(0.01181)			(0.01596)			(0.01629)			(0.01799)
DTR^2			**0.00305*****			**0.00088****			0.00081			0.00044			0.00044
			(0.00067)			(0.00042)			(0.00076)			(0.00074)			(0.00090)
Prec	**-0.03440***	-0.02545	-0.00537	-0.01655	**0.02867***	0.02511	-0.01122	**0.05282****	0.03626	-0.02074	0.02424	0.01177	-0.01864	**0.05558***	0.04522
	(0.02035)	(0.03980)	(0.03860)	(0.01032)	(0.01576)	(0.01531)	(0.01428)	(0.02682)	(0.02625)	(0.01369)	(0.02551)	(0.02501)	(0.01494)	(0.03026)	(0.02956)
$(Prec)^2$	0.00057	0.00044	0.00074	0.00023	0.00027	0.00028	-0.00010	-0.00024	-0.00027	0.00040	0.00031	0.00029	-0.00002	-0.00005	-0.00006
	(0.00092)	(0.00107)	(0.00105)	(0.00041)	(0.00041)	(0.00041)	(0.00055)	(0.00056)	(0.00056)	(0.00051)	(0.00052)	(0.00052)	(0.00052)	(0.00052)	(0.00052)
ETc		**0.46315*****	**0.41526*****		**0.26413*****	**0.25985*****		**0.39320*****	**0.43532*****		**0.34540*****	**0.35045*****		**0.38343*****	**0.38349*****
		(0.07092)	(0.06859)		(0.04400)	(0.04298)		(0.11347)	(0.11229)		(0.10206)	(0.10097)		(0.14019)	(0.13852)
CWD		0.01520	0.06053		**0.05088*****	**0.04741*****		**0.05481****	**0.03882***		0.04049*	0.02777		**0.06316*****	**0.05421****
		(0.07528)	(0.07166)		(0.01539)	(0.01476)		(0.02189)	(0.02124)		(0.02274)	(0.02211)		(0.02406)	(0.02341)
Obs.	22,746	22,746	22,746	62,559	62,559	62,559	35,215	35,215	35,215	34,060	34,060	34,060	28,963	28,963	28,963

Focusing on the development stage, high temperatures seem to have no effect and irregularities emerged in BGA specification which captures the opposite relationship of low temperature and precipitation to the other specifications and, likewise, for DTR. The negative effect of low temperatures (clearly, excluding BGA specifications) is always stable among specifications. The effect of crop evapotranspiration is always positive, and it is independent of the approaches used.

Table 11. Relationship among durum wheat yields and weather conditions using different temporal and design specifications in flowering stage.

	BGA			FAO 56			GDD 15			GDD 25			GDD EU		
	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
T min	-0.00611	0.07508		0.09715	0.18535		**0.13949****	**0.14277****		**0.26033*****	**0.27162*****		0.10570	0.11048	
	(0.14895)	(0.15072)		(0.11433)	(0.11528)		(0.06170)	(0.06173)		(0.07543)	(0.07552)		(0.06890)	(0.06891)	
$(T\ min)^2$	-0.00331	-0.00631		-0.00693	**-0.01025****		**-0.00865***	**-0.00865***		**-0.01990*****	**-0.02011*****		-0.00565	-0.00536	
	(0.00558)	(0.00565)		(0.00448)	(0.00452)		(0.00455)	(0.00455)		(0.00507)	(0.00507)		(0.00534)	(0.00534)	
T max	**0.59654*****	**0.69347*****		**0.53529*****	**0.67048*****		0.01816	0.03664		**0.20011****	**0.25175****		**-0.29323*****	**-0.26843*****	
	(0.15739)	(0.16004)		(0.13078)	(0.13295)		(0.08382)	(0.08469)		(0.09928)	(0.10084)		(0.08304)	(0.08356)	
$(T\ max)^2$	**-0.01228*****	**-0.01456*****		**-0.01059*****	**-0.01382*****		0.00028	-0.00013		**-0.00585***	**-0.00720****		**0.01160*****	**0.01106*****	
	(0.00337)	(0.00343)		(0.00286)	(0.00291)		(0.00274)	(0.00275)		(0.00308)	(0.00311)		(0.00276)	(0.00277)	
DTR			**0.22450*****			**0.15151*****			**-0.07859****			-0.00022			**-0.13133*****
			(0.04830)			(0.03767)			(0.03219)			(0.03533)			(0.03796)
DTR^2			**-0.00451*****			**-0.00255*****			**0.00365*****			0.00078			**0.00648*****
			(0.00102)			(0.00081)			(0.00112)			(0.00115)			(0.00130)
Prec	-0.00864	-0.00635	-0.01925	-0.00877	-0.00639	-0.01764	0.02479	0.02765	0.02593	0.03729	0.04096	0.03361	0.01779	0.02309	0.02479
	(0.03223)	(0.03223)	(0.03190)	(0.02634)	(0.02633)	(0.02611)	(0.02226)	(0.02279)	(0.02275)	(0.02582)	(0.02683)	(0.02679)	(0.03065)	(0.03115)	(0.03113)
$(Prec)^2$	0.00091	0.00073	0.00081	0.00046	0.00024	0.00020	-0.00030	-0.00041	-0.00038	-0.00107	-0.00130	-0.00115	-0.00025	-0.00049	-0.00047
	(0.00127)	(0.00127)	(0.00127)	(0.00104)	(0.00104)	(0.00104)	(0.00075)	(0.00076)	(0.00076)	(0.00099)	(0.00100)	(0.00100)	(0.00115)	(0.00115)	(0.00115)
ETc		**0.22025*****	**0.14044****		**0.31185*****	**0.22138*****		0.16555	0.13164		**0.28979*****	**0.22201****		**0.33541****	**0.38240*****
		(0.06449)	(0.06171)		(0.05579)	(0.05367)		(0.10877)	(0.10620)		(0.10037)	(0.09745)		(0.13072)	(0.12813)
CWD		-0.00134	-0.00159		-0.00138	-0.00165		-0.00140	-0.00120		-0.00457	-0.00351		-0.00372	-0.00429
		(0.00252)	(0.00252)		(0.00251)	(0.00251)		(0.00745)	(0.00745)		(0.01266)	(0.01267)		(0.00736)	(0.00735)
Obs.	9,366	9,366	9,366	13,826	13,826	13,826	10,523	10,523	10,523	9,733	9,733	9,733	8,320	8,320	8,320

Focusing on the flowering stage, precipitation seems to have no effect, while regularities emerge among design approaches, within the temporal specifications: the effects of temperatures and crop evapotranspiration on yields are the same among A-B, and B-C specifications. Irregularities emerge among temporal approaches: high temperatures positively affect the yields except in GDD EU specifications in which, according to the literature (Farooq et al., 2014; Zampieri et al., 2017), the relationship is negative.

Table 12. Relationship among durum wheat yields and weather conditions using different temporal and design specifications in maturity stage.

	BGA			FAO 56			GDD 15			GDD 25			GDD EU		
	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
T min	**-0.37334*** **	**-0.37913*** **		-0.13784	-0.10064		-0.02572	-0.01137		-0.09798	-0.06438		0.08918	0.11826	
	(0.11263)	(0.11265)		(0.12993)	(0.13138)		(0.07999)	(0.08000)		(0.08796)	(0.08804)		(0.08439)	(0.08494)	
$(T\ min)^2$	**0.01023*** **	**0.01060*** **		0.00220	0.00100		-0.00162	-0.00171		0.00360	0.00242		-0.00702	-0.00810	
	(0.00347)	(0.00348)		(0.00463)	(0.00467)		(0.00469)	(0.00469)		(0.00482)	(0.00482)		(0.00494)	(0.00495)	
T max	-0.01358	0.01765		**0.65506*** **	**0.70619*** **		-0.15447	-0.06513		**-0.27295*** **	-0.17456		-0.05627	-0.02941	
	(0.12090)	(0.12211)		(0.14099)	(0.14383)		(0.09737)	(0.09884)		(0.10581)	(0.10694)		(0.10024)	(0.10080)	
$(T\ max)^2$	0.00089	0.00033		**-0.01328*** **	**-0.01444*** **		**0.00456* **	0.00236		**0.00931*** **	**0.00687** **		0.00176	0.00114	
	(0.00227)	(0.00229)		(0.00288)	(0.00295)		(0.00274)	(0.00277)		(0.00283)	(0.00285)		(0.00284)	(0.00285)	
DTR			0.05376			**0.19044*** **			0.04800			-0.03622			0.00446
			(0.03723)			(0.04125)			(0.03427)			(0.03586)			(0.04059)
$(DTR^2$			-0.00032			**-0.00384*** **			-0.00078			**0.00317*** **			0.00026
			(0.00064)			(0.00080)			(0.00102)			(0.00100)			(0.00116)
Prec	-0.00074	-0.03811	-0.04444	0.03846	0.03815	0.02097	-0.03247	-0.03272	-0.03021	-0.01711	-0.00480	-0.00067	**-0.08944** **	**-0.08145** **	**-0.08118** **
	(0.02437)	(0.03251)	(0.03245)	(0.02753)	(0.02755)	(0.02708)	(0.02520)	(0.02695)	(0.02687)	(0.02692)	(0.02699)	(0.02685)	(0.03481)	(0.03583)	(0.03583)
$(Prec)^2$	-0.00080	-0.00132	-0.00136	-0.00094	-0.00102	-0.00079	0.00017	-0.00041	-0.00046	-0.00005	-0.00067	-0.00074	0.00194	0.00161	0.00163
	(0.00092)	(0.00097)	(0.00096)	(0.00099)	(0.00100)	(0.00099)	(0.00102)	(0.00103)	(0.00103)	(0.00111)	(0.00111)	(0.00111)	(0.00151)	(0.00152)	(0.00152)
ETc		0.01991	0.01393		**0.09875* **	0.03310		**0.40524*** **	**0.42765*** **		**0.47143*** **	**0.50595*** **		**0.28030*** **	**0.27057*** **
		(0.01865)	(0.01850)		(0.05283)	(0.05023)		(0.08132)	(0.07906)		(0.07901)	(0.07705)		(0.09531)	(0.09333)
CWD		**-0.13153* **	**-0.15214** **		-0.00153	-0.00177		-0.02463	-0.02628		-0.00110	-0.00123		0.00048	0.00019
		(0.07681)	(0.07590)		(0.00251)	(0.00252)		(0.01993)	(0.01988)		(0.00255)	(0.00255)		(0.01759)	(0.01756)
Obs.	18,286	18,286	18,286	12,934	12,934	12,934	12,073	12,073	12,073	11,332	11,332	11,332	9,178	9,178	9,178

Focusing on the maturity stage, temporal and design approaches heavily affect the relationship yields-weather: the negative effect of low temperatures and precipitation is captured only in BGA and GDD EU, respectively, while the effect of high temperature is captured both in FAO 56 and GDD 15, although there are irregularities between specification. Moreover, the negative effect of crop water deficit emerged only in BGA.

Table 13. Relationship among durum wheat yields and weather conditions using different temporal and design specifications in end stage

	BGA			FAO 56			GDD 15			GDD 25			GDD EU		
	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
T min	**-0.89806*****	**-0.90668*****		**-1.07104*****	**-0.97157*****		**-0.33464***	-0.29524		0.15128	0.13080		0.04270	0.11882	
	(0.24879)	(0.25268)		(0.19485)	(0.19768)		(0.20040)	(0.20200)		(0.25445)	(0.25550)		(0.22877)	(0.23223)	
$(T\ min)^2$	**0.02657*****	**0.02678*****		**0.03009*****	**0.02769*****		0.01595	0.01315		-0.00765	-0.00739		-0.00608	-0.01025	
	(0.00668)	(0.00677)		(0.00533)	(0.00539)		(0.01008)	(0.01017)		(0.01158)	(0.01163)		(0.01147)	(0.01164)	
T max	**0.61715****	**0.80632*****		0.12082	0.21623		-0.21556	-0.12902		0.15077	0.27495		-0.20209	-0.19573	
	(0.25485)	(0.27820)		(0.19883)	(0.21949)		(0.21750)	(0.22654)		(0.24956)	(0.26278)		(0.27092)	(0.28746)	
$(T\ max)^2$	**-0.00855****	**-0.01166****		-0.00030	-0.00208		**0.00983***	0.00923		-0.00080	-0.00285		**0.01259***	**0.01364***	
	(0.00430)	(0.00468)		(0.00340)	(0.00373)		(0.00549)	(0.00565)		(0.00595)	(0.00618)		(0.00686)	(0.00714)	
DTR			**-0.35830*****			**-0.19934*****			**-0.13960***			-0.06303			**-0.17483***
			(0.06415)			(0.05091)			(0.07397)			(0.08239)			(0.09170)
DTR^2			**0.00788*****			**0.00496*****			**0.00967*****			**0.00489****			**0.01316*****
			(0.00105)			(0.00084)			(0.00208)			(0.00212)			(0.00255)
Prec	**-0.11547****	**-0.34154****	-0.19514	-0.01553	0.06087	0.09715	0.00649	0.00404	0.00490	**-0.15376****	**-0.23842****	**-0.20973***	0.07902	0.17782	0.17620
	(0.05688)	(0.15870)	(0.15350)	(0.03583)	(0.08889)	(0.08584)	(0.04762)	(0.09549)	(0.09416)	(0.06278)	(0.11386)	(0.11205)	(0.06774)	(0.11794)	(0.11474)
$(Prec)^2$	0.00391	0.00269	0.00536	-0.00145	0.00040	0.00175	-0.00035	-0.00007	0.00006	**0.00671****	**0.00596***	**0.00644***	-0.00287	-0.00095	-0.00095
	(0.00340)	(0.00350)	(0.00346)	(0.00173)	(0.00232)	(0.00225)	(0.00183)	(0.00204)	(0.00203)	(0.00302)	(0.00332)	(0.00330)	(0.00300)	(0.00337)	(0.00336)
ETc		0.03537	0.03429		**0.16767*****	**0.19978*****		**0.40697*****	**0.43824*****		0.21101	0.18342		**0.37090****	**0.37985****
		(0.05960)	(0.05677)		(0.04730)	(0.04537)		(0.14773)	(0.14569)		(0.14738)	(0.14628)		(0.17731)	(0.17338)
CWD		-1.62832	-0.20619		0.72720	**1.19979***		0.07984	0.10319		-0.35360	-0.18636		0.56697	0.56275
		(1.08240)	(1.02036)		(0.67277)	(0.63120)		(0.39077)	(0.38214)		(0.48807)	(0.47327)		(0.48333)	(0.46774)
Obs.	8,920	8,920	8,920	13,380	13,380	13,380	3,016	3,016	3,016	2,804	2,804	2,804	2,263	2,263	2,263

Focusing on the end stage, DTR seems to have a nonlinear negative effect on yield, while BGA specifications seem to capture more relationships yields-weather than others. More specifically, minimum temperatures and precipitation have a negative effect on yields, while maximum temperatures have a positive effect. Although the effect of precipitation seems not to be influenced by design specifications (e.g., GDD 25), the relationships are not captured among temporal specifications.

Table 14. Spatial clusters among Italian provinces

VARIABLES	all provinces			
	baseline	NS	CI	NSCI
T min	-0.03692***	-0.03692***	-0.03692***	-0.03692***
	(0.01007)	(0.00082)	(0.00539)	(0.00361)
$(T\ min)^2$	0.00103**	0.00103***	0.00103	0.00103
	(0.00042)	(0.00039)	(0.00167)	(0.00136)
T max	0.04546***	0.04546***	0.04546***	0.04546***
	(0.01184)	(0.00075)	(0.01535)	(0.00996)
$(T\ max)^2$	-0.00081***	-0.00081***	-0.00081	-0.00081
	(0.00029)	(0.00021)	(0.00105)	(0.00082)
Prec	0.01120*	0.01120***	0.01120	0.01120
	(0.00603)	(0.00101)	(0.01288)	(0.00935)
$(Prec)^2$	-0.00041*	-0.00041***	-0.00041*	-0.00041**
	(0.00021)	(0.00004)	(0.00022)	(0.00020)
Obs.	162,909	162,909	162,909	162,909
No. of prov	30	30	30	30

Notes: baseline shows the general relationships yield-weather variables. NS includes clusters Northern and Southern provinces; CI includes clusters Coastal and Internal provinces; NSCI includes a combination of thereof. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

We provide spatial clusters among Italian provinces. The results remain robust among specifications, the effects of weather on yields are statistically significant, and the relationships on the first moment of the distribution (i.e., the estimated coefficients of the first order variables) are confirmed.

Table 15. Further combinations of clusters among Italian provinces

VARIABLES	All provinces	CI provinces		NS provinces	
	Baseline	N	S	C	I
T min	-0.03692***	-0.03705***	-0.04145	-0.03761***	-0.04193***
	(0.01007)	(0.00433)	(0.02565)	(0.00839)	(0.00559)
$(T\ min)^2$	0.00103**	0.00114***	0.00192	-0.00155**	0.00227
	(0.00042)	(0.00027)	(0.00366)	(0.00072)	(0.00148)
T max	0.04546***	0.04061***	0.04165	0.02751	0.05693***
	(0.01184)	(0.00498)	(0.03049)	(0.02339)	(0.01245)
$(T\ max)^2$	-0.00081***	-0.00072***	-0.00111	0.00094	-0.00156
	(0.00029)	(0.00014)	(0.00209)	(0.00072)	(0.00096)
Prec	0.01120*	0.01088***	0.01287	0.03079***	0.00176

	(0.00603)	(0.00210)	(0.01330)	(0.00125)	(0.00539)
$(Prec)^2$	-0.00041*	-0.00043***	-0.00034	-0.00081***	-0.00025*
	(0.00021)	(0.00006)	(0.00033)	(0.00024)	(0.00013)
Obs.	162,909	71,227	91,682	42,371	120,538
No. of prov	30	13	17	8	22

Notes: baseline shows the general relationships yield-weather variables. CI includes Coastal and Internal provinces clustered by Northern (N) and Southern (S); NS includes Northern and Southern provinces clustered by Coastal (I) and Internal provinces. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Focusing on the further combinations of spatial clusters among Italian provinces, interesting evidence emerged. Clustering for coastal and internal provinces (CI provinces), the yield-weather relationships are captured only in Northern provinces. Clustering for northern and southern provinces (NS provinces), the effects of low temperatures on yields is captured both in coastal and internal provinces, while the effects of high temperatures is captured in the internal provinces and the effect of precipitation is captured only in the coastal provinces. These results suggest that the weather indexes could be different based on the spatial locations, in other words, some weather variables are more important in some provinces than others.

Chapter 4

Earliness, phenological phases and yield-temperature relationships: evidence from durum wheat in Italy

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Earliness, phenological phases and yield-temperature relationships: evidence from durum wheat in Italy

Abstract

The impacts of extreme weather events on crop production are largely heterogeneous along the timing dimension of the shocks, and the varieties being affected. We investigate the yield-temperature relationships for three categories of earliness of durum wheat: early-maturing, middle-maturing, and late-maturing. We disentangle the time dimension distinguishing five phenological stages, as identified by the Growing Degree Days approach. Our panel regression models show that the starting, growing, and anthesis stages are sensitive to changes in minimum temperatures, regardless of wheat earliness. Raises in maximum temperatures during the starting stage are associated with increases in yields until a certain threshold above of which decrease; the opposite is true for increases in maximum temperatures in the maturity stage for late-maturing varieties, and in the end stage for early-maturing varieties. Results imply that farmers and policymakers may adopt ex-ante and ex-post risk management strategies, i.e., choice of variety to avoid severe yield losses and incentives to crop insurance uptake, respectively.

Keywords: climate change, crop insurance, growing degree days, risk management, weather index

1. Introduction

The climate variability and the increased frequency of extreme weather events threaten the agricultural sector (Auci et al., 2021). The simulations on projected yields under climate change conditions show losses in crop production (Challinor et al., 2014). In turn, these, may impact the market dynamics with price increases and changes in firms' profitability margins (Stevanovic et al., 2016). The risk management interventions subsidised by the Common Agricultural Policy (CAP) of European Union (EU), e.g., crop insurances, mutual funds, may help farmers to cope with the potential losses due to climatic changes (Severini et al., 2016; Meuwissen et al., 2018; Shirsath et al., 2019; Giampietri et al., 2020; Cordier and Santeramo, 2020; Rippo and Cerroni, 2022), even better if combined with other ex-ante practices, e.g., agroecological strategies (Altieri et al., 2015). The weather-index insurances (WIIs) emerged as promising tools to indemnify farmers affected by weather damages (Anghileri et al., 2022). The working principle of the WIIs is a compensation based on a proxy (the weather index) correlated with potential yield losses (Abdi et al., 2022). The WIIs may contribute solving the market failures due to moral hazard and adverse selection issues, which are common in traditional indemnity insurance (Santeramo, 2019; Bucheli et al., 2022). The main threat to the well-functioning WIIs relies on the possible low correlation between triggered pay-outs and the occurrence of loss events, a peculiarity referred to as 'basis risk' (Cesarini et al., 2021). The basis risk may assume multiple forms. The temporal basis risk may result from the discrepancy between the timing of the weather index fails and the evolution of the crop growth stages (Masiza et al., 2022). The phenology information collected in publicly available datasets (e.g., through satellite remote sensors) may help reduce the temporal basis risk (Dalhaus et al., 2018; Afshar et al., 2021). Indeed, the phenological stages show different susceptibilities to the weather conditions, a relevant aspect for the weather index definition. As for durum wheat, the timing of the undesired weather events matter. For instance, low temperatures are detrimental in all stages of growth, but the most severe negative impacts are observed during the reproductive stage (Barlow et al., 2015). High temperatures severely compromise the physiological processes during the flowering and grain filling stages (Rezaei et al., 2015; Makinen et al., 2018, Gagliardi et al., 2020). As a matter of fact, taking into consideration the phenological stages within which the weather event occur is crucial to understand the weather-yields relationships better: this concept directly translates into better modelling of the temporal basis risk. Although remote sensing imagery represents a promising technique for identifying phenological stages, many factors, such as the atmospheric conditions (e.g., clouds) or the biotic and abiotic environmental perturbations, may also be relevant to analyse the physiological process (Zeng et al., 2020), but are complex in nature and computation. On the other hand, a fixed calendar approach may be oversimplistic and misleading. A second-best solution is to use the Growing Degree Days (GDD), adopted to schedule management activities. It represents a suitable method to predict specific crop stages based on the amount of daily temperature degree (Miller et al., 2001). Conradt et al., 2015 showed that the GDD approach accurately identifies the phenological phases. However, the timing of the phenological stages is not homogenous across varieties. Apart from the studies just mentioned, the literature on the role of varieties in shaping the relationships between yield and weather is quite limited. Thus, departing from a vast literature on the yield-weather nexus (Di Falco et al., 2012; Powell and Reinhard, 2016; Delerce et al., 2016; Chavas et al., 2019), we deepen on the heterogeneities that the yield-temperatures relationship may show across different phenological stages and earliness of durum wheat, hereafter defined as early-maturing, middle-maturing, and late-maturing. Building up the works of Tappi et al. (2022), who show the need to collect more refined data to investigate the relationships between yields and weather variables, and of Tappi et al. (2022), who focus on the role of temporal and design approaches in yield-weather assessment, the aim of our paper is to assess whether the relationships yield-temperature control for three categories of durum wheat earliness (i.e., early-maturing, middle-maturing, and late-maturing) among five phenological stages identified by the GDD approach, focusing on the most representative Italian provinces in terms of durum wheat production. Apart from the new knowledge, our paper has direct implications for farmers aiming to adopt ex-ante risk management strategies (e.g., choice of variety) and for policymakers planning ex-post risk management strategies (e.g., incentives to crop insurance uptake). The Italian participation level in crop insurance schemes is still low, limited to few products, and concentrated in few areas (Santeramo, 2018, 2019; Coletta et al., 2018). Therefore, the focus on the yield-temperature relationship may directly speak with the ongoing debate on how to improve the attractiveness of innovative insurances in a more and more warming climate change scenario.

2. Data and methodology

Durum wheat is the main crop in the Mediterranean area for making pasta, couscous, semolina, and other products (Carucci et al., 2020). We collected yields and weather data from 2006 to 2020 of 30 main durum wheat-producing Italian provinces, located in Central and Southern Italy (Figure 1, in the Appendix). Specifically, yearly durum wheat yield data (quintals of production/cultivated hectares) have been collected from the National Institute of Statistics (ISTAT). In contrast, daily weather data have been collected from JRC - Agri4Cast Meteorological database of European Commission that includes maximum temperatures (°C) and minimum temperatures (°C). Descriptive statistics of the dataset are shown in Table 1. More specifically, maximum temperatures show a mean value of 13.5 °C, a median value of 13.6 °C, in a range between -5.3 °C and 33 °C; minimum temperatures show a mean value of 5.9 °C, a median value of 6.1 °C, in a range between -11.6 °C and 19.9 °C.

Table 1. Descriptive statistics of daily temperatures and yearly yield variables from 2006 to 2020 among 30 main durum-wheat producing Italian provinces

Variable (unit)	Obs.	Mean	Median	St. dev	Min	Max
Maximum temperature (°C)	68,832	13.55749	13.63	4.59804	-5.336364	32.98
Minimum temperature (°C)	68,832	5.899284	6.07	3.919422	-11.65	19.95
Yield (q/ha)	68,299	36.81634	33	12.98301	17	81.42377

Furthermore, maximum temperatures exceed 30 °C in some Southern provinces, e.g., Agrigento, Caltanissetta, Catania, Enna, Matera, Palermo, Trapani, while minimum temperatures exceed -2 °C in some Northern provinces, e.g., Bologna, Ferrara, Perugia, Pisa, Ravenna, Rovigo, Siena (Table 2, in the Appendix). We selected weather variables within the timeframe of the wheat production cycle. Several approaches are available to assess econometrically the weather impacts on society and the economy: cross-sections, linear and non-linear panel, long-differences, and partitioning variation (Hsiang, 2016; Kolstad and Moore, 2020). Cross-sectional and panel regression analyses are the most used to assess the climate impacts on agriculture (Carter et al., 2018). Generally, panel model approach uses crop yields as the output of production function, while the cross-section uses a proxy for land productivity, e.g., revenue or profit (Blanc and Schlenker, 2020). According to Hsiang (2016), climate may affect social outcomes in two ways: directly, i.e., the effects of weather in a certain time, and indirectly (i.e., belief effect), i.e., the consequent effects of weather on decisions and actions also referred to as adaptation. Belief effects and other unobservable variables may cause bias in estimates (Hsiang, 2016). In this complex scenario and considering the trade-off among econometrics models, the panel approach presents some advantages for controlling unobserved omitted variables, removing a possible source of bias (Hsiang, 2016; Kolstad and Moore, 2020). Moreover, nonlinear panel models with fixed effects may capture partially long-run adaptive response to climate change (Carter et al., 2018), also contributing to overcoming the main limitations of panel regression: the short-run response to weather fluctuations (Kolstad and Moore, 2020). Therefore, our yield response equation is based on a non-linear panel regression:

$$y_{it} = f(w_{it};\boldsymbol{\beta}) + \boldsymbol{\alpha_i} + \boldsymbol{\alpha_t} + \epsilon_{it} \quad (1)$$

where y_{it} represents the vector of durum wheat yield data for the 30 main Italian provinces (i) in terms of production volumes and time horizon covered (t). The function $f(w_{it};\beta)$ is explained in the formula (2) below. The estimated coefficients (in bold) are collected in the matrix of first and second-order coefficients noted as $\boldsymbol{\beta}$, whereas $\boldsymbol{\alpha_i}$ and $\boldsymbol{\alpha_t}$ are the vectors of the location-specific and year-specific fixed effects, controlling for unobserved heterogeneity over space and time. The error term is noted by the ϵ_{it} (Hsiang, 2016; Tack et al., 2015; Kolstad and Moore, 2020). Five phenological stages of durum wheat have been identified through the GDD approach, starting from the sowing date in the middle of November for wheat crop cultivated in the Mediterranean area (Miller et al., 2001): (i) starting, from emergence to two leaves unfolded; (ii) growing, from the end of two leaves unfolded to the beginning of anthesis (first anthers are visible); (iii) anthesis, from the beginning of anthesis to beginning of seed fill; (iv) maturity, from the beginning of seed fill to dough stage; (v) end, from dough stage to full maturity. The GDD approach predicts plants stages from seeding to maturity using the accumulation of heat or temperature units above a threshold or base temperature below which no growth occurs (Miller et al., 2001). The function $f(w_{itv};\beta)$ is explicated as follows:

$$f(w_{it};\beta) = \sum_{x=1}^{2}\sum_{s=1}^{s=5}\beta_{xs}{}^{x}\ tmin_{it}{}^{x} + \sum_{x=1}^{2}\sum_{s=1}^{s=5}\beta_{xs}{}^{x}\ tmax_{it}{}^{x} \quad (2)$$ [13]

where $tmin_{it}$ and $tmax_{it}$, are the daily minimum and maximum temperatures across space (i) and time (t). The index s ($s = \{1,2,3,4,5\}$) indicates the phenological stage of durum wheat. The apex x indicates the linearity of the term. Furthermore, based on phenology calculation combined with the Universal Growth Staging Scale reported in Miller et al. (2001) for the wheat crop, we identified three categories of earliness, i.e., early-maturing, middle-maturing, and late-maturing, also identifying the dates of occurrence of phenological stages (table 3):

Table 3. Dates of occurrence and GDD values of durum wheat among phenological stages

	starting		growing		anthesis		maturity		end	
	start	end	start	end	start	end	start	end	start	end
Early-maturing (GDD)	Nov, 15 (0)	Dec, 1 (168)	Dec, 2 (169)	Mar, 29 (806)	Mar, 30 (807)	Apr, 19 (1067)	Apr, 20 (1068)	May, 16 (1433)	May, 17 (1434)	May, 22 (1538)
Middle-maturing (GDD)	Nov, 15 (0)	Dec, 5 (188)	Dec, 6 (189)	Apr, 1 (853)	Apr, 2 (854)	Apr, 22 (1120)	Apr, 23 (1121)	May, 20 (1494)	May, 21 (1495)	May, 26 (1602)
Late-maturing	Nov, 15 (0)	Dec, 8 (207)	Dec, 9 (208)	Apr, 5 (900)	Apr, 6 (901)	Apr, 25 (1173)	Apr, 26 (1174)	May, 23 (1555)	May, 24 (1556)	May, 30 (1665)

[13] We focused on how the temperatures may affect the yields, considering the precipitations as control factor mainly because its effect on yields is difficult to catch (being affected by other variables such as soil texture, management practices, irrigation, etc.). A single rain event may impact on a smaller portion of territory than changes in temperatures affecting entire areas. Therefore, the evaluation of the effect of precipitation on the yields needs of further investigation. Moreover, we controlled for the market shocks, i.e., on how unfavourable years in terms of durum wheat price. The results are robust.

(GDD)

Note: Referred to the year 2020

We assume that the sowing date is the same for all varieties (i.e., November 15[14]), although it represents a limit of our paper. However, it is useful to assess yield-temperature relationships among different earliness identified by GDD approach. Instead, the daily thermal sum that determines the transition from one phenological phase to the next, changes. It is interesting to highlight that the shift between early-maturing and late-maturing varieties is just one week. This aspect may play a decisive role in assessing of the yield-temperature relationship and, hence, both on farmers decisions (e.g., choice of earliness) and policymakers to plan risk management policies.

3. Results and discussion

Results display a strong relationship between durum wheat yields and temperatures among different earliness, focusing on the each phenological phase (table 4, more details in the table 7, in the Appendix). More specifically, minimum temperatures that occur in the starting phase negatively affect the yields in a non-linear way, until 8-9 °C for all categories of earliness, while maximum temperatures seem to have a positive effect, until 14-15 °C, above of which the yield decrease (table 4 and table 5; more details in the table 7, in the Appendix). Yield is negatively impacted by minimum temperatures linearly occurring in growing stage (table 4, more details in the table 7, in the Appendix). According to the scientific literature, 85% of worldwide wheat cultivation is yearly affected by spring frost causing severe yield losses due to damage of micro-organelles of the cells, excessive production of reactive oxygen species (ROS) and lipid peroxidation (Hassan et al., 2021). Moreover, low temperatures in the fall season may cause yield losses until 9 percent (Tack et al., 2015). Makinen et al. (2018) found that damages due to frost negatively affect all phenological stages, even more the reproductive phase (i.e., flowering). However, focusing on the anthesis stage, our results showed contradictory evidence: minimum temperatures seem to positively affect the yields in a non-linear way, although turning points of temperatures showed that the positive relationship is true until 7-9 °C for all varieties, above of which yields decrease (table 4 and table 5; more details in the table 7, in the Appendix). It is still interesting to highlight that the effect of minimum temperatures on yields is not affected by earliness. Although the end stage lasts just a week, minimum temperatures may negatively affect the yields of early-maturing (until 10 °C) and middle-maturing varieties. Maximum temperatures occurring in starting stage positively affect the yields of all varieties in nonlinear way

[14] Generally, the sowing date of wheat is set on the middle of November in the Mediterranean area (Allen et al., 1998)

until 14-15 °C above of which decrease (table 5). At the same time, the adverse effects have been highlighted only in maturity for late-maturing varieties and end stages for early-maturing varieties until a certain threshold, i.e., 17 °C and 13 °C, respectively.

Table 4. Effect of temperatures on yields among phenological stages and earliness of durum wheat

	starting			growing			anthesis			maturity			end		
	EM	MM	LM	EM	MM	LM	EM	MM	LM	EM	MM	LM	EM	MM	LM
Minimum temperature															
Maximum temperature															

Notes: EM, MM, and LM indicate the early-, middle-, and late-maturing durum wheat earliness, respectively. Red cells indicate a negative impact of temperatures on yields, blue cells a positive impact, white cells for the uncaptured relationships.

Table 5. Turning points of temperatures among phenological stages and earliness (°C)

	starting			anthesis			maturity			end		
	EM	MM	LM	EM	MM	LM	EM	MM	LM	EM	MM	LM
Minimum temperature	-8+	-8+	-9+	+8-	+9-	+7-	NS	NS	NS	-10+	NS	NS
Maximum temperature	+15-	+14-	+14-	NS	NS	NS	NS	NS	-17+	-13+	NS	NS

Notes: EM, MM, and LM, indicate the early-, middle-, and late-maturing durum wheat earliness, respectively. The values show the threshold temperatures beyond which there is a change of sign in the regression estimates (table 7, in the Appendix). NS: not significant.

We also estimated the impacts of statistically significant weather coefficients among earliness and phenological stages, hence, the confidence level of temperature distributions. Results show a high confidence level, highlighting no differences among coefficients (table 6). Therefore, the temperatures' effects on yields do not vary between earliness within each phenological phase.

Table 6. Confidence levels of temperatures distribution

	starting		growing		anthesis		maturity		end	
	em	*ml*	*em*	*ml*	*em*	*ml*	*em*	*ml*	*em*	*ml*
Minimum temperature	-0.50580	-0.79056	-0.41006	0.16589	0.17650	-1.11070	-	-	-0.03887	-
Maximum temperature	1.50379	0.83624	-	-	-	-	-	-	-	-

Notes: *em* indicates the differences among coefficients of early-maturing and middle-maturing varieties divided by standard errors of baseline (i.e., middle-maturing variety); *ml* indicates the differences among coefficients of middle-maturing and late-maturing varieties divided by standard errors of baseline (i.e., middle-maturing variety).

It follows that early-maturing varieties are the most susceptible to changes in temperature, although the general relationship between yield and temperature is the same among earliness. Damages due to low temperatures are more likely among earliness than losses due to high temperatures. Sure enough, the vegetative stage lasts about four months, while maturity about a month and ends in just a week. Therefore, it is difficult to escape from low temperatures during starting and growing stages. Although wheat crop needs low temperature to complete vernalization processes, frost events occurring toward the end of the vegetative phase may cause severe damage such as the tiller, spike number, leaf area reduction and photosynthetic capacity, leading to a heavy yield losses (Xiao et al., 2018).

4. Conclusions

Given the potential impact of climate change on yields, deepening the yield-weather relationships is helping farmers cope with the weather risks. Therefore, we assess the effects of temperatures on durum wheat yields among early-maturing, middle-maturing, and late-maturing varieties. We distinguished the effects across five phenological stages (i.e., starting, growing, anthesis, maturity, and end) identified through the GDD approach, starting from the middle of November as sowing date. The levels and changes in temperatures affect durum wheat yields in several ways. More specifically, upward changes in the minimum temperatures are detrimental for to yields when they occur in the starting and growing phases, regardless of the earliness. Increases in maximum temperatures are indeed positively correlated (until a threshold of 14-15 °C) with the yields if they occur in the starting stage, whereas a negative effect is found when the event occurs at the maturity for late-maturing varieties or end stage for early-maturing varieties. Generally, the impacts of chronic heat stress, i.e., high temperatures for a longer duration, are lower than the heat shocks, i.e., extreme high temperatures for a short duration (Li et al., 2013). However, early-maturing varieties provides a better adaptation under warming conditions (Mondal et at., 2013), also because they may escape from the damages due to high temperatures by anticipating the crop cycle. Cold stress may cause morphological, physiological, biochemical, and molecular modifications in wheat. Phenotypic screening of cold-tolerant genes, pre-sowing seed treatments, and exogenous application of growth hormones may be a suitable solution tolerating severe low temperature extremes (Hassan et al., 2021). In conclusion, a better knowledge of the yield-temperature relationships, along with a deeper comprehension of the informative content of the secondary data on weather dynamics, may help both the farmers for the application of agronomic strategies, and policymakers for the planning of interventions to boost uptake in innovative crop insurance, such as the WIIs. Promoting greater comprehensibility of contracts' conditions, increasing transparency of indemnities and losses, and also improving the dissemination of risk management tools among farmers, may improve the trust, hence the adoption of subsidised insurance schemes (Giampietri et al., 2020). The main limitation of our study is the neglet of the effects of temperatures events on grain quality, although this is far beyond the scope of the analysis and will be addressed in future research. Further investigations are required to assess the effects of precipitation on yields and the choice of sowing dates to cope with climate risks.

5. References

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6. Appendix

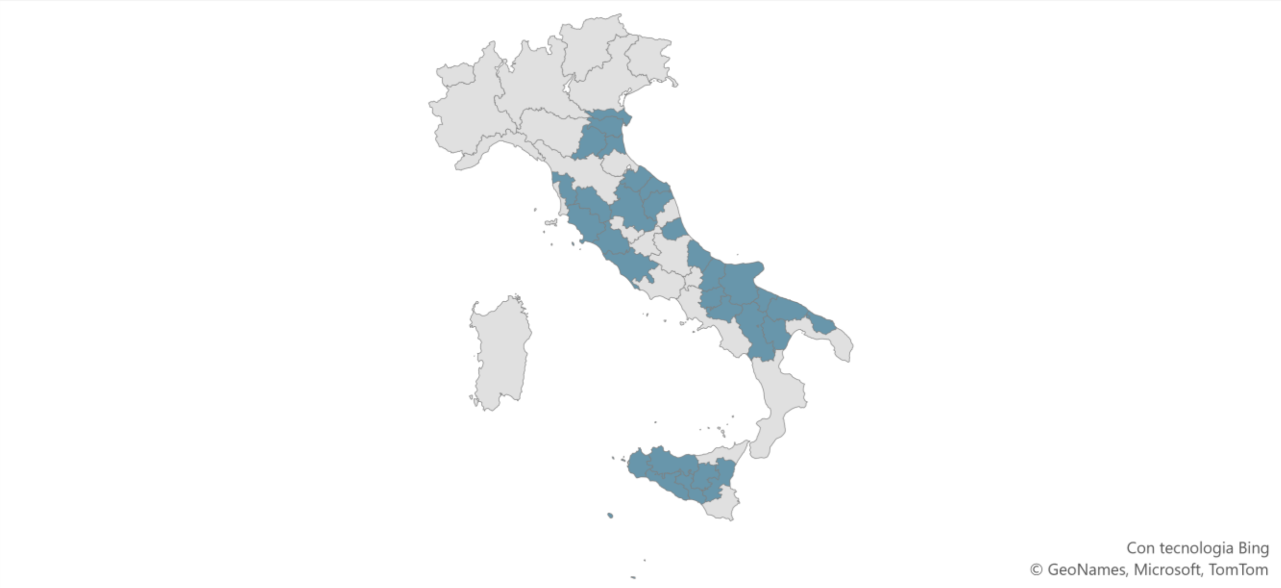

Figure 1. Main durum wheat-producing Italian provinces in Italy. Notes: the main durum wheat-producing Italian provinces in decreasing order are: Foggia (Puglia region), Campobasso (Molise region), Palermo (Sicilia region), Ancona (Marche region), Potenza (Basilicata region), Matera (Basilicata region), Enna (Sicilia region), Macerata (Marche region), Avellino (Campania region), Catania (Sicilia region), Ferrara (Emilia-Romagna region), Caltanissetta (Sicilia region), Perugia (Umbria region), Bari (Puglia region), Viterbo (Lazio region), Bologna (Emilia-Romagna region), Ravenna (Emilia-Romagna region), Brindisi (Puglia region), Siena (Toscana region), Agrigento (Siclia region), Benevento (Campania region), Grosseto (Toscana region), Pisa (Toscara region), Chieti (Abruzzo region), Trapani (Sicilia region), Teramo (Abruzzo), Roma (Lazio), Barletta-Andria-Trani (Puglia region), Rovigo (Veneto), Pesaro-Urbino (Marche region) (ISTAT, 2020).

Table 2. Descriptive statistics of daily temperatures, cumulative precipitation, and yearly yield variables for 30 main durum wheat producing provinces, 2020 year.

province	variable	Obs.	Mean	Median	St. dev	Min	Max
Agrigento	Maximum temperature	198	17.27042	16.475	3.656134	10.52143	31.60714
	Minimum temperature	198	10.53427	9.921429	3.269273	4.15	21.2
	Yield	198	27	27	0	27	27

Ancona	Maximum temperature	198	15.0523	14.80455	4.87341	5.245454	28.81818
	Minimum temperature	198	6.42034	5.990909	4.345694	-1.463636	16.89091
	Yield	198	45.3306	45.3306	0	45.3306	45.3306
Avellino	Maximum temperature	198	15.16203	14.54545	4.195631	4.790909	28.70909
	Minimum temperature	198	8.191552	8.095455	3.676873	-.0090909	18.63636
	Yield	198	32.81769	35	3.921524	25.80645	35
Barletta-Andria-Trani	Maximum temperature	198	16.11383	15.70625	4.502608	6.375	28.525
	Minimum temperature	198	7.62822	7.15625	3.886316	-1.1625	17.4875
	Yield	198	21.92088	22	.1421842	21.66667	22
Bari	Maximum temperature	198	15.81414	15.45833	4.549949	6.333333	29.175
	Minimum temperature	198	7.309596	6.741667	3.7425	-1.9	15.99167
	Yield	198	20.24346	20	.4374887	20	21.02564
Benevento	Maximum temperature	198	15.37965	14.735	4.230869	4.54	28.35
	Minimum temperature	198	8.102222	7.995	3.768435	-.1	18.14
	Yield	198	32.00147	31.97674	.0444387	31.97674	32.08092
Brindisi	Maximum temperature	198	16.79045	16.59	4.067458	8.61	28.66
	Minimum temperature	198	8.679343	8.05	3.772157	-.2	18.74
	Yield	198	34.8064	34.52381	.5077994	34.52381	35.71429
Bologna	Maximum temperature	198	14.48802	13.37143	5.873645	2.014286	28.45714
	Minimum temperature	198	5.333694	4.835714	4.361542	-2.635714	15.53571
	Yield	198	54.32178	55.5577	2.220902	50.35106	55.5577
Caltanissetta	Maximum temperature	198	16.8204	15.89	4.028488	9.41	32.56
	Minimum temperature	198	9.514748	8.94	3.520087	2.61	22
	Yield	198	28	28	0	28	28
Campobasso	Maximum temperature	198	15.20285	14.95455	4.480825	3.372727	26.70909
	Minimum temperature	198	8.140358	8.2	3.817845	-1.163636	17.9
	Yield	198	35.76263	36	.4265517	35	36
Catania	Maximum temperature	198	17.3101	16.73889	4.048381	9.516666	31.79445
	Minimum temperature	198	8.244501	7.669444	3.742443	.3722222	19.37222
	Yield	198	28.57143	28.57143	0	28.57143	28.57143

	Maximum temperature	198	15.16586	14.795	4.622042	3.25	26.89
Chieti	Minimum temperature	198	7.781061	7.65	3.902836	-1.2	18.08
	Yield	198	32.6417	32.84671	.3684098	31.98302	32.84671
	Maximum temperature	198	16.58646	15.75455	4.356249	8.218182	32.06364
Enna	Minimum temperature	198	8.238797	7.754546	3.665236	.4818182	20.07273
	Yield	198	30	30	0	30	30
	Maximum temperature	198	15.09104	14	6.145688	1.991667	29.18333
Ferrara	Minimum temperature	198	5.57319	5.341667	4.807333	-2.8	17.08333
	Yield	198	60.20202	64	6.824827	48	64
	Maximum temperature	198	15.9456	15.52292	4.463743	5.341667	27.81667
Foggia	Minimum temperature	198	8.216098	7.877083	3.775962	-.8	18.29583
	Yield	198	31.25	31.25	0	31.25	31.25
	Maximum temperature	198	17.01996	16	4.174036	9.141176	27.51765
Grosseto	Minimum temperature	198	7.026352	6.997059	4.34386	-1.876471	16.59412
	Yield	198	38.79645	38.84181	.0815015	38.65074	38.84181
	Maximum temperature	198	14.77406	14.60909	4.793149	5.263637	28.03636
Macerata	Minimum temperature	198	6.397888	6.027273	4.163119	-.9909091	16.48182
	Yield	198	42.00229	42.00229	0	42.00229	42.00229
	Maximum temperature	198	16.14141	15.80333	4.373894	6.466667	30.13333
Matera	Minimum temperature	198	7.865387	7.27	3.649867	.06	17.63333
	Yield	198	29.68525	29.68525	0	29.68525	29.68525
	Maximum temperature	198	16.95558	16.17143	3.899543	9.852381	33.84762
Palermo	Minimum temperature	198	10.14218	9.728571	3.256468	3.638095	19.40952
	Yield	198	25.99503	25.99503	0	25.99503	25.99503
	Maximum temperature	198	14.29614	13.5125	4.94103	4.515	26.96
Perugia	Minimum temperature	198	5.502298	5.37	4.366943	-2.92	15.535
	Yield	198	45.45914	44.86486	1.067896	44.86486	47.36842
	Maximum temperature	198	14.78035	14.34091	4.952188	4.390909	28.68182
Pesaro-Urbino	Minimum temperature	198	6.921442	6.786364	4.275691	-.9363636	17.32727
	Yield	198	38.00858	38.00858	0	38.00858	38.00858

	Maximum temperature	198	16.72483	15.875	4.305614	7.983333	27
Pisa	Minimum temperature	198	7.081019	7.179167	4.555321	-2.35	16.78333
	Yield	198	37.21282	40.33502	5.610488	27.1819	40.33502
	Maximum temperature	198	14.74603	14.36087	4.311705	4.573913	28.35217
Potenza	Minimum temperature	198	7.983707	7.556522	3.500149	-.1913043	18.28696
	Yield	198	27.29257	27.29257	0	27.29257	27.29257
	Maximum temperature	198	14.83678	14.03182	5.718577	2.609091	28.87273
Ravenna	Minimum temperature	198	5.954132	5.440909	4.503898	-2.563636	16.74545
	Yield	198	66.57576	68	2.55931	62	68
	Maximum temperature	198	17.05811	16.0775	3.893504	9.67	27.955
Roma	Minimum temperature	198	7.608207	7.3925	4.132565	-.35	19.59
	Yield	198	29.23737	29	.4265517	29	30
	Maximum temperature	198	14.97117	13.71818	5.981333	2.472727	28.05455
Rovigo	Minimum temperature	198	5.668916	5.363636	4.904146	-2.936364	17.71818
	Yield	198	56.23271	59.41509	5.718627	46.00845	59.41509
	Maximum temperature	198	15.97519	14.77813	4.710545	6.7125	27.15
Siena	Minimum temperature	198	5.882323	5.953125	4.678793	-3.45	16.81875
	Yield	198	37.53158	38	.8417409	36.02664	38
	Maximum temperature	198	14.60795	14.2125	4.647457	3.6875	26.6625
Teramo	Minimum temperature	198	7.074495	6.925	3.945144	-1.1	17.55
	Yield	198	39.80582	39.80582	0	39.80582	39.80582
	Maximum temperature	198	17.92341	17.12143	3.75761	10.22857	33.5
Trapani	Minimum temperature	198	10.757	10.63571	3.492239	2.428571	21.32857
	Yield	198	22.90524	23.80952	1.624959	20	23.80952
	Maximum temperature	198	16.60761	15.75	4.229603	8.413333	27.76667
Viterbo	Minimum temperature	198	7.143199	6.993333	4.106516	-.5666667	17.82
	Yield	198	38.73369	38.02031	1.281932	38.02031	41.02564

Table 7. Effects of earliness on the relationship between durum wheat yield and weather conditions

	starting			growing			anthesis			maturity			end		
	EM	MM	LM	EM	MM	LM	EM	MM	LM	EM	MM	LM	EM	MM	LM
Minimum	**-0.21574*** **	**-0.18915*** **	**-0.14759*** **	**-0.06015*** **	**-0.05224*** **	**-0.05544*** **	**0.15038*** **	**0.13949** **	**0.20802*** **	0.07918	-0.02572	0.00233	**-0.34243* **	**-0.33464* **	0.04429
temperature	(0.05802)	(0.05257)	(0.04752)	(0.01944)	(0.01929)	(0.01927)	(0.05808)	(0.06170)	(0.06669)	(0.07492)	(0.07999)	(0.08207)	(0.19684)	(0.20040)	(0.20892)
Minimum	**0.01431*** **	**0.01298*** **	**0.00917*** **	**-0.00322* **	**-0.00413** **	**-0.00298* **	**-0.00987** **	**-0.00865* **	**-0.01692*** **	**-0.00880* **	-0.00162	-0.00158	**0.01720* **	0.01595	-0.00285
temperature (sq)	(0.00394)	(0.00364)	(0.00335)	(0.00173)	(0.00171)	(0.00170)	(0.00446)	(0.00455)	(0.00472)	(0.00456)	(0.00469)	(0.00465)	(0.01028)	(0.01008)	(0.01005)
Maximum	**0.48706*** **	**0.33811*** **	**0.25528*** **	0.01712	0.00387	0.00921	-0.02972	0.01816	0.13013	0.00072	-0.15447	**-0.26802*** **	**-0.37884* **	-0.21556	-0.00099
temperature	(0.11419)	(0.09905)	(0.08780)	(0.03572)	(0.03472)	(0.03381)	(0.07884)	(0.08382)	(0.08923)	(0.09370)	(0.09737)	(0.09974)	(0.22896)	(0.21750)	(0.22702)
Maximum	**-0.01716*** **	**-0.01237*** **	**-0.00938*** **	0.00180	**0.00269* **	0.00222	0.00275	0.00028	-0.00333	-0.00035	**0.00456* **	**0.00836*** **	**0.01483** **	**0.00983* **	0.00423
temperature (sq)	(0.00422)	(0.00375)	(0.00340)	(0.00158)	(0.00150)	(0.00143)	(0.00265)	(0.00274)	(0.00285)	(0.00271)	(0.00274)	(0.00273)	(0.00592)	(0.00549)	(0.00555)
Prov FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,496	7,472	8,447	34,105	35,215	36,217	10,667	10,523	10,401	12,235	12,073	11,953	3,006	3,016	2,958
No. of prov	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30

Notes: EM, MM, and LM, indicate the early-, middle-, and late-maturing durum wheat earliness, respectively. Results show the estimates of the regressions model (1) for each year. Standard errors are shown in parenthesis. Phenological stages have been identified through the GDD approach, starting from November 15 as sowing date.

Chapter 5

General conclusions

Main findings

Given the potential impact of weather events on crop yields, understanding the dynamics yield-weather may help the farmers to cope with climate risks. First, the thesis deepened the linkages between durum weather yields and weather events. The overall results showed that temperatures and precipitation affect durum wheat yields in a nonlinear way. However, these relationships are valid only in certain phenological stages and most variables are not statistically significant: this limit opens a reflection on the need to collect more spatially and temporally refined data. Second, the thesis investigated how weather events that occur in phenological stages identified by different approaches (i.e., temporal specifications), and how different weather variables and combinations of thereof (i.e., design specifications) within the econometric model may lead to different results in the yield-weather assessment. The evidence suggests that the number of observations is not related to the number of yields-weather relationship and, in general, crop evapotranspiration and diurnal temperature range positively affect the yields in all phenological stages. The choice of sowing dates may also play a crucial role: a 10-days shift may lead to a different estimation of yield losses due to changes in weather. Clustering for spatial dummies among provinces, it emerged that some weather variables are more important in some provinces than others. Another implication is that the choice of specifications of the econometric model is very important to catch the relationships weather-yields. The negative effect of low temperatures, especially during the early stages, is always caught, regardless of specifications. The Growing Degree Days model based on sowing dates provided by Agri4Cast dataset seems to be the best that is likely closest to what could happen on farms supported by the agronomic literature: minimum temperatures negatively affect the yields when they occur in the starting and development stages (Baldoni and Giardini, 2000; Whaley et al., 2004; Angelini, 2007; Barlow et al., 2015), maximum temperatures negatively affect the yields when they occur in the flowering stage (Farooq et al., 2014; Rezaei et al., 2015; Zampieri et al., 2017; Mäkinen et al., 2018), heavily precipitation negatively affect the yields when it occurs in the maturity stage (Zampieri et al., 2017; Mäkinen et al., 2018). Third, the thesis assessed the effects of temperatures on durum wheat yields among early-maturing, middle-maturing, and late-maturing varieties, distinguishing the effects across five phenological stages (i.e., starting, growing, anthesis, maturity, and end) identified through the Growing Degree Days approach, starting from the middle of November as sowing date. The levels and changes in temperatures affect durum wheat yields in several ways. More specifically, upward changes in the minimum temperatures are detrimental for to yields when they occur in the starting and growing phases, regardless of the earliness. Increases in maximum temperatures are indeed positively correlated (until a threshold of 14-15 °C) with the yields if they occur in the starting stage, whereas a negative effect is found when the event occurs at the maturity for late-maturing varieties or end stage for early-maturing varieties. Generally, the impacts of chronic heat stress, i.e., high temperatures for a longer duration, are lower than the heat shocks, i.e., extreme high temperatures for a short duration (Li et al., 2013). However, early maturing varieties provides a better adaptation under warming conditions (Mondal et at., 2013), also because they may escape from the damages due to high temperatures by anticipating the crop cycle. Cold stress may cause morphological, physiological, biochemical, and molecular modifications in wheat. Phenotypic screening of cold-tolerant genes, pre-sowing seed treatments, and exogenous application of growth hormones may be a suitable solution tolerating severe low temperature extremes (Hassan et al., 2021).

Limitation and future research

The limitations of the research work are at least twofold: first, weather stations are not widely distributed, therefore, it makes difficult to collect more refined data (e.g., at farm-level) for further empirical estimates; second, the effect of weather variables on crop quality has been neglected. The weather index-based insurance, whose working principle is based on the relationship between weather variables and yield, is a promising risk management tool although it presents a major limitation, i.e., basis risk (Barnett and Mahul, 2007; Anghileri et al., 2022). In conclusion, several challenges need to be addressed to maximize the potential of insurance schemes based on the weather-indexes: (i) investments in weather monitoring systems, remote sensing technologies, and data collection networks to ensure accurate index calculations and timely payouts, e.g., using satellite-derived datasets based on Normalized Difference Vegetation Index, also supported by low-cost in situ sensors (Enenkel et al., 2019); (ii) design appropriate indices that accurately reflect the risk exposure of farmers and calibrated them to capture variations in crop performance due to changes in weather, also considering the phenological stages more susceptible (Tappi et al., 2023); (iii) affordability and accessibility of weather index insurance remain significand barriers for small-scale and marginalized farmers, e.g., premium costs should be affordable, and insurance products need to be tailored to the specific needs and limitation of different farming systems and regions; (iv) knowledge and awareness, e.g., dissemination through seminars and workshops, partnerships between stakeholders, public institutions, and insurance companies, in order to improve the participation in crop insurance schemes which il still low (Santeramo and Ramsey, 2017). Premium subsidies encourage farms to increase both crop acreage and insurance coverage (Yu et al., 2018). Clearly, insurance does not compensate for the entire loss but represented an aid to the farmer to stay in the market. Farmers need to be informed about the availability of these tools and encouraged to adopt them, and only through a combination of complementary risk management strategies (e.g., agricultural diversification together to crop insurances or mutual funds) may build more resilient farms. Furthermore, it is essential to involve the stakeholders, policymakers, researchers, professional association, and agronomist to develop effective risk management solutions and protect agricultural and environmental heritage for generations to come.

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