Temporal and design approaches and yield-weather relationships

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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.

JEL codes: G22; Q14; Q18; Q54

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 (Di Falco et al., 2014; 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., 2015; Dalhaus and Finger, 2016; Dalhaus et al., 2018; Belissa et al., 2020; Shirsath et al., 2019; Vroege and Finger, 2020; Bucheli et al., 2021). 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., 2015; 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., 2015) 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;

[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 Ramsey, 2017)

(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 (Dalhaus et al., 2016). 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., 2016, and 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., 2015, 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 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; Chavas et al., 2019, investigated the weather effects and their long-term impact on yields; Webber et al., 2020, used a novel combination of dynamic, processd-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., 2015, showed the advantages of quantile regression to

[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.

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; ISTAT, 2020). 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 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., 2016; Santeramo et al., 2016). 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.

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; Blanc and Schlemder, 2017). This approach gives an estimate of the short-run response to weather variation (Kolstad and Moore, 2020). Merel 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:

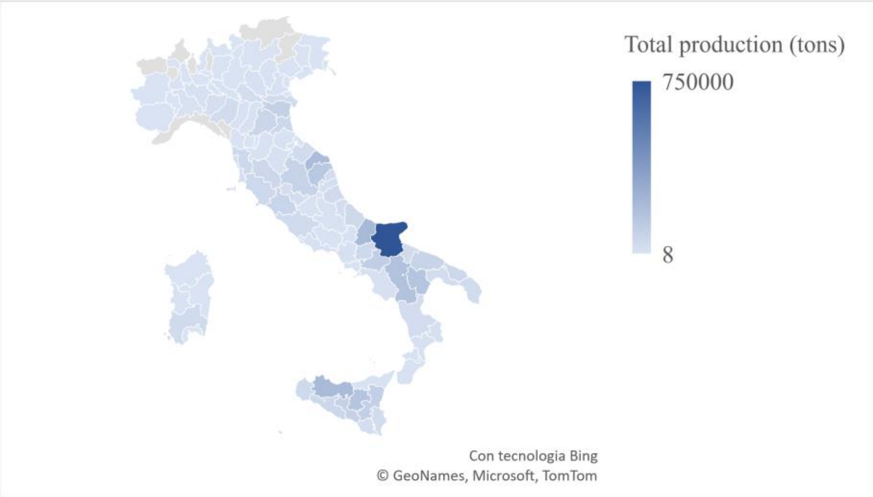
$$y_{it} = f(w_{it}) + \theta_{it} + \epsilon_{it}$$

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 (ISTAT, 2020). 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 (Figure 1)

Figure 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 25x25 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

[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 (ISTAT, 2020).

[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.

speed, vapour pressure and potential evapotranspiration variables have been included to calculate further variables that may affect the yields: crop evapotranspiration (ET_c)[7] and crop water deficit (CWD)[8].Descriptive statistics of collected variables are shown in the table 1:

Table 1. Descriptive statistic 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: ET_c 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]

[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).
[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.

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 survival (Whaley et al., 2004; Barlow et al., 2015). Moreover, the flowering stage is susceptible to frost (Baldoni and Giardini, 2000; Makinen et al., 2018). 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; Makinen et al., 2018). 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; Makinen et al., 2018). 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 4, while the latter in the table 2:

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

Stage	BGA (Macro-region)	FAO 56
	2nd - 3rd decade of October (Northern Italy)	
Starting	1st - 2nd decade of November (Center of Italy)	November 15 – December 14
	2nd - 3rd decade of November (Southern Italy and Islands)	
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. 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

Notes. 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.

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

[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).

nonlinear positive impact on yields both in *pooled* specification and in *panels* that include fixed effects by year, exclusively (table 4).

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

Notes: 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 ET_c, CWD, and DTR to assess yields-weather relationships) and in temporal specifications (i.e., using different approaches to identify the phenological stages also related to ET_c) of our econometric model seems to have no effect on the negative relationship low temperatures-yields and on the positive relationship ET_c-yields. However, the positive effects of high temperatures and the negative effects of precipitation on

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

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)	
(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)	
(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)
(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 ET_c 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 ET_c 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; Makinen 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

Notes: 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.

Conclusions

Weather conditions severely affect crop yields. Crop insurance schemes may mitigate unexpected yield losses, thus stabilizing farmers' incomes (Di Falco et al., 2014; Shirsath et al., 2019; Vroege and Finger, 2020). In particular, WIBI, which's working principle is based on yield-weather relationship, seems to be a promising risk management tool (Barnett and Mahul, 2007; Anghileri et al., 2022) although it presents a major limitation (i.e., basis risk). Some authors provide solutions to reduce the basis risk (Norton et al., 2013; Conradt et al., 2015; Dalhaus et al., 2016; Dalhaus et al., 2018; Boyd et al., 2019; Afshar et al., 2021; Leppert et al., 2021). Other authors provided empirical evidence on approaches to yield-weather assessment (Carter et al., 2018; Chavas et al., 2019; Auffhammer et al., 2020). However, literature is still lacking in 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,

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

respectively, it emerged that the former captured more. In general, ET_c and DTR positively affect the yields in all phenological stages, 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; Makinen et al., 2018), heavily precipitation negatively affect the yields when it occurs in the maturity stage (Zampieri et al., 2017; Makinen 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 ET_c-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).

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Online 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)	
$(\text{T min})^2$	-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)	
$(\text{T max})^2$	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)
$(\text{Prec})^2$	**-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)	
$(\text{T min})^2$	-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)	
$(\text{T max})^2$	**-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)
$(\text{Prec})^2$	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

	all provinces			
VARIABLES	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 Baseline	CI provinces N	CI provinces S	NS provinces C	NS provinces I
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.