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An integrated approach for the estimation of agricultural drought costs

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ABSTRACT

This study proposes a novel method to assess the overall economic effects of agricultural droughts using a coupled agronomic-economic approach that accounts for the direct and indirect impacts of this hazard in the economy. The proposed methodology is applied to Italy, where years showing different drought severity levels were analysed. Agricultural drought stress was measured using the fraction of Absorbed Photosynthetically Active Radiation (fAPAR). Using a comprehensive, field-level dataset on agricultural yields, fAPAR-based statistical models were applied to major Italian crops and direct crop productivity impacts were estimated. Local-level, crop-dependent productivity shocks were fed into a regionalised Computable General Equilibrium model specifically calibrated for the Italian economy. Direct and indirect aggregate impacts after allowing for inter-regional trade and input reallocation were obtained. Total estimated damages ranged from 0.55 to 1.75 billion euro, depending on the overall drought severity experienced, while regional losses showed large spatial variability. Although most of the losses were concentrated on agriculture, other related sectors, such as food industry manufacturing and wholesale services, were also substantially affected. Moreover, our simulations suggested the presence of a land-use substitution effect from less to more drought-resistant crops following a drought. This study sheds light on the characterisation of the total damages caused by droughts while provides a tool with applicability in the implementation of drought risk management plans and the evaluation of drought management policies.

1. Introduction

Droughts are, after tropical cyclones, the costliest natural hazard (NOAA, 2019). The average drought costs the US economy \$9.4 billion (sd: ± 10.57) and total damages can range from \$2 − 43 billion, depending on the surface affected and the intensity of the event. However, these figures are subject to considerable uncertainty. The economic assessment of natural hazards, such as droughts, is an intrinsically complex topic, featuring many methodological challenges. These challenges include: an accurate definition, characterisation, and measurement of the intensity of the hazard; the delimitation of the affected areas; and the quantification of direct and indirect effects (Seneviratne et al., 2012). The European Commission (2012a,b) has recognised that there is a lack of information about the economic impacts of droughts and a need for further and more accurate cost analyses. The expected increase in the frequency and intensity of drought events due to climate change reinforces the necessity to improve the quality and reliability of these assessment exercises and to embed these estimates into the assessment of the costs of climate change.

Different tools of different nature have been used for the assessment of drought costs (see Meyer et al., 2013 and Logar and van den Bergh, 2013 for a review). The methods traditionally used, showing all a strong focus on direct costs, have strengths and limitations, some of which are briefly described here. A first suite of methods is based on the use of statistical and econometric approaches, typically relating a dependent variable that measures the quantity of damages observed to a set of climatic variables describing meteorological drought severity or simply to a dummy variable characterising the presence of a drought. These works provide an effective way to estimate the direct costs of droughts at different spatial levels but tend to suffer from measurement error problems in either the dependent or the independent variables (or in both) associated with the difficulty of accurately measuring damages and specific drought stress. Also, most of them usually fail to control for possible confounding factors, resulting in biased estimates. Examples of this approach are Raddatz (2009); Mysiak et al. (2013); Naumann et al. (2015) or Stagge et al. (2015).

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Lott and Ross (2006) implemented in the US what they called a "method to the madness", consisting of collecting statistics for drought events from a wide variety of sources, ranging from government agencies to news media. This approach can yield accurate figures but shows a poor timing, since it cannot be applied until several months after the event occurs. Martín-Ortega et al. (2012) accounted for direct and indirect drought costs by applying a method that combined direct impacts from collected statistics at the basin level with input-output tables. Input-output tables alone can allow for indirect costs estimations but do not account for behavioural changes and input substitution. These models tend to underestimate the ability of the economy to accommodate labour and other factor uses among sectors. Hence, their results may be considered an upper bound estimate of total losses. Smith and Katz (2013) considered public and private insurance coverage data and adopted a factor approach to convert from insured losses to total (insured and uninsured) direct losses. Identified losses reflected the direct effects of droughts, *i.e.*, not including indirect effects. They identified potential sources of bias and uncertainty, including those associated with the factor approach, which suggested an underestimation of average losses (10–15 %). Again, in this case, economic losses estimates are often not reliable for several months to years after a drought occurs due to the time it takes to receive, process, and verify insurance claims. They also found it difficult to attribute the trend in losses to climate variations or change.

Howitt et al. (2015) combined a set of hydrological models to estimate the direct costs of droughts with an input-output model to estimate the multiplier effects (indirect and induced) and job losses resulting from these direct economic costs. As stated above, the use of input-output tables does not allow for price and production factor adjustments, which limits the accuracy of the indirect effects' estimates. Importantly, the authors found that the effects of droughts were unevenly distributed over regions, where regions with limited groundwater reserves showed very severe economic and employment impacts. In general, combined biophysical and agro-economic models that integrated crop models with economic assessments, as in Fischer et al. (2005), were found the most popular within the assessments specifically focused on agriculture.

An accurate assessment of drought costs requires a precise definition and characterisation of this hazard. Droughts can be broadly classified into four groups, including meteorological (deficit in precipitation), agricultural (deficit in soil moisture), hydrological (deficit in runoff, groundwater, or total water storage), and socioeconomic (considering water supply, demand, and social response) droughts (Wilhite, 2005). All types of droughts can be associated with a sustained precipitation deficit and are very challenging to characterise, partly due to their slow onset (Ault, 2020). In this study we focus on agricultural droughts, which represent the impact of meteorological and/or hydrological droughts (precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits or reduced groundwater or reservoir levels) on crop yields. Each crop needs specific temperature, moisture and nutrient conditions during its growth cycle to achieve optimum growth. If moisture availability falls below the required amount during the growth cycle, then crop growth will be impaired and yields reduced. Crop yield reductions thus represent the direct effects of agricultural droughts.

Historically, droughts have been monitored and investigated using ground-based observations or interpolated grids (AghaKouchak et al., 2015). However, the use of climate gridded data presents some problems that may result in biased drought signals, especially in high-resolution assessments (Auffhammer et al., 2013). Satellite-based indicators have gained relevance in recent years and are increasingly used to monitor droughts. Vegetation indicators reflect well agricultural drought stress, since plant water stress caused by drought affects the capacity of vegetation canopies (e.g., agricultural crops and natural vegetation) to intercept solar radiation, thereby reducing vegetation growth rate (Gobron et al., 2005). There are several examples in the literature documenting robust statistical relationships between satellite-based vegetation indicators and crop yields of different species (Clevers, 1997; López-Lozano et al., 2015; Al-Gaadi et al., 2016; García-León et al., 2019).

When it comes to the measurement of the economic impacts of droughts at a country-wide level, a sufficiently detailed spatial disaggregation must be considered, as droughts are unevenly distributed over regions. Adopting a sub-national resolution can thus offer a first useful step to measure more accurately the economic consequences of this hazard, to produce more relevant information for local planners and businesses, and to better capture the economic feedbacks between regions (Bosello and Standardi, 2015). But as important as featuring sufficiently high spatial resolution is to account for the indirect costs induced by direct damages. These losses include, for example, induced production losses of suppliers and customers of companies directly affected by the hazard.

Computable General Equilibrium (CGE) economic models incorporate economy-wide feedbacks to examine different impacts on various economic sectors, thus allowing an assessment of both the direct and indirect effects within the entire socio-economic system (Císcar et al., 2018). These effects occur through market adjustments: impacts in one economic sector affect other sectors and regions via the adjustment in market prices. CGE models rely on the notion of market equilibrium (supply equals demand) after a shock; economic agents (households, firms) adjust their choices (production factors) based on relative prices until a new equilibrium is reached in the economic system. The use of CGE models in hazard economic assessments has already been explored for different hazards, from flooding to sea level rise or droughts (Darwin and Tol, 2001; Horridge et al., 2005; Bosello et al., 2012; Carrera et al., 2015).

The integrated approach described in this paper proposes the combination of two modelling techniques (statistical-agronomic and CGE modelling) to estimate the overall (direct and indirect) economic effects of agricultural droughts at a country-wide level. This methodology is conceptually divided into four parts: i) the local characterisation (affected area and intensity) of the drought events; ii) the estimation of local-level, direct impacts of droughts on crop yields using statistical models calibrated for each crop; iii) the (area-weighted) aggregation of those impacts to the regional level and their conversion into factor productivity drought shocks for each agricultural production sector and administrative unit; and iv) the identification of indirect impacts at the sectoral, regional and country-wide level with CGE model simulations. Regional and country-wide impacts as a percentage of total activity (% GDP) were calculated across Italy for a selection of years classified according to their drought severity level over the period 2001–2016.

2. Data

2.1. Crop yield data

The study has been conducted in Italy, using geo-referenced data of land use and agricultural production at the farm-level provided by the Italian Council for Agricultural Research and Economics (Consiglio per la Ricerca in agricoltura e l'analisi dell'Economia Agraria – CREA) within the Rete di Informazione Contabile Agricola (RICA) database. RICA data are collected annually through field surveys on agricultural and livestock variables, covering a sample of around 11,000 farms. RICA is built in accordance with the European Union Regulation CE 79/65 (updated CE 1217/2009) to provide micro-economic data of farms, serving as instruments for defining and evaluating the EU's Common Agricultural Policy (CAP).

The data used span the period 2001–2016 and cover all the main agricultural species produced in Italy. Farm-level information about crop production and cultivated surface were retrieved and annual productivity, as total harvested product per unit of surface (tonnes/ha),

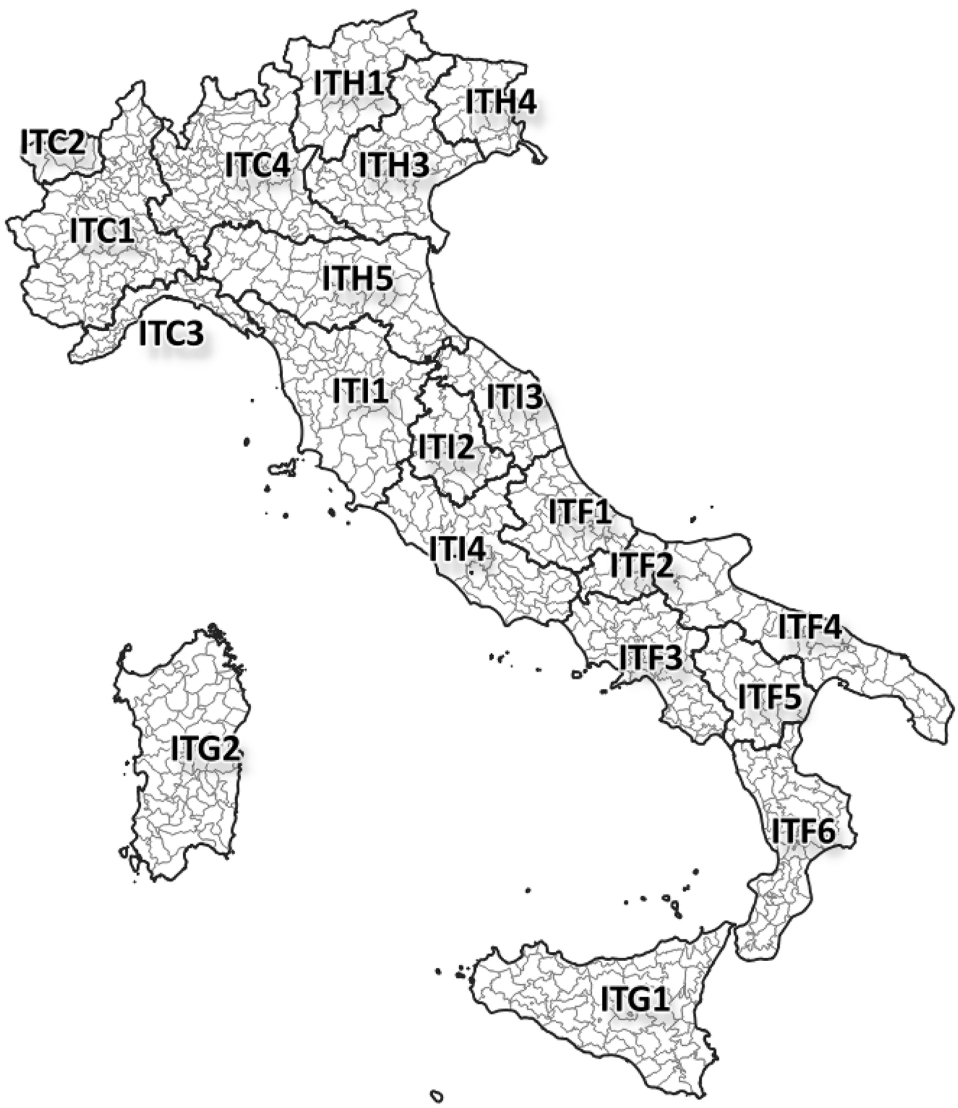

Fig. 1. Map of the studied area. Italy was classified into 20 administrative regions. These regions were then subdivided into 789 agricultural districts, which represent the basic spatial unit of analysis for the identification of crop-specific drought impacts.
The 20 studied regions correspond to the 21 NUTS2 regions in Italy corresponding to the second level of the 'nomenclature of territorial units for statistics' (NUTS) created by the European Office for Statistics (Eurostat), where Trentino (ITH10) and Alto Adige (ITH20) are aggregated in one single region: (from north to south, left to right) Piedmont (ITC1), Aosta Valley (ITC2), Lombardy (ITC4), Trentino-Alto Adige (ITH1), Veneto (ITH3), Friuli-Venezia Giulia (ITH4), Liguria (ITC3), Emilia-Romagna (ITH5), Tuscany (ITI1), Umbria (ITI2), Marche (ITI3), Lazio (ITI4), Abruzzo (ITF1), Molise (ITF2), Campania (ITF3), Apulia (ITF4), Basilicata (ITF5), Calabria (ITF6), Sicily (ITG1) and Sardinia (ITG2).

was obtained for every year, crop, and administrative unit. For the analysis, the data have been aggregated at the agricultural district (*Regione Agraria,* in Italian) level (Fig. 1). Spatial aggregation was advised due to: i) the lack of precision of geo-referenced information before year 2010, when only the municipality of the farm was available; ii) to address potential biases associated to survey respondents reporting inaccurate data.

2.2. A satellite-based indicator of agricultural drought

The fraction of Absorbed Photosynthetically Active Radiation or fAPAR was considered the reference index to quantify agricultural drought stress. fAPAR is a spectral vegetation index measuring the fraction of the solar radiation absorbed by live leaves for the photosynthesis activity. It refers only to the green and alive elements of the canopy. In this sense, fAPAR is very similar to other satellite-derived variables that measure vegetation health status, such as NDVI (Myneni and Williams, 1994). fAPAR values and their anomalies are used by many institutions, such as the European Drought Observatory (EDO, http://edo.jrc.ec.europa.eu/), to detect and monitor the impacts on vegetation growth and productivity of environmental stress factors, especially plant water stress due to drought. fAPAR data used in this study refers to version 2 of the data provided by the Copernicus Global Land Service (2017), where a neural network algorithm is applied on top-of-canopy input reflectances in visible, near infrared and shortwave infrared bands, at 1 km resolution, to a combination of observations from satellites SPOT/VGT and PROBA-V (Verger et al., 2014).

fAPAR anomalies were calculated by comparing the 10-day composite fAPAR maps with their average values over the study period. For every 10-day period (starting from January 2001) up to the last available observation (December 2016), fAPAR anomalies were computed as follows:

$$fAPAR_{ijt} = \sum_{d=1}^{36} \frac{X_{ijtd} - \overline{X}_{ijd}}{\sigma_{X_{ijd}}} \tag{1}$$

where $fAPAR_{ijt}$ represents the annual cumulative fAPAR anomaly of crop species i, agricultural district j at year t and X refers to fAPAR observed values. $\bar{X}_d$ represents the long-term average fAPAR value and σ_{X_d} is the standard deviation, both calculated for the same dekad or 10-day period using the available time series. The total sum of anomalies for the studied period must be equal to 0, which ensures a combination of dry and non-dry years. Each agricultural district with a negative fAPAR anomaly (implying a fAPAR value lower than the long-term mean for that location), indicates conditions of relative vegetation stress. Conversely, positive fAPAR anomalies indicate relatively favourable vegetation growth conditions. A description of the annual fAPAR anomalies at each agricultural district is shown in Fig. 2.

Different crop masks obtained from the 5th (2018) CORINE Land

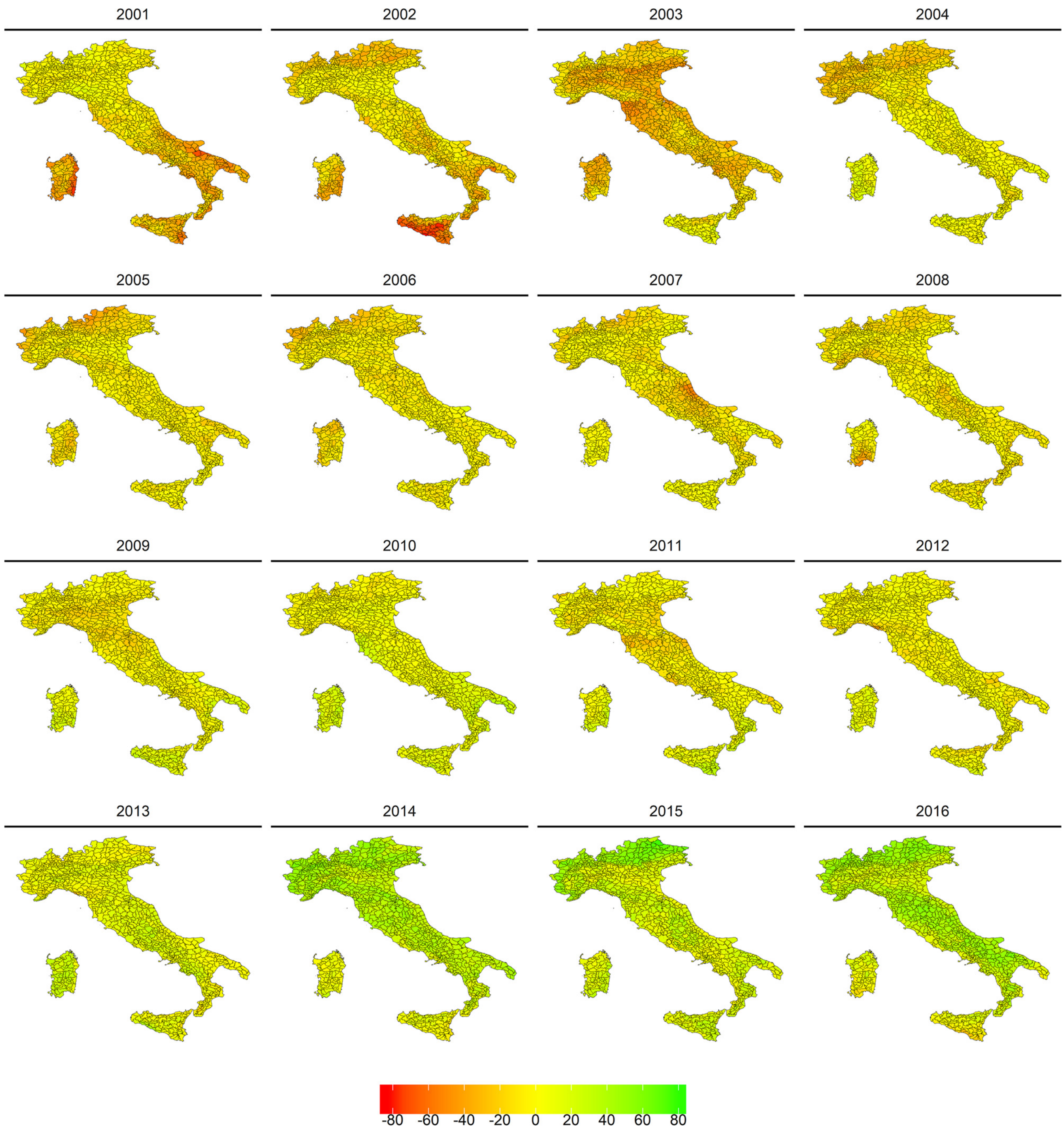

Fig. 2. Spatial distribution of fAPAR annual cumulative anomalies at the agricultural district level over the study period (2001-2016).

Cover inventory in Europe (Buttner et al., 2004) were used to trim and aggregate fAPAR values at the district level. Non-irrigated arable land, rice fields, vineyards, and olive groves masks (Fig. S1) were applied to cereal, rice, vineyards, and olive statistical models, respectively. fAPAR cumulative anomalies for the rest of species were obtained using district-level averages.

3. Methods

3.1. Statistical models

Crop-specific drought impacts were captured with statistical models. Statistical relationships between district-level crop yields and drought stress were built as follows

$$log\ (y_{ijt}) = \alpha_{i0} + \alpha_{i1} \bullet Year + \alpha_{i2} \bullet NUTS3 + \beta_i \bullet fAPAR_{ijt} + \varepsilon_{ijt} \tag{2}$$

where the yield (y) of crop species i at agricultural district j and year t relates to the annual cumulative fAPAR anomaly ($fAPAR_{ijt}$), a year dummy (*Year*), a provincial fixed effect (*NUTS3*[1]) and a constant term, being ε_{ijt} a residual random error term. Yields were expressed in logarithms, which implicitly assumes that changes in the independent variables have the same percent impact on yields regardless of yield level. The parameter β describes the crop-specific sensitivity to drought as it represents, for each crop, the percentage effect on crop productivity of an additional unit of cumulative fAPAR anomaly. Eq. 2 was

[1] NUTS3 correspond to the third level of the geographical areas defined by the 'nomenclature of territorial units for statistics' (NUTS) created by Eurostat.

applied to each crop using Ordinary Least Squares.

The statistical relationships estimated with Eq. 2 provide the crop-specific impact of drought on crop productivity. Major trends on crop production as well as the effect of managerial practices were captured by spatio-temporal fixed effects (*Year* and *NUTS3*), isolating in this way the effect of transient drought stress on the overall performance of the crop. This drought effect was captured for each crop with the coefficient β. A positive sign of this parameter was expected, reflecting that larger positive anomalies are associated to higher yields and, negative anomalies, typical of dry years, are linked to a decrease in average crop productivity.

3.2. A regionalised CGE model for the Italian economy

The sub-national CGE model used is based on the GTAP model (Hertel, 1997) and was calibrated on the GTAP 8 database for the reference year 2007 (Narayanan et al., 2012). The maximum level of spatial detail in GTAP is the country level. For this reason, we complemented the GTAP database on the national Social Accounting Matrices (SAMs) with Italian, regional economic information (Bosello and Standardi, 2015). The rest of the EU and the rest of the world were also considered. The model follows the neoclassical paradigm, where investments are saving-driven and primary factors (land, natural resources, labour and capital) are fully employed. More specifically, labour and capital can move between different sectors of the economy but not outside the region they belong to. Land is used only in the agricultural sector and can be shifted from one crop use to another (including livestock). Consequently, endogenous land use changes in the agricultural sector are expected following a drought shock. Production is a Leontief technology between intermediate inputs and value added, which is in turn a Constant Elasticity of Substitution (CES) function between the primary factors. When a shock hits the economic system, agents (households and firms) adjust their economic decisions (consumption, production, primary factors allocation) based on relative price changes.

One relevant feature of our sub-national version of the GTAP model concerns the specification of the trade relationships between regions. In CGE modelling, including the GTAP framework, the Armington assumption is typically used to model the trade structure (Armington, 1969). Armington elasticities imply an imperfect substitution between domestic and foreign products, which prevents an unrealistic sectoral specialisation after a shock hits the model. We have developed the trade structure of the GTAP model regionally to disentangle not only the international but also, the intra-national trade flows (Fig. S2).

The CGE model includes land productivity for different crop categories in each sub-national region. These productivities are exogenous variables and are part of the value-added functions. Our sub-country CGE model can capture the substitution effects taking place within the country through the bilateral trade flows between Italian regions. This includes the possibility for the representative consumer and the representative firm in each region to substitute domestic and imported products. Regional Value Added (*VA*) for region *r* and crop-sector *s* is represented in the model with a constant return to scale function of land, capital and labour as follows:

$$VA_{rs} = \left(\phi_{rs} Z_{rs}^{\frac{\sigma_S-1}{\sigma_S}} \chi_{rs} K_{rs}^{\frac{\sigma_S-1}{\sigma_S}} \psi_{rs} L_{rs}^{\frac{\sigma_S-1}{\sigma_S}}\right)^{\frac{\sigma_S-1}{\sigma_S}} \tag{3}$$

where total value added generated by region *r* in sector *s* in a certain year depends on the combined use of land (*Z*), capital (*K*) and labour (*L*), each of them with a specific degree of region-sector factor productivity: φ, χ and ψ, respectively. The parameter σ_S denotes the elasticity of substitution between primary factors.

3.3. Coupling between the CGE and statistical models

To create a drought-specific shock with an impact on the economy, a uniform decrease in the productivity of all primary factors was assumed for each agricultural sector. Land becomes less productive during droughts, but the intensity of the use of the remaining primary factors (capital and labour) is also likely to decrease due to this productivity fall. For instance, the use of the labour force and physical capital, e.g. tractors, will be temporarily constrained by the reduced fertility of land. Hence, during a dry year, the productivity of all primary factors (of agricultural sector *s* in region *r*) gets reduced by a proportionally equal amount[2], τ_{rs}, that is,

$$\begin{aligned} \alpha'_{rs} &= (1-\tau_{rs})\alpha_{rs} \\ \beta'_{rs} &= (1-\tau_{rs})\beta_{rs} \\ \gamma'_{rs} &= (1-\tau_{rs})\gamma_{rs} \end{aligned} \tag{4}$$

We calculated τ for each region-sector combination at each of the representative dry years. Crop-specific drought shocks were calculated for selected dry years (t_{dry}) as the product of the observed drought anomaly and the crop-specific estimated drought sensitivity, as obtained from Eq. 2. Drought shocks for crop species *i* and agricultural district *j* at year t_{dry} were obtained as

$$shock_{ijt_{dry}} = \hat{\beta}_i \bullet fAPAR_{ijt_{dry}} \tag{5}$$

where $\hat{\beta}_i$ stands for the drought crop coefficient associated to species ***i***. These shocks went through a double aggregation process. First, district-level GTAP shocks were obtained as

$$gtap_{sjt_{dry}} = \sum_i \omega_i \bullet shock_{ijt_{dry}} \tag{6}$$

Then, district-level GTAP shocks were transformed into regional-level shocks

$$\hat{\tau}_{st_{dry}} = \sum_j \omega_j' \bullet gtap_{sjt_{dry}} \tag{7}$$

where ω represents a vector of weights describing the relative observed frequency of that crop within the RICA survey and ω' denotes the fraction of cultivated area of that GTAP sector within the total cultivated area in region ***r***.

3.3.1. Assigning individual crops to production sectors

It was necessary to assign each crop species surveyed in RICA to each of the agricultural production sectors considered by GTAP. We identified 12 primary sectors as being susceptible to be directly affected by agricultural droughts among all the production sectors that constitute the GTAP database (57 sectors). These 12 sectors and their product composition are described with detail in Table 1.

Of the 415 species observed within the RICA survey, 214 initially matched the product classification of the economic sectors documented in GTAP. Some of these sectors consisted of a single or a few species (pdr, wht, gro, osd, and c_b), while others, such as v_f and ocr, showed great heterogeneity or included a large number of species. In these last two cases, we ordered each sector by the product sampling intensity in RICA and retained species until reaching 90 % of the observations in the survey (Table S1). 58 species were finally considered for analysis. The cattle (ctl), raw milk (rml) and wool (wol) sectors were made dependent on the evolution of pastures, assuming that cattle feeding rests predominantly on grass and forage plants. Analogously, other animal products (oap), where poultry productions industry dominates in Italy, were linked to the evolution of other grains (gro), on the basis that these animals are primarily fed with this family of grains.

To ease the estimation procedure, the rest of sectors considered in

[2] In principle, land, labour, and capital can be affected asymmetrically by droughts. In absence of a better empirical information, we rely on the assumption of a uniform shock to all factors of production.

Table 1
Description of GTAP agricultural sectors. Each plant species observed in the RICA database was assigned to a GTAP sector. Livestock sectors were made dependent on the evolution of pastures and grains, presuming that they are mainly fed with these products.

GTAP Sectors		RICA Plant Species
Code	Description	
pdr	Paddy Rice	Rice
wht	Wheat	Soft wheat, Durum Wheat
gro	Other Grains	Maize, Barley, Oats
v_f	Veg & Fruit	
	Vineyards	Vineyards
	Rest of Veg & Fruit	Apple, Peach, Potato, Tomato, Orange, Apricot, Kiwi, Pear and 24 more species*
osd	Oil Seeds	
	Olive	Olive
	Rest of Oil seeds	Soy, Sunflower
c_b	Cane & Beet	Sugar Beet
pfb	Plant Fibres	–
ocr	Other Crops	Alfalfa, Flowers, Tobacco, Eucalyptus, Ruscus, Rose, Genisteae, Acacia and 15 more species*
ctl	Cattle	Pastures
oap	Other Animal Products	Other Grains
rmk	Raw milk	Pastures
wol	Wool	Pastures

* Refer to Table S1 for a detailed list of all the species included in each sector.

GTAP were grouped in macro-sectors, as described in Table 2. This sector grouping let us specifically consider the indirect effects of droughts.

4. Results and discussion

4.1. Drought level characterisation

In order to define and characterise each year according to its level of drought severity, a country-wide synthetic measure of agricultural drought stress was built using fAPAR data. District-based annual anomalies were averaged to the country level and a synthetic agricultural drought indicator was obtained, summarising the country-wide drought state according to vegetation conditions (Table 3). Values of the synthetic index over 0 describe normal and favourable vegetation conditions while values below 0 indicate drought stress. We distinguished between three types of drought severity levels (mild, moderate and extreme) according to the variability of our synthetic measure. Three representative years of each state were selected to describe each scenario. Solar years 2003, 2006 and 2011 were studied as extreme, moderate and mild dry years, respectively. Our classification of dry years in Italy correlates well with that obtained using alternative meteorological drought indices, such as the Standardised Precipitation Index (SPI) calculated at the Italian Drought Observatory (https://drought.climateservices.it/), especially for shorter accumulation periods, which are typically more connected with reduced soil moisture. For instance, spring precipitation anomalies, as measured by the SPI-3, were -1.15 in 2003, -0.43 in 2006, and -0.45 in 2011 (the reader is referred to Fig. S3 for the detailed evolution of SPI-3 and SPI-6 in Italy over 2001–2016).

Table 3
fAPAR Italy-wide cumulative anomalies and their associated drought level characterisation. Negative anomalies indicate overall drought stress. The mean of the drought index over the study period is equal to 0 by construction ($\bar{fAPAR} = 0$; $\sigma_{fAPAR} = 19.44$). Three drought severity levels were defined: mild (-1/2σ,0], moderate (-3/2σ,-1/2σ] and extreme [< -3/2σ]. Positive values denote normal/wet growing conditions.

Year	fAPAR	Drought severity
2001	−16.78	Moderate
2002	−20.00	Moderate
2003	−28.06	Extreme*
2004	−9.55	Mild
2005	−10.59	Moderate
2006	−11.19	Moderate
2007	−8.08	Mild
2008	−9.99	Moderate
2009	−4.17	Mild
2010	9.05	Normal/Wet
2011	−3.54	Mild
2012	−0.72	Mild
2013	12.76	Normal/Wet
2014	37.12	Normal/Wet
2015	28.75	Normal/Wet
2016	35.00	Normal/Wet

* -1/2σ = -9.72 and -3/2σ = -29.16. In order to analyse an example of each scenario, we chose to characterise year 2003 as an extreme dry year, while according to our criteria it should be a moderate-extreme year.

4.2. Drought impacts on crop productivity

The estimated β coefficients for each crop are shown in Table 4. Only coefficients showing high significance (p-value < 0.1) were kept in our analysis. Not retained crops belonged exclusively to the vegetable and fruits (v_f) and other crops (ocr) sectors and were mainly affected by poor sample representativity. 21 out of the 58 crop species initially considered, (around 250,000 crop-year observations, 60 % of the total observations available in RICA) were finally used. Except for olives, all species showed a positive relation to fAPAR, with β taking values in the interval [0.001, 0.008]. This is interpreted as an expected increase in crop yields ranging from 0.1 % to 0.8 % per additional unit of cumulative fAPAR anomaly. Most species lied in the interval [0.001,0.004] and only some fruits showed higher drought sensitivity values. It must be noted that these estimates do not account for precise phenology. For simplicity, it was identified the solar year as the growing season for all species. There is no lag effect in our drought identification, since fAPAR reflects the effect of droughts. However, impacts observed in a specific year may well be the result of a drought process whose onset took place in the preceding year.

Bearing in mind that the country-level sample standard deviation of $fAPAR$ is equal to ± 19.44 ($f\bar{A}PAR = 0$, by construction), it is expected an average variation of yields between 1.95 % and 15.55 %, attributable to drought conditions. Looking at the cases of wheat, soft and

Table 2
Macro-sectors of activity resulting from the aggregation of non-agricultural production sectors of the GTAP database.

Macro-sector	Description
Rest of Primary	Forestry, fishing, and extraction
Food Industry	Meat products; vegetable oil and fats; dairy products; processed rice; sugar; food products not elsewhere classified; beverages and tobacco products
Rest of Industry	All other sectors in manufactures
Trade Services	All retail sales; wholesale trade and commission trade; hotels and restaurants; repairs of motor vehicles and personal and household goods; retail sale of automotive fuel
Rest of Services	All other sectors in services

Table 4
Summary of the estimated crop-specific drought coefficients. Only species showing significant coefficients (threshold set at p-value < 0.1) were retained for the simulation of the economic model.

Crop	Coefficient (β)	p-value	Adj-R^2	N	Economic sector (GTAP)
Rice	0.0018	0.003	0.349	181	Paddy Rice
Durum Wheat	0.0020	0.000	0.788	1136	Wheat
Soft Wheat	0.0010	0.001	0.731	1144	Wheat
Maize	0.0020	0.000	0.533	1108	Other Grains
Barley	0.0006	0.046	0.721	1356	Other Grains
Oats	0.0010	0.026	0.524	873	Other Grains
Vineyards	0.0007	0.091	0.670	1052	Vineyards
Beans	0.0019	0.000	0.446	712	Rest of Veg & Fruit
Apples	0.0046	0.000	0.625	496	Rest of Veg & Fruit
Potatoes	0.0019	0.012	0.582	664	Rest of Veg & Fruit
Tomatoes	0.0034	0.000	0.594	723	Rest of Veg & Fruit
Plums	0.0078	0.000	0.470	356	Rest of Veg & Fruit
Lettuce	0.0043	0.010	0.548	345	Rest of Veg & Fruit
Peppers	0.0064	0.003	0.483	256	Rest of Veg & Fruit
Olives	−0.0012	0.009	0.550	1064	Olive
Soy	0.0011	0.016	0.440	534	Rest of Oil seeds
Sunflower	0.0015	0.010	0.473	578	Rest of Oil seeds
Sugar beet	0.0021	0.001	0.433	549	Cane & Beet
Pastures	0.0032	0.005	0.479	541	Other Crops

durum, their associated drought coefficients were 0.00101 ($p = 0.001$) and 0.00205 ($p = 0.000$), respectively, suggesting higher sensitivity of durum wheat with respect to soft wheat. Drought impacts at the district level for these two crops in the studied dry years can be seen in Fig. S4, with observed marked and spatially homogeneous negative impacts in extremely dry years, whereas positive and negative impacts coexist in moderate and mild dry years, depending on the exposure to drought of the specific district.

Olive crops deserve special attention. The coefficient associated to olives was found negative ($\hat{\beta} = -0.0017$, $p = 0.010$), a sign and significance robust to different sub-samples and different geographic areas. Olive (*Olea europaea* L.) is considered highly tolerant to drought and trees can survive on shallow soils with little supplemental water beyond winter rainfall. This species has developed a series of physiological mechanisms to tolerate drought stress and grow under adverse climatic conditions taking benefit of a higher root/leaf ratio if compared to well-watered plants (Sofo et al., 2008). Also, drought and high temperatures favour the removal of insects attacking olive fruits. This drought tolerance results in high olive yields even when a deficit water provision is observed.

4.3. Total costs of agricultural droughts

Table 5 shows the economic effects of agricultural droughts on the Italian economy that stem from three different levels of drought severity, as described in our sample by years 2003, 2006 and 2011. These results are originated from the simulation of our regional CGE model after the economy being hit by the drought shocks described in Section 3.3. Our estimates of total GDP losses range from 0.03 % under mild drought stress to 0.05 % and 0.10 % under moderate and extreme drought levels, respectively. Total estimated effects on GDP, though relatively small due to the reduced weight of the agricultural sector in the Italian economy, remain quite substantial in monetary terms. Total GDP losses, once CPI-adjusted to 2017 nominal prices, represent a cost of 0.56, 0.92 and 1.75 billion euro in a mild, moderate,and high dry year, respectively.

Droughts caused a significant direct effect on agricultural output. In 2003, it was estimated a decrease in agricultural output of -3.74 % (equivalent to €2.06 billion). All agricultural sectors were affected, but with different degrees of intensity. This intensity rested on the crop sensitivity to drought, the fraction of land affected and the severity of the drought. Droughts also showed an indirect impact on the rest of the economy. These impacts are identified in the last rows of Table 5. Food manufacturing industries were clearly affected, with an estimated production decline of -0.53 % attributable to the effect of droughts. The provision of services with a clear link to agricultural outputs, such as wholesale, accommodation, and restaurants, was also damaged (-0.10 %). According to our estimates, of the total estimated fall of production, 60 % can be attributed to the agricultural sector while the remaining 40 % is contributed by sectors linked to agricultural activities, half of which (20 %) correspond to the food manufacturing industry.[3] These sectoral impacts were proportionally equivalent across drought scenarios (second and third columns of Table 5). Production damages are not fully reflected in the economy-wide total cost because of the mitigating action of market adjustments, namely, trade and production factor reallocation. These price-driven effects, discussed in detail below, operate in the general equilibrium framework, and ameliorate the total impact of droughts in the economy.

Table 5
Overall effects of droughts on total economic activity in response to different drought severity levels (% change with respect to benchmark scenario). Total effect on GDP and breakdown of production losses by macro-sectors of activity and agricultural sectors.

	2003	2006	2011
GDP (%)	−0.10	−0.05	−0.03
GDP (M€)*	−1748.1	−924.3	−560.7
Agricultural Production (%)	−3.74	−1.99	−1.16
Agricultural Production (M€)*	−2061.9	−1098.8	−638.2
Rice	−6.51	−2.50	−2.53
Wheat	−5.75	−2.08	−1.53
Other grains	−4.17	−1.35	−1.53
Veg & Fruit	−8.69	−2.50	−1.84
Oil seeds	−0.43	−0.40	−0.53
Sugar beet	−0.44	−0.19	−0.15
Other crops	−1.77	−2.45	−1.02
Rest of primary	0.08	0.05	0.02
Food Industry	−0.53	−0.31	−0.18
Rest of Industry	0.11	0.06	0.03
Trade Services	−0.10	−0.06	−0.04
Rest of Services	−0.03	−0.02	−0.01

* The total cost of droughts (in € million) has been estimated by multiplying the net effect on GDP (%) by the last available nominal GDP of Italy (2017), as obtained from Eurostat. The monetary value of agricultural production losses has been obtained as the product of the estimated production effect on the agricultural sector and the total nominal value of agricultural production from Eurostat.

It can be seen from Fig. 3 that the total estimated cost of droughts varied considerably across Italian regions. Regional damages depended on the combined effect of the agricultural land regional use (crop mix), the amount of drought-affected areas, but also on factor mobility and trade relationships between regions. Losses were relatively more concentrated in the northern part, partly reflecting that Italian economic activity is polarised to the north. However, given that the share of the primary sector is relatively higher in the south, considerable monetary losses were also identified in that area, as for example, in Apulia and Sicily during 2003. All these cost estimates are representative from mild, moderate and severe droughts. However, the total amount and the spatial pattern of the costs of a specific drought event will critically depend, as highlighted above, on the spatial characteristics of the drought episode analysed.

The costs here estimated compare with other figures found in the

[3] Output by industry at basic prices was retrieved from http://dati.istat.it/. Output data from year 2016 were used to obtain the relative weight of each sector within total estimated production losses.

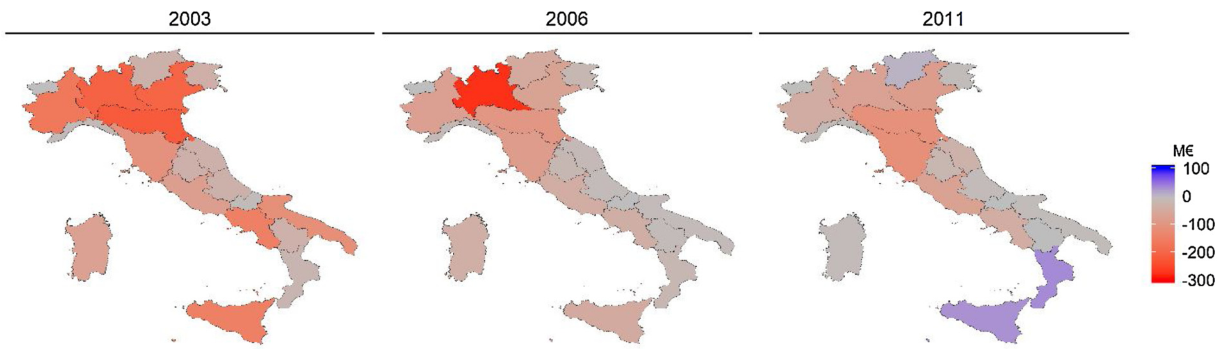

Fig. 3. Regional variation of GDP (in € million) in response to agricultural drought shocks at the three scenarios/years studied.

literature. The US National Oceanic and Atmospheric Administration (NOAA, 2019) has calculated the costs of a series of drought events taking place in the US over the period 1980 – 2018. An average cost of 0.05 % (sd: ± 0.05 %) of US GDP was identified, an amount that overlaps with the estimates provided here. Their definition of drought, however, is much broader and accounts for the effects on physical assets. Our cost estimates also resemble those obtained by Howitt et. al (2015) for the economy of California in 2015, an extremely dry year in that region. They identified overall losses of $2.7 billion (0.11 % of California's GDP), two-thirds of which were attributable to agriculture, also featuring unevenly distributed impacts over the region. Martin-Ortega et al. (2012) appraised the total losses of the drought that affected the Spanish region of Catalonia during 2007 and 2008 at €1.6 billion, which corresponds to 0.48 % of the Catalonian GDP. In Italy, the Italian Association of Farmers (Il Punto Coldiretti, 2017) estimated total production losses of €2 billion following the 2017 drought, an episode with similar characteristics to the drought occurring in 2003. Meanwhile, Horridge et al. (2005), using a regionalised CGE model of Australia, projected that the drought experienced in that country during 2002–2003 would make Australian real GDP to lower by 1.6 %, one percentage point (62.5 %) of which was related to reductions in value added of the agricultural sector. Their CGE model (TERM) differs from our version of GTAP in some respects. We assume full use of primary factors and, therefore, full use of labour, while in the TERM model, total employment replicates the decrease in the total aggregate demand during the drought event. More importantly, in our study we implement the productivity shocks only in the agricultural sector, while in Horridge et al. (2005) the productivity of the industrial sector is also negatively affected.

Two features, absent from our analysis, could play a role in the determination of total drought costs. First, insured losses are not included in our damage estimates. They can play a minor but relevant role in the direct costs of droughts to agriculture as insurance products against weather extreme effect, although still not widespread in Italy, are becoming increasingly demanded. Second, our approach does not consider the costs incurred in the damage of physical assets, such as buildings, public infrastructure and machinery or irreversible damages to cultivated land. We believe, however, that these damages are secondary in terms of their monetary magnitude.

4.4. Trade effects and factor reallocation

Every year a myriad of different shocks (e.g. political, environmental) hit an economic system. It is hard to disentangle the contribution of each one when all are considered simultaneously. Using the comparative static framework, we are able to isolate the economic impact of a single economic shock (a drought shock in this case) and analyse the effects in the economic system ceteris paribus, i.e. given the other conditions do not change and other types of shocks are absent. The CGE model then captures the market adjustments taking place between sectors and factors of production through the intra- and international trade channels. These adjustments do not replicate exactly the actual observed economic impacts but are very helpful to understand the fundamental economic mechanisms underlying the propagation of a shock.

Keeping this in mind, we analysed the results of year 2003 to reconstruct the economic causal chain of the impact of a severe drought. The economic dynamics are similar under moderate (year 2006) and mild drought stress (year 2011). First, it is observed an increase in Italian agricultural prices due to the decreased productivity capacity of Italian regions. This price increase depends both on the productivity shock to that specific region and crop-sector and the Armington elasticity regulating trade fluidity within and outside the country. In our experiment for 2003, observed price increases were more pronounced in sugar (between 11 % and 14 % depending on the region), vegetables and fruits (between 5% and 9%) and other cereals (between 5% and 9%). Then, the price signal is detected by the representative household and firm in each region, which decides to substitute the domestic crop with the imported one. An increase in imports from the rest of Europe and the rest of the world is therefore observed for all crops. While the increase in international imports is quite uniform across Italian regions, reaching 40 % in the case of sugar, the sub-country import dynamics can be differentiated, especially for those crops featuring less sensitivity to droughts, such as oil seeds, other crops, and livestock or for those regions exhibiting specific climate characteristics. For example, the oil seeds sector is the combination of olive oil and sunflower oil. As the first crop is prevailing in the south and is less drought sensitive, we can observe a recomposition of land use and production of the entire sector with positive relative changes in the south and negative relative changes in the north. More septentrional regions, such as Veneto, Friuli, and Marche raise their oil seeds imports from the rest of Italy, respectively by 4.2 %, 1.9 % and 4%. Conversely, southern regions, especially Basilicata, Sicily and Sardinia, experience substantial increases in oil seeds exports, 14.9 %, 9.1 % and 11.3 % respectively, towards both the foreign and the national markets.

The reallocation of land use between different crops, both at the national and sub-national level is closely related to these trade dynamics as well the labour and capital recomposition, which involves the agricultural sector and the rest of the economy. Concerning land use changes at the country level, it is observed a reallocation of land from wheat (-1.6 %) to other cereals (2.1 %) and from vegetables and fruits (-1%) to livestock (0.45 % for cattle and 3.1 % for other animals) and the sugar sector (6.5 %) due to the observed relative price increase of this crop. Labour and capital reallocation in the agricultural sector are consistent with the land use change. We also notice a light shift of workers from food industry (-0.5 %) to the rest of the industry sector (0.1 %).

5. Conclusions and policy implications

A systematic and harmonised method to assess the economy-wide costs of agricultural droughts with significant spatial detail is proposed in this study. This method is based on an integrated agronomic–economic modelling framework, consisting in the coupling between statistical tools that identify crop-specific drought shocks and a regionalised CGE model. The present methodology enables the joint assessment of the direct and indirect impacts of agricultural droughts: direct impacts of droughts on the agricultural sector are precisely identified using spatially detailed agricultural and drought data, while a CGE model disaggregated at the regional level identifies the impacts on adjacent industries and allows for regional trade dynamics.

One of the main sources of uncertainty in cost assessments for natural hazards is the lack of sufficient, detailed, comparable and reliable data (Meyer et al., 2013). Such exercises require high spatial resolution data on land use, crop yields and drought indicators as input data. These demands are addressed in this paper with the use of a comprehensive, survey-based dataset of the Italian agricultural sector and the retrieval of high-resolution, remote-sensing vegetation health data. The latter data were used to construct a country-wide, synthetic measure of drought severity, upon which three different drought scenarios were characterised.

Our estimates indicate that the total damages caused by agricultural droughts in the Italian economy can range from $0.01-0.10\%$ of Italian GDP, that is, from approximately €0.55 to €1.75 billion. These damages concentrate but extend beyond the agricultural sector, with substantial identified impacts on food industry manufacturing and wholesale and trade services. Our estimated overall effect on GDP is similar to other outcomes obtained in different exercises carried out in other areas of the US and Spain. Moreover, the agricultural production loss identified under severe drought conditions (€2 billion) is very consistent with the figure reported by the Italian Association of farmers in 2017. What differs our approach from other alternatives available is that ours is fully systematic and scalable and thus could be applied to more specific areas or could be expanded to implement large pan-European drought cost assessments, provided a good calibration of the CGE model is performed. Moreover, it allows a deeper inspection of the overall economic system at the national and sub-national level and a more coherent examination of the trade effects, land use changes as well as the production and factor reallocation.

A lack of comprehensive knowledge of the costs of droughts is a barrier to the improvement of policy approaches to managing drought risks (European Commission, 2012a, b; OECD, 2016). Two types of government responses to drought can be distinguished: pre-impact (mitigation) and post-impact (response) interventions. Drought mitigation refers to actions taken in advance of a drought that reduce potential drought-related impacts when the event occurs. Examples of such measures include the development of an early warning system, preparedness plans, increased water supply, demand reduction (e.g., water conservation programs), crop insurance against droughts, water rights, and increasing water recycling and reuse. Post-impact interventions are reactive since measures are implemented after a drought occurs and focus on treating the symptoms instead of the causes. These measures typically include compensation mechanisms.

Ideally, stand-alone drought plans should incorporate both mitigation and response interventions. Therefore, government policies should be designed to comprehensively address the various stages of a drought, covering from an efficient land-use allocation that maximises overall drought resilienceto the design of efficient and locally targeted compensation mechanisms. The methodology proposed in this paper can be used at different stages of a drought to help improve land use and drought management policies. We envisage a couple of potential applications of this tool in these two areas:

- The creation of regional-level agricultural drought risk maps. Paying attention to the actual regional land use patterns, estimated crop drought sensitivity, and different drought severity scenarios, a regional risk measure could be derived. Actions to reduce the vulnerability (crop mix) and exposure (agricultural share) of regions to droughts could be implemented.
- The development of high-resolution efficient insurance systems that reflect the true costs of droughts and the design of efficient compensation mechanisms. The declaration of calamity states and the associated payments to farmers can be estimated with high precision and avoiding temporal lags using the methods proposed in this study.

Finally, we have identified a series of research opportunities to expand our approach and enhance its usability. First, other agricultural drought indicators, such as evapotranspiration or soil moisture, should be explored as alternative drought reference indices. In particular, their short-term predictability should be investigated. This would increase the usability of this tool as a short-term policy tool by improving the short-run efficiency of water allocation in the event of a drought. Second, crop-specific drought sensitivity assessments should incorporate adequate phenology patterns to improve the accuracy of direct damages to agricultural output. Third, potential asymmetries in the effect of drought shocks on production factors should be allowed. Though this would require a previous and rigorous empirical identification of the effect of droughts on land, capital, and labour. Fourth, it would be interesting to include some flexibility in the choice of intermediate inputs, such as fertilisers, within the CGE model. This would increase the adaptation capacity of the representative farmer, capturing an additional type of market adaptation in the general equilibrium framework. Lastly, more in-depth case studies are needed to help characterise drought costs at a larger scale and address feasible European adaptation strategies within the context of climate change.

Author contributions

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2020.104923.

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