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The impact of drought on farm economic performance: evidence from Sweden

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Abstract

We estimate the effect of drought on farm economic performance, examine the sensitivity of farms' historical performance to drought conditions, and determine the effect of a future increase in drought conditions on farm economic performance. Since the effects of drought are both spatially and temporally heterogeneous, we adopt a panel regression method that accounts for multidimensional fixed effects in all regression parameters. We apply this method to a dataset from south-central Sweden spanning the period from 2001 to 2018. The results indicate that an increase in consecutive dry days or drought leads to a decrease in farm income by about 5%, on average, with systematic variation in the effects across municipalities. The findings further suggest significant sensitivity of farm income to drought from 2003 to 2004 and from 2014 to 2018. The results also indicate that drought negatively affects other farm outcome variable such as farm resource use efficiency and farm net value added.

Keywords Droughts · Farm performance · Climate change · Mean observation OLS

1 Introduction

Europe has witnessed severe extreme weather events in the recent decade, leading to disrupted agricultural production and causing significant economic and environmental damage. Particularly notable are the drought events[1] of 2014–2018 in Europe and the

[1] Drought is defined as an extended period of dry weather, particularly one that is detrimental to crops or plants. It is often described as a "creeping phenomenon" due to its gradual onset and protracted development, influenced by various factors such as human activities and climate change (Haile et al. 2020; Wilhite and Glantz 1985). As a result of its complex nature, the full impact of drought evolves slowly over time, making it challenging to accurately assess its effects (Moravec et al. 2021). Moreover, determining the precise onset and duration of drought poses considerable difficulty (Moravec et al. 2021).

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drought of 2022 exacerbated by heat waves in Central Europe (Moravec et al. 2021; Toreti et al. 2022).The recurrence pattern of compound drought in Europe has raised the awareness of the urgent need for climate change adaptation and the corresponding need for research on the economic effects associated with climatic extremes exposed to agriculture (Thompson and Nardone 1999; Ciais et al. 2005; Webb et al. 2020; Markonis et al. 2021; Moravec et al. 2021). Although one would expect farmers to adjust their production practices to changing climatic conditions, a few recent studies in Europe (e.g. Dalhaus et al. 2020; Schmitt et al. 2022; Stetter and Sauer 2024) have shown farmers' gradual response to climate change. Evidence from Northern Europe is scarce. The lack of broad evidence complicates effective policy measures and agricultural advice aimed at farmers to improve their economic performance in the face of climate change.

Droughts in Northern Europe, especially in Sweden, are a relatively new phenomenon (King et al. 2019). Consequently, farmers have had only limited, if any, experience in dealing with severe drought (Chen et al. 2021; Moravec et al. 2021). Compared to southern European countries, such as Greece, Italy, or Spain, where agriculture has long been harder hit by droughts, Swedish farmers have historically had lower incentives to mitigate the potential effects of climate change leading to drought, although agricultural production is predominantly rain-fed (Campana et al. 2022), and the majority of the farms (mainly family farms) grow cereal crops (i.e. wheat, barley) with shallow root systems and thus dependence on soil moisture. Climate-change models predict high variability in precipitation patterns, indicating that drought events and heat waves will occur more frequently in Northern Europe, with faster warming in the boreal forest zones (Grusson et al. 2021). Yet, existing evidence on the effects of drought and its severity on farm economic outcomes from a Northern European perspective is limited, highlighting the need for further research to broaden geographic coverage and enhance our understanding of how extreme climatic events, such as drought, impact farm performance.

In this paper, we examine the effect of drought on farm economic performance, assess the sensitivity of farms' historical performance to drought conditions, and evaluate the potential impact of future increases in drought on farm economic outcomes. Since the effects of drought are both spatially and temporally heterogeneous (Moravec et al. 2021), we adopt a panel regression method called "mean observation OLS" (MO-OLS) proposed by Keane and Neal (2020a, b) and that considers multidimensional fixed effects in the slopes or all the regression parameters, thereby accounting for the variation in the drought effect across space and over time simultaneously in the estimates.[2] Capturing heterogeneity in the effects of drought across space and over time helps account for differences in farmers' responses to drought or farmers' adaptation.[3] We apply the MO-OLS method to a comprehensive dataset compiled from

[2] Baltagi et al. (2023) have extended the MO-OLS method to a spatial dynamic form.

[3] Following Kean and Neal (2020a, b), we define farmers' responses or adaptation to include all sources of covariation between drought and drought sensitivity. We note that drought and drought sensitivity may occur across space and overtime. Farmers' responses to drought may include active adaptation to growing techniques that counteract low soil moisture (e.g. low-tilling methods, change to drought resistant crops), as well as other impacts (not under the farmers' control) that cause yields (and thus farm income) to be less sensitive under dry spell.

several population-based registers spanning the municipalities of south-central Sweden and the period 2001–2018. The dataset consists of information on farm net value added per annual work units (AWU), here farm income, consecutive dry days (CDD), temperature and precipitation. We triangulate our main findings using other panel regression approaches (e.g. mean group OLS, interactive fixed effects and dynamic spatial panel regression) that allow for variation in the drought effect across either space or over time in the model estimation.

The present study contributes to the literature in three main ways. First, the study contributes to the literature that examines the effects of drought on farm performance (e.g. Horridge et al. 2005; Howitt et al. 2014; Medellín-Azuara et al. 2016; Kingwell and Xayavong 2017; Riebsame 2019). Specifically, previous studies have examined the effects of drought on farm performance using either the conventional fixed effects method (e.g. Horridge et al. 2005; Howitt et al. 2014; Medellín-Azuara et al. 2016) or the standard linear regression or quantile regression approach (e.g. Kingwell and Xayavong 2017). However, the aforementioned methods do not account for variation in the effect or assumes homogeneous slope coefficients, although the effects of drought are both spatially and temporally heterogeneous (Moravec et al. 2021). Moreover, recent advancement in econometrics has shown that the conventional two-way fixed effect estimators in the presence of heterogeneity recover difficult-to-interpret weighted average individual effects (see De Chaisemartin and d'Haultfoeuille 2020). Thus, the current study complements previous studies by using the MO-OLS approach, which allows for heterogeneity across both space and over time in estimating the effects of drought on farm economic performance.

Second, the current study contributes to the broader literature that examines the impacts of climatic extremes on farm performance. Previous studies (e.g. Burke and Emerick, 2016; Cui and Xie 2022; Cui and Zhong 2024) relied on simple temperature and precipitation to examine the impact of climatic extremes on farm performance. However, climatic extremes such as drought are difficult to capture using a simple function of temperature and precipitation (Couttenier and Soubeyan 2014). Hence, following Couttenier and Soubeyran (2014) and Levy et al. (2005), we adopt a drought indicator—consecutive dry days (CDD)—which explicitly captures the length of dry spells (Chen et al. 2020). This enables us to directly examine the impact of drought on farm economic performance. Thus, the present study complements existing literature by offering new insights into the effects of climatic extremes, such as drought, on farm economic outcomes in a Nordic context.

Finally, the current study contributes to expanding the limited research on the impacts of climatic extremes such as drought on farm performance in Europe, particularly in a Northern European context. Prior studies indicated that climate change may have negligible or even beneficial effects in cold climates (see Dell et al. 2012; Burke et al. 2015; Kalkuhl and Wenz 2020). For example, Eckersten et al (2012) suggested that future increases in temperature will extend the growing period in cold climates, allowing farmers to grow crops that require a longer maturity period. The majority of the earlier studies (e.g. Eckersten et al. 2012; Dell et al. 2012; Burke et al. 2015; Kalkuhl and Wenz 2020) that examine the effect of climatic extremes relied on country-level data. However, this impedes the examination of heterogeneity associated with the effects of climatic extremes on farm performance at a more localized level. Hence, besides using a drought indicator that captures the effects of climatic extremes, the current study relies on municipal-level data. This approach facilitates the examination of both average and heterogeneous effects of climatic extremes—such as drought—on farm economic performance within a Nordic context, thereby offering a better understanding of their impact in Northern Europe.

The rest of the paper is set up as follows. The next section presents the data sources and variables used, Sect. 3 presents the estimation strategy employed, whereas Sect. 4 presents the main results. Section 5 presents the discussion and conclusion of the study.

2 Data sources and variables used

We use data from several registers audited by Statistics Sweden (SCB) and the Swedish Board of Agriculture to obtain a comprehensive longitudinal dataset of economic and land use data. We combine weather variables and land use information based on historical meteorological data and use farm level information from the Sweden's Land Parcel Identification System (LPIS) data, managed by the Swedish Board of Agriculture. The Swedish LPIS covers about 99.7% of arable land in Sweden. We focused on crop producing farms in Sweden.

2.1 Consecutive dry days or CDD

Drought is initiated by an intense and persistent lack of precipitation, often leading to lagged effects in multiple dynamic dimensions, including severity, duration, and spatial extent (Zargar et al. 2011). We follow previous studies (e.g. Couttenier and Soubeyan, 2014; Levy et al. 2005) by using a drought index instead of relying on simple temperature and precipitation. To this end, we use the Geographical Position System (GPS) coordinates of farms' field locations to measure drought using information on consecutive dry days (CDD) from Copernicus E-OBS.[4] It is important to note that CDD captures the length of dry spells (Chen et al. 2020). Moreover, it captures the effect of climate change rather than just indicating temperature and precipitation. For example, two regions with similar temperature and rainfall patterns may have different values of CDD because of the differences in regional characteristics (e.g. soil type) between the regions (Peterson et al. 2001).

Copernicus E-OBS defines CDD as the maximum number of consecutive dry days in a row with daily precipitation less than 1 mm in a year.[5] The indicator is derived

[4] Our use of climate data follows previous studies such as Schlenker and Lobell (2010), Moore and Lobell (2014), and Cui (2020).

[5] According to Copernicus E-OBS, CDD is calculate in years rather than in months or seasons because drought can extend beyond these shorter periods. For example, a crop such as winter wheat is planted at the end of the main cropping season (from spring to autumn) and harvested in the following year, and thus focusing only on the main cropping season would lead to an underestimation of the full impact of drought on farm performance.https://surfobs.climate.copernicus.eu/documents/C3S_D311a_Lot4.3.1.2_201809_user_guidance_indices_v1.pdf

In addition, a drought indicator based on a monthly time step limits it usefulness in terms of its ability to capture the spatiotemporal nature of droughts events or droughts onset, duration, and ends as well as the accumulated effects (Bradford 2000).

from the Copernicus E-OBS at 0.22^0 spatial resolution. CDD forms part of the climate indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) considered to influence plant growth (Karl et al. 1999; Peterson et al. 2001).[6] Several studies have evaluated extreme drought using CDD (e.g. Alexander et al. 2006; Field 2012; de los Milagros Skansi et al. 2013; Wang et al. 2016; Shi et al. 2018; Oikonomou et al. 2010; Zhang et al. 2011). In economics, Kim et al. (2025) employed CDD as drought indicator in building Actuaries Climate Index to examine the effects of severe weather shocks on the US macroeconomy over the past 60 years.

2.2 Temperature and precipitation

We use the GPS coordinates of farms' field locations to also account for temperature and precipitation computed using the Copernicus E-OBS database. Temperature and precipitation were obtained at a gridded field spacing of $0.25^0 \times 0.25^0$ in regular latitude and longitude coordinates (Cornes et al. 2018). Copernicus E-OBS defines temperature as daily mean air temperature, usually at the height of 2 m, whereas precipitation is defined as the total daily amount of rain, snow, and hail measured as the height of the equivalent liquid water in a square metre.

2.3 Farm net value added per annual work unit (AWU) or farm income

The information obtained from SCB comprises of farm net value added. We combine this information with total number of workers, measured as Full Time Equivalents (FTEs), to estimate the farm net value added per annual work unit (AWU), which we use as a proxy for farm economic performance in terms of farm income (Reidsma et al. 2007). The farm net value added per AWU is calculated as the value of total production minus the values of intermediate inputs and consumption of fixed capital (depreciation + subsidies) divided by the number of employees. It is important to note that farm net value added per AWU enables comparison of farm income directly to GDP per capital and thus relates farm performance to general socio-economic performance of farms (Reidsma et al. 2007). In addition, directly measuring farm income or revenue accounts for the direct impacts of drought on farm outputs (e.g. yield), the indirect replacement of various inputs, introduction of different farm activities, and adjustment to different climates (Mendelson et al. 1994; Reidma et al. 2007). As a robustness check, we compare the farm net value added per AWU to farm net value added per hectare, farm net value added only, and farm resource use efficiency.

Given the limited number of farmer field information across some municipalities over time and following previous studies (e.g. Cui and Xie 2022; Cui and Zhong 2024; Burke and Emerick 2016), we used the farm-level information to calculate the average consecutive dry days, temperature, and precipitation for each municipality. This provided a dataset that combines information on farm net value added per AWU aggregated at the municipal level for the period 2001 to 2018.

[6] http://etccdi.pacificclimate.org/list_27_indices.shtml

Table 1 Summary statistics

Variables	Description	Mean	Std.Dev	Min	Max
Drought or CDD	Maximum number of consecutive dry days (CDD)	23.292	1.546	19.695	29.843
Temperature	Temperature in degree Celsius	6.801	0.859	3.751	9.118
Precipitation	Precipitation in millimetres	342.991	66.999	242.047	560.486
Farm income	Farm net value added per annual work unit (AWU) in thousands of kSEK	36,000	599.4231	320.000	368,909.60

The analysis centred on 215 (i.e. 74% of the 290 municipalities in Sweden) municipalities in south-central Sweden

We focus our analysis on municipalities in south-central Sweden, as this region accounts for the majority of food production in the country. The southern part of Sweden has the longest growing seasons—up to 240 days—and more favourable soil conditions, primarily lowland areas suitable for crop production. In contrast, Northern Sweden has shorter growing seasons and predominantly mountainous terrain, which is less conducive to agriculture. Furthermore, the municipalities across south-central Sweden have the highest number of farms and farmers in Sweden.[7] Eckerson et al. (2012) projected that climate change would increase temperatures across South of Sweden, which will allow farmers to grow crops that required longer maturity period to grow.[8] However, the recent soil moisture droughts in Northern Europe, including Sweden and Denmark (Moravec et al. 2021) had a more devastating effect on farms in South and Central Sweden than those in the North. On the whole, the present study centred on 215 municipalities, constituting about 74% of the 290 municipalities in Sweden. We focus our analysis at the municipal level.

2.4. Summary of variables used.

Table 1 presents the summary statistics of our main variables for the regression analysis. The table shows that the mean consecutive dry days (or drought), temperature, and precipitation is about 23 days, 7 degrees Celsius and 343 mm, respectively. In addition, the average farm net value added per AWU or farm income is about kSEK 36,000. Figure 1 illustrates the spatial variation in the variables used. The figure shows both variations and similarities in each variable across the municipalities in south-central Sweden.

[7] Previous studies, including Butler and Huybers (2013), Schlenker and Roberts (2009) and Burke and Emerick (2016), have examined the effects of climate change on farm performance across specific regions (e.g. deep south or Corn Belt) in the USA due to the importance of the regions to agricultural production in the USA.

[8] This may suggest potential increases in the frequency and intensity of drought in the future.

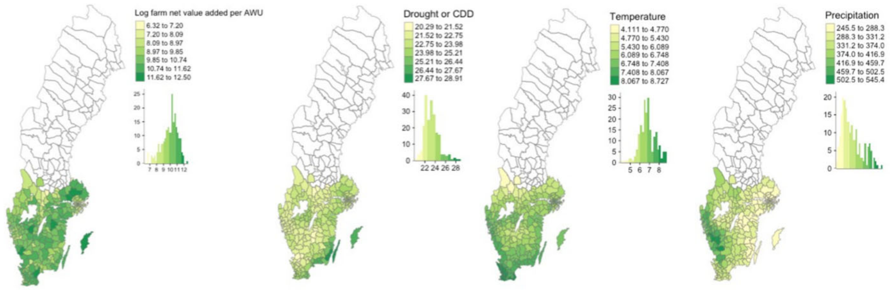

Fig. 1 Spatial variation in the variables used. Maps of averages per municipality

3 Estimation strategy

To examine how drought influence farm performance, we build on previous studies (e.g. Cui and Xie 2022; Burke and Emerick 2016) and consider the following agricultural production function;

$$Y_{it} = A_t \epsilon_i H_{it}(1 + \beta_1 D_{it} + \beta_2 T_{it} + \beta_3 P_{it}) \tag{1}$$

where Y_{it} is the output (e.g. value of production per AWU) of region i at time$t$, A_t is the total factor productivity, H_{it} is an indicator of land quality, T_{it} is the temperature, P_{it} is the precipitation, D_{it} is the drought duration, and ϵ_{it} denotes other unobservables not captured in the production function.[9]

To estimate Eq. (1) is not straightforward because of the nonlinear relationship between, for example, drought and farm output. For instance, the development of plants depends on the weather condition at a given time and location, meaning that the marginal effect for drought will depend on its own value and the values of other inputs. Therefore, the vast literature on climate change (e.g. Burke and Emerick 2016; Zhang et al. 2017; Cui and Xie 2022) often estimates the regression:

$$Y_{it} = \beta_1 D_{it} + \beta_2 T_{it} + \beta_3 P_{it} + \beta_4 P_{it}^2 + f_i + f_t + \epsilon_{it} \tag{2}$$

where f_i and f_t represent region and time fixed effects, respectively. The region fixed effects f_i absorb region specific intercept heterogeneity (e.g. land quality), while the time fixed effects absorb changes in total factor productivity (A_t) that vary between years but are common to all regions. In addition, the time fixed effects may absorb changes in agricultural policies that could influence farmers to adopt new agricultural technologies across time.

Generally, Eq. (2) can be estimated using either the one-way or the two-way fixed effects (FE-OLS) approach. The FE-OLS estimators account for heterogeneity in the intercept term, and thus, it accommodates homogeneous slopes. However, the FE-OLS estimators do not consider the variation in both the intercept and slopes at the same time. This implies that they cannot be used to examine the variation in drought effect

[9] Most studies use fixed effects over unit and time to control for $A_t, \epsilon_i,$ and H_{it} terms.

across both region (which could be due to farms' response to drought) and over time (which may be attributed to farms' adjustment to droughts through the adoption of improved agricultural technologies). This is important since one would expect drought to have less adverse effects on crop yield and farm income in drier regions if farmers in those regions adopt improved agricultural technologies to reduce plants sensitivity to drought. This underscores the need to capture the variations in the effects of drought across both space and over time.

As alternative to the conventional fixed effects approaches, one can adopt the long difference approach of Burker and Emerick (2016) to estimate Eq. (2):

$$\Delta Y_{it} = \beta_1 \Delta D_{it} + \beta_2 \Delta T_{it} + \beta_3 \Delta P_{it} + \beta_4 \Delta P_{it}^2 + f_{\mathrm{i}} + f_t + \Delta \epsilon_{it} \tag{3}$$

The long-difference approach helps to estimate the response of farm income to, for example, long term changes to drought. The long-difference method helps account for farms' response to drought in the estimation. However, the long-difference approach still relies on the fixed effects model with homogeneous slopes to provide consistent estimates.

To account for heterogeneity in the estimation, one can follow Butler and Huyber (2013) and account for farmers' adjustment to drought by adopting the Pesaran and Smith (1995) proposed mean-group estimator (MG-OLS) to account for heterogeneity in the slope coefficients across regions by estimating the regression:

$$y_{it} = \beta_{1,i} D_{it} + \beta_{2,i} T_{it} + \beta_{3,i} P_{it} + \beta_{4,i} P_{it}^2 + \beta_{5,i} t + f_i + \epsilon_{it}. \tag{4}$$

Equation (4) can be estimated by running region-specific panel regressions. It is important to note that the estimation of Eq. (4) includes region or municipal-specific time trends $\beta_{5,i} t$, which makes the equation somewhat restrictive compared to the inclusion of time fixed effects as in Eq. (2). However, the estimation of Eq. (4) ignores the fact that the effect of drought on farm performance could change over time due to changes in response to drought or farmers' adoption of agricultural technologies that are common across regions over time (Keane and Neal 2020b).

Given the limitations of Eqs. (2), (3), and (4) and the fact that the effects of drought are both spatially and temporally heterogeneous, we follow Keane and Neal (2020a, b) by estimating the following regression:

$$y_{it} = \beta_{0it} + \beta_{1it} D_{it} + \beta_{2it} T_{it} + \beta_{3it} P_{it} + \beta_{4it} P_{it}^2 + \beta_{5,i} t + \epsilon_{it} \tag{5}$$

$$\text{where } \beta_{k,it} = \beta_k + \varphi_{k,i} + \emptyset_{k,t},\ k = 0, \ldots, 4. \tag{6}$$

Kean and Neal (2020a, b) proposed a panel regression method called "mean observation OLS" (MO-OLS) in estimating Eq. (5). Specifically, Keane and Neal (2020a, b) suggested running a pooled OLS to obtain $\hat{\beta}$, followed by running another regression by region and time to estimate β_i and β_t, respectively. They then computed $\beta_{it} = \beta_i + \beta_t - \beta$. In addition, they allowed β_{kit} to be unrestricted, resulting in a larger number of parameters. They proposed an MO-OLS algorithm to correct the bias in estimating the model.

Table 2 The effect of drought on Log farm net value added per AWU or farm income

	FE-OLS		MO-OLS	
	(1)	(2)	(1)	(2)
Drought or CDD	– 0.0589*** (0.0146)	– 0.0817*** (0.0193)	– 0.0453** (0.0175)	– 0.0490** (0.0160)
Control	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Municipal fixed effects	Yes	Yes	Yes	Yes
R^2	0.4560	0.4700	0.9625	0.9902
Observations	3870	3870	3870	3870

Robust standard errors in parentheses are clustered at the municipal level.*$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$. The control includes temperature, precipitation and its squared covariates. Tables 3, 4 and 5 report the full set of model estimates. The MO-OLS accounts for multidimensional fixed effects in the slope coefficients, as well as potential serial correlation in the model estimation. Note that the MO-OLS estimates (i.e. model 1) are our preferred model estimate

It is worth noting that the additive fixed effects in the slope as in Eq. (6) ensures that each region's relative sensitivity to weather condition is fixed over time, while the time fixed effect shift all regions sensitivities up and down to the same degree (Keane and Neal 2020a, b). Thus, the φ_k accounts for the responses of yield (and thus farm income) due to permanent differences in a region climates, whereas the $\emptyset_k$ accounts for the responses to aggregated time effects in the regions' weather conditions (Keane and Neal 2020a, b). Overall, the MO-OLS identified long-term response by farms (in the form of a slope heterogeneity) that is driven by regional level climates, or by common time effects (Keane and Neal 2020a, b).

Overall, the advantage of the MO-OLS method is that it allows for multidimensional fixed effects in all regression parameters (i.e. both intercept and slope coefficients), thereby flexibly capturing the nonlinearity between the outcome variable and the regressors. It also facilitates the examination of historical trends in the data and is robust to the presence of serial correlation (Keane and Neal 2020a), which the standard two-way fixed effects models (or FE-OLS) tend to ignore (Wooldridge 2010; Drukker 2003).

As a robustness check, we compare the MO-OLS estimates with those from other panel regression methods—namely, the mean group and interactive fixed effects estimators—which allow for heterogeneity in slope coefficients across either regions or time and also account for potential serial correlation in panel data.

4 Empirical results

4.1 The effect of drought on farm economic performance

Table 2 reports the effect of drought on farm net value added per AWU, or farm income. For comparative purposes, we estimate the model using both the FE-OLS and MO-OLS. For both estimators, column 1 reports the direct effect of drought on farm net value added per AWU, or farm income, whereas column 2 tests the sensitivity of the drought estimate when temperature and precipitation are included in the model estimation.

Overall, both estimators (the FE-OLS and MO-OLS) suggest that an increase in drought or consecutive dry days in a given year has a negative and statistically significant effect on farm income. Specifically, the FE-OLS suggests that an increase in drought leads to a decrease in farm income by about 6% when temperature and precipitation are excluded from the model, and about 8% when temperature and precipitation are controlled for in the estimation.

In contrast, the MO-OLS indicates that an increase in drought leads to a decrease in farm income by about 5%, regardless of whether temperature and precipitation are controlled for or excluded from the model specification. This finding suggests that accounting for both spatial and temporal heterogeneity reduces the overall estimated adverse effect of drought on farm income by 1.39 percentage points or about 24%. This indicates that the MO-OLS provides more precise estimates and helps avoid overestimating the effect of drought on farm economic performance. It is worth noting that the magnitude of the MO-OLS estimate is about half that of Moore and Lobell (2014), who estimated an effect of about 9.7% for increased temperature on agricultural profits in Europe.[10] Their estimation was based on the FE-OLS method.

Furthermore, the result suggests that accounting for both space and time in the parameters improved the model performance (i.e. increase the R^2). In addition, the finding indicates that controlling both temperature and precipitation does not improve the model performance (i.e. the R^2 is almost similar to the model without temperature and precipitation). This may suggest that CDD captures an important association between temperature and precipitation. Moreover, Fig. 8 and Tables 7 and 8 indicate a positive association between CDD and temperature, and a negative association between CDD and precipitation.

4.2 Historical sensitivity of farm income to drought

To examine the historical sensitivity of farm income to drought across the study period, we plot the coefficient of drought from the MO-OLS against the study period (Fig. 2). We follow Cattaneo and Farrel (2013) and Cattaneo et al. (2020) by adopting a nonparametric partition-based least squares regression approach to uncover the relationship between the sensitivity of farm income and the time period. Results highlight a decrease

[10] They estimated farm profits as total value of farm production minus all costs plus subsidies received minus taxes. They then divided the profit by the total agricultural area. This is similar to our outcome variable used in the robustness check.

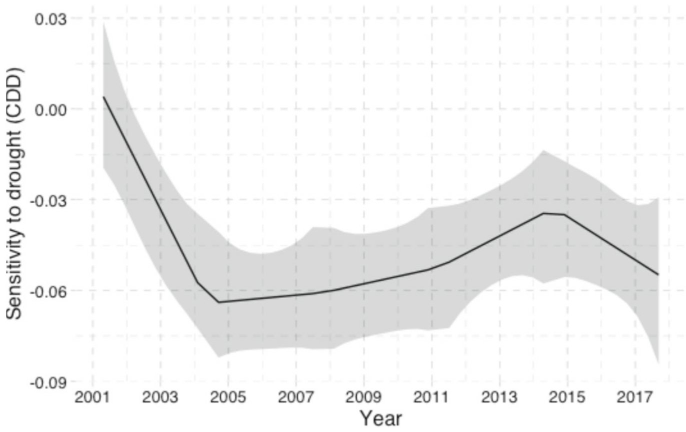

Fig. 2 Distribution of coefficient of drought (or sensitivity of farm net value added per AWU to drought) across time. The black line and the shaded region represent the regression line and the robust 95% confidence intervals, respectively

in the drought coefficient from 2001 to 2004, followed by a slight increase from 2005 to 2014, and another decline from 2014 to 2018 (Fig. 2).

It is vital to note that the observed negative and significant trend from 2003 to 2004 coincided with the 2003 European heat wave or drought (Bradford 2000; Fink et al 2004; Teutschbein et al. 2022), while the negative and significant trend from 2014 to 2018 coincided with the 2014–2018 soil-moisture drought in Europe (including Scandinavia countries such as Sweden and Denmark). It is also worth noting that the 2014–2018 multi-year droughts had large adverse effects on agricultural production as it lasted for a long period and covered a larger area than most previous droughts that impacted Europe (Moravec et al. 2021; Rakovec, 2022). Overall, the results imply a high sensitivity of farm income to drought, especially from 2003 to 2018, although there was a marginal decline in the effect from 2005 to 2014.

4.3 Variations in the sensitivity of farm income to drought across space.

We also examine the geographical pattern of the sensitivity of farm income to drought across the municipalities in south-central Sweden. For this purpose, we map the average values of the coefficient of the drought for each municipality (Fig. 3). Results suggest that the highest sensitivity, which range from − 1 to 0.5, can be observed across few municipalities (Fig. 3). This is followed by a moderate sensitivity (ranging from − 0.5 to 0.0), which characterised the majority of the municipalities. The rest of the municipalities are characterised by low sensitivity (i.e. ranging from 0.00 to 1.00). Furthermore, the result shows greater drought sensitivity from 2010-2018 compared to 2001–2009.

Overall, the figure implies that the effect of drought on farm income is heterogeneous across municipalities, as well as cluster among nearby municipalities.

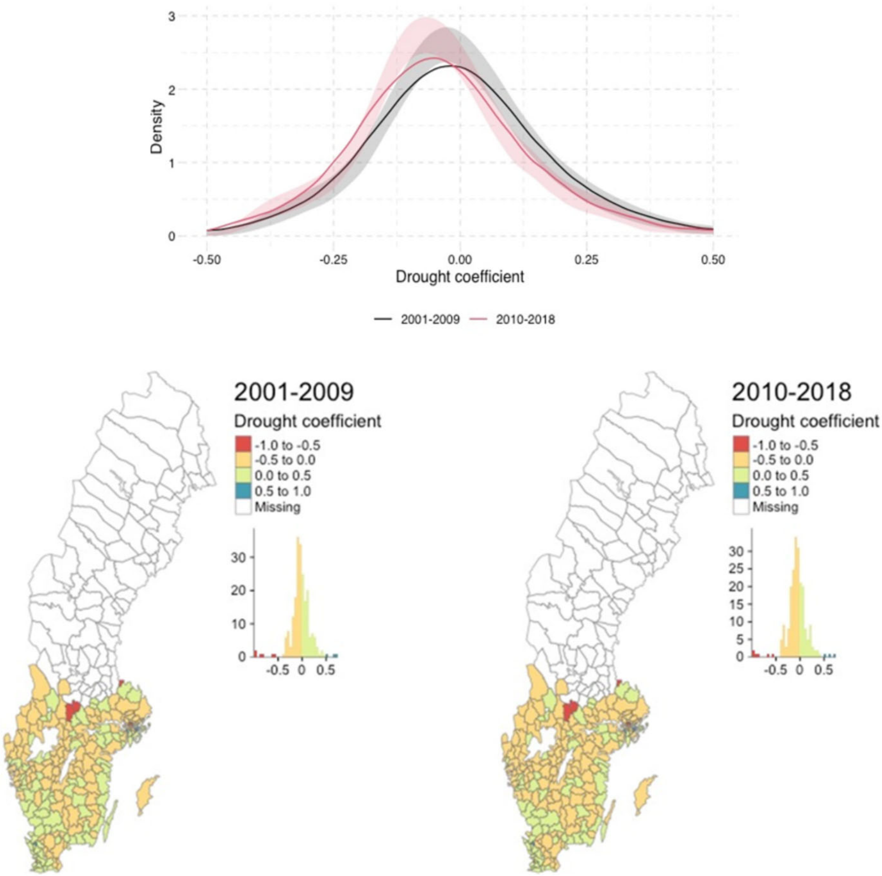

Fig. 3 Distribution of coefficient of drought by subperiod. The top panel depicts the kernel density distribution curve, while the bottom panel denotes the spatial distribution. Estimates were obtained from the MO-OLS method

4.4 Relationship between sensitivity of farm income and drought

We also examine the effect of historical farm responses or sensitivity of farm income against drought. To this end, we plot the coefficient of drought (i.e. sensitivity of farm income to drought) against consecutive dry days (or drought). Furthermore, we were agnostic about the functional form specification and thus adopt the nonparametric regression approach to uncover the relationship between the coefficient of drought and consecutive dry days (Cattaneo and Farrell 2013; Cattaneo et al. 2020).[11] Figure 3 plots the relationship. The curve indicates a negative marginal effect across all levels of CDD. However, at higher levels, the curve somewhat flattens out, indicating that

[11] Our approach is in contrast to previous studies (e.g. Butler and Hyubers 2013: Keane and Neal 2020a), that imposed a logarithmic functional form specification on the relation, although our method also unravels a nonlinear relationship similar to the earlier studies.

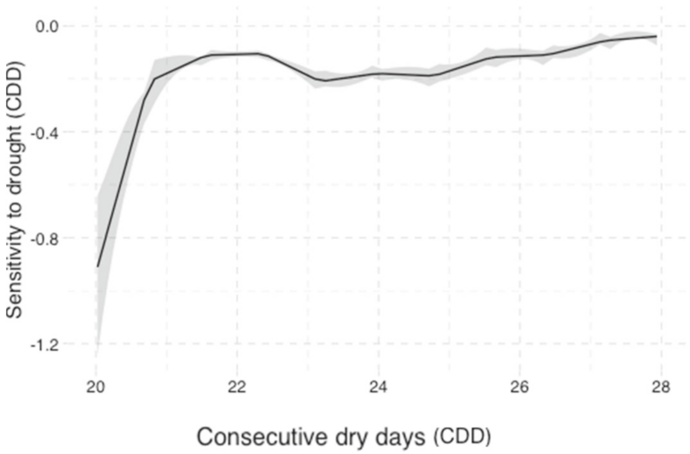

Fig. 4 Relationship between coefficient of drought (or sensitivity of farm income to drought) and consecutive dry days or drought. The solid line and the shaded regions denote the local regression line and the 95% confidence intervals, respectively

farmers have limited capacity to respond to increases in drought. In summary, the finding suggests that farm income is highly sensitive to drought (Fig. 4).

4.5 Estimating the effect of extended future drought on farm economic performance

Based on the previous findings, we examine the effect of a 50% future increase in drought on farm income with MO-OLS and FE-OLS. We assume past temperature and precipitation will follow their historical trends. We measure the impact of drought as the percentage change in predicted farm income relative to 2001–2018 historical average:

$$NT^{-1}\sum_{n=1}^{N}\sum_{t}^{N}((\epsilon^{\widehat{y}_{it}\prime} - \epsilon^{\widehat{y}_{it}})/\epsilon^{\widehat{y}_{it}}) \tag{7}$$

where $\widehat{y}_{it}\prime$ is the predicted farm net value per AWU per regions when drought increases by 50%, and $\widehat{y}_{it}$ denotes the baseline average, which uses the actual historical farm net value added per AWU per region.

Figure 5 depicts the relationship between the percentage change in farm net value added per AWU and consecutive dry days per regions. The black and red lines denote estimates from the MO-OLS and FE-OLS, respectively. Figure 6 also examines the heterogeneous effect across municipalities. Overall, Figs. 5 and 6 indicate substantial damages to farm income associated with a 50% increase in drought in the future. The finding also reveals that current adaptation among farms can reduce cumulative

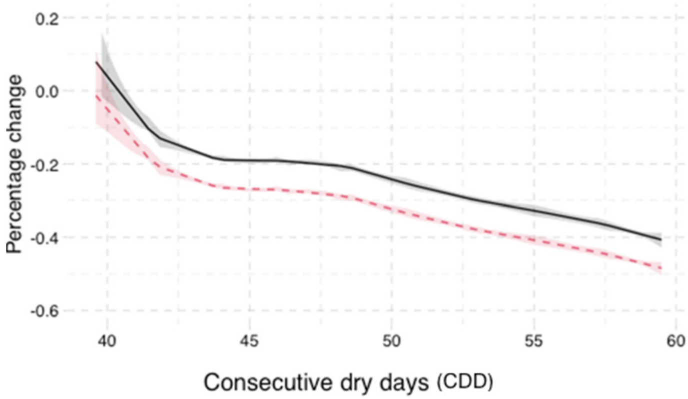

Fig. 5 The effect of a 50% increase in consecutive dry days on farm net value added per AWU with and without adjustment to drought. The graph presents projected percentage change in farm net value added per AWU (related to the 2001–2018 historical average under two scenarios). The solid line denotes average projection and the shaded region represents the 95% confidence interval. The thick black line represents the MO-OLS estimates, while the dotted red line represents the FE-OLS estimates

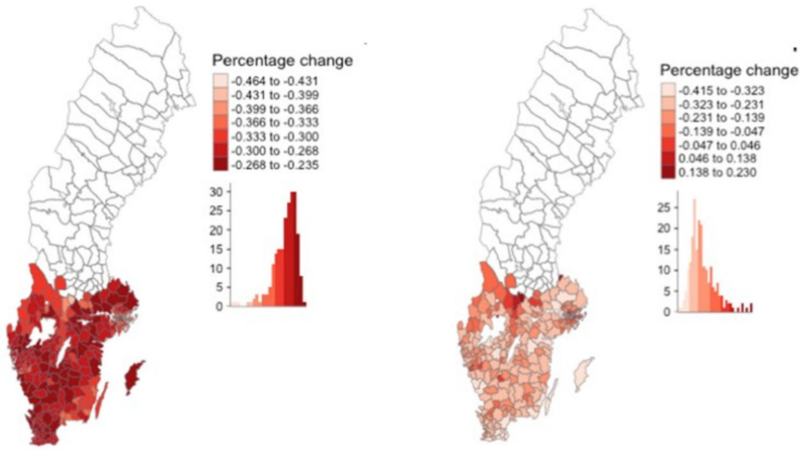

Fig. 6 Effect of a 50% increase in consecutive dry days on farm income. The left panel indicates the effect using FE-OLS and right panel depicts the effect using MO-OLS. The graph presents the average percentage decrease or increase across the municipalities in south-central Sweden

damages by 27%.[12] This finding underscores the need for more robust and proactive mitigation policies to minimise the adverse impacts of drought in the future.

[12] This is calculated as $1 - \frac{\text{Loss withMO-OLS}}{\text{Loss FE-OLS}}$, where the loss $= \sum(\widehat{y}_{\text{projectedscenario}} - \overline{y}_{\text{historicalaverage}})$

4.6 Robustness checks

4.6.1 Alternative heterogeneous specification approach

To check the sensitive of our baseline estimates to different model specifications, we followed Butler and Huybers (2013) by accommodating farms response to drought by adopting the mean group OLS (MG-OLS) method of Pesaran and Smith (1995). The MG-OLS method includes municipal-specific time trends and therefore accounts for heterogeneity in the slopes across the municipalities only. In other words, the MG-OLS accounts for the changes in drought or sensitivity associated with a shift in local climate conditions. Overall, the MG-OLS suggests that an increase in drought predicts a decrease in farm income by 5.19% when temperature and precipitation are excluded from model estimation (Table 8). Overall, the MG-OLS estimate is qualitative similar to our baseline MO-OLS estimate.

Furthermore, we compare the MO-OLS estimates with those obtained from the interactive fixed effects (IFE) approach proposed by Bai (2009). The IFE method helps to mitigate omitted variable bias arising from unobserved time-varying factors. The IFE can be interpreted as a form of principal component analysis and is closely related to the synthetic control estimator (Abadie et al. 2010; Gobillon and Magnac 2016). Table 9 presents the IFE estimation results. Consistent with our baseline findings, the result suggests that an increase in drought is associated with a negative effects on farm income. More specifically, the finding suggests that an increase drought predicts a 3.1% decrease in farm income when temperature and precipitation are excluded from the model specification. Overall, the qualitative finding from the IFE estimate aligns with the finding from our baseline.

4.6.2 A *dynamic spatial panel data model approach*

It is also worth noting that although the MO-OLS, MG-OLS, and IFE estimators account for temporal and spatial heterogeneity in different ways, they do not explicitly account for spatio-temporal dependence. Following Bresson et al. (2023) we adopt a dynamic spatial panel data model, specifically a dynamic spatial autoregressive (SAR) model, to explicitly account for spatio-temporal dependence in the model estimation process. This modelling choice aligns with the recommendations of Lesage (2014) and is implemented according to the approach proposed by Lee and Yu (2010). The dynamic SAR model captures both spatial spillovers and temporal autocorrelation—features that are particularly relevant for analysing environmental shocks such as droughts, where impacts can extend across neighbouring regions and persist over time.

Table 9 reports the result estimates. The finding shows that the coefficient of lagged farm income (0.553, SE = 0.014) is positive and statistically significant, indicating the presence of positive temporal dependence in farm income and, hence, a persistence effect. This suggests that past farm economic performance influences future farm economic performance. The result also reveals spatial and spatio-temporal dependence in the impact of drought on farm income. While the spatial autoregressive coefficient

(0.150, SE = 0.061) is positive and significant, the spatio-temporal autoregressive coefficient (-0.175, SE = 0.071) is negative and significant. These opposing effects roughly offset each other (Table 10). A positive spatial effect implies that farm performance in one municipality benefits from strong performance in neighbouring municipalities, possibly due to knowledge or information sharing among farmers. Conversely, the negative spatio-temporal effect suggests that current farm performance in a municipality may be adversely affected by past performance in neighbouring areas—perhaps due to farmers reacting to prior negative drought impacts on farm incomes of farmers in nearby municipalities. The result also indicates that an increase in drought predicts a 2.46% decrease farm income in the short-run and a 4.44% decrease in the long-run. Overall, the findings are akin to our baseline result.

4.6.3 Different drought variable (Drought Deciles Index)

We follow Gibbs and Maher (1967) in computing an alternative drought index: the Drought Deciles Index (DDI). DDI has been used in various contexts to monitor drought (e.g. Keyantash and Dracup 2002; Quesada-Montano et al. 2019). For this analysis, we adopt a 12-month time scale (Suliman et al. 2024). We compute DDI by grouping long-term annual precipitation data and dividing it into deciles to categorize drought severity (Mckee et al. 1993; Dikici 2020). Specifically, total yearly precipitation values from a long-term dataset are ranked from highest to lowest to construct a cumulative frequency distribution. This distribution is then divided into ten deciles. The first decile includes precipitation values not exceeded by the lowest 10% of the dataset; the second decile covers values between the 10th and 20th deciles, etc. Current precipitation values are then compared and interpreted relative to these deciles.

Table 11 presents the effect of extreme dry condition on farm income. The result shows that an increase in extreme dry condition relative to normal rainfall predicts a decrease of 4.9% in farm income. In addition, the result indicates that an increase in extreme precipitation (or rainfall) relative to normal levels is associated with a decrease of 5.9% in farm income. In summary, our baseline finding is robust to the use of different drought index, especially the effect of drought or dry conditions on farm income.

4.6.4 Different independent variables and controlling for other factors

We also check the sensitivity of our baseline estimates by dividing the farm net value added by land size (in hectares) instead of the total number of FTE workers adopted for the baseline. In addition, we check the sensitivity of our baseline outcome variable using farm net value added. Table 12 and 13 present the result estimates for farm net value added per hectares and farm net value added, respectively. Table 12 suggests that an increase in drought is associated with a decline in farm net value added per hectare by 4.85%, on average, while Table 13 indicates that an increase in drought predicts a decline in farm net value added by 6.23%, on average.

Furthermore, we also examine the effect of drought on farm resource use efficiency. Farm resource use efficiency indicates a farm's ability to pay for factors of production (e.g. interest payments, payment of wage workers, etc.) that are sourced outside the farm at a given farm net value added (Van der Ploeg et al. 2019). We follow Van der Ploeg et al. (2019) and calculate the farm resource use efficiency as the ratio of farm net value added and gross value of production. Here, we expect that increases in drought should not only reduce farm income but also farm resource use efficiency. Table 14 presents the result. Overall, the finding shows that an increase in drought decreases farm resource use efficiency by 1.17 unit, on average. In other words, the finding suggests that increased drought conditions lead to greater dependence on external inputs by farmers, potentially raising production costs and thereby reducing farm income.

Finally, we test the sensitivity of our estimates by accounting for additional factors (e.g. land size, labour, capital, intermediate input costs, subsidies, etc.) that may influence farm income in the regression estimation. We estimate the model using both the FE-OLS and MO-OLS. Table 15 shows that our baseline MO-OLS estimate remains robust when these variables are included in the model estimation.

5 Discussion and conclusion

We studied the effect of drought (measured as consecutive dry days) on farm economic performance, examined the sensitivity of farms' historical economic performance to drought, and assessed potential impact of future increases in drought. Since the effects of climatic extremes such as drought are both spatially and temporally heterogeneous, we adopted a panel regression method (i.e. MO-OLS) that accounts for multidimensional fixed effects in the slopes or across all regression parameters. This approach allowed us to capture heterogeneity in the effects across both regions and over time. Thus, the regression method implicitly adjusted for potential farms responses to

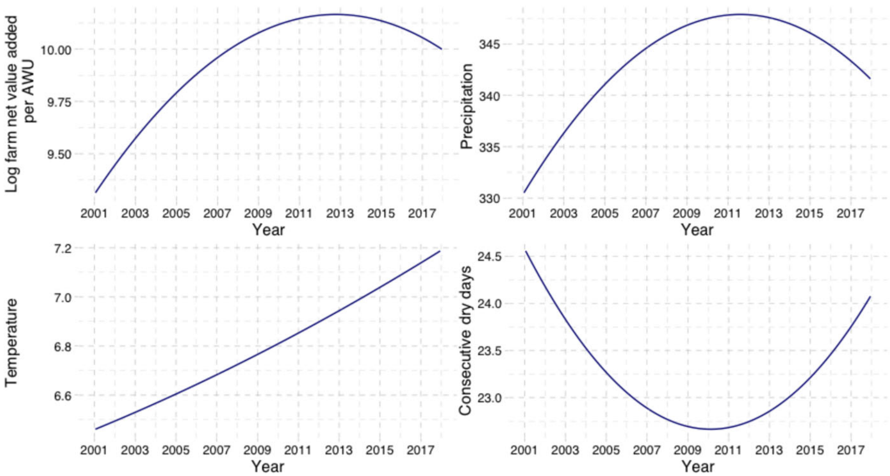

Fig. 7 Relationship between the log farm net value added per AWU, temperature, precipitation, and consecutive dry days (or drought). The solid line denotes the local regression line. The local regression line was obtained using a binscatter regression

drought conditions in the estimation. We applied this method to dataset that covered the period 2001–2018 using municipal level data from south-central Sweden.

In summary, the findings suggest that an increase in consecutive dry days or drought leads to a reduction in farm income by about 5%, on average. The observed negative and significant impact of drought on farm income aligns with the general findings of previous studies in other climates (e.g. Lobell et al. 2014;Medellín-Azuara et al. 2016; Zipper et al. 2016; Kingwell and Xayavong 2017; Riebsame 2019; Pourzand et al. 2020), which also found that climatic extremes negatively impact farm economic performance.

The results also reveal significant variation in the effect of drought on farm income across the municipalities in Sweden. This is consistent with the findings that the incidence of drought events and its impacts on farm performance vary across both geographical locations and over time (Mishra and Singh 2010; Moravec et al. 2021; Orth et al. 2022; Mondal et al. 2023). Moreover, the findings imply that previous studies that employed country-level data in examining the effects of climatic extremes on farm economic performance, especially in cold climates, may have understated the true effects. Finally, the results indicate that increases in drought also negatively affected other farm outcome variables, such as farm resource use efficiency and farm net value added per hectare.

In terms of policy implications, the findings suggest the need for policies that support the development and dissemination of agricultural practices that can maintain soil moisture over an extended period in cold climates. This is crucial since predicting drought, especially its onset, duration, and end period, is challenging across both regions and time. Furthermore, adaptation to climatic extremes such as drought could significantly impact future food security, indicating the need for further studies. These studies should focus on identifying crop varieties better suited to droughts in cold climates. Specifically, studies that examine the sensitivity and adaptability of crop varieties under various climatic conditions are required to mitigate the adverse effects of climatic extremes such as droughts across Europe, including Scandinavia.

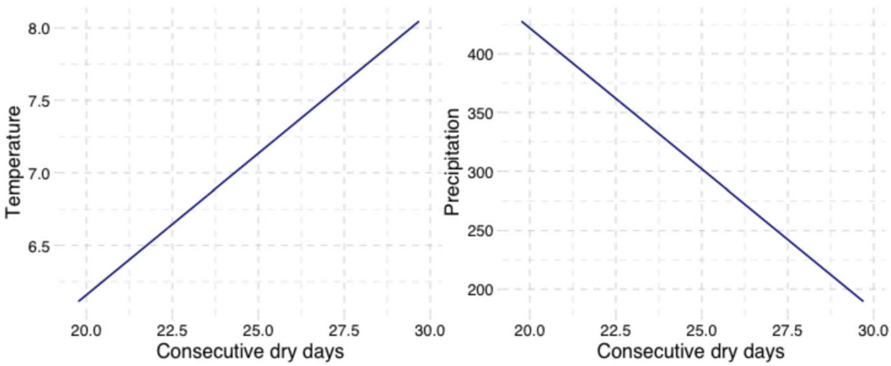

Fig. 8 Relationship between CDD and temperature and precipitation

Table 3 Effect of drought on Log farm net value added per AWU (models 1 and 2)

	FE-OLS	
	(1)	(2)
CDD	− 0.0589*** (0.0146)	− 0.0817*** (0.0193)
Temperature	–	0.8646** (0.3885)
Precipitation	–	− 0.0013 (0.0048)
Precipitation^2 (/10000)	–	− 0.0125 (0.0501)
Constant	10.8429*** (0.3468)	6.3343*** (2.4122)
R^2	0.4560	0.4700
Observation	3,870	3,870

Time and municipal fixed effects were considered in all the estimations. Standard errors are reported in parentheses and clustered at the municipal level. $p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

Table 4 Effect of drought on Log farm net value added per AWU based on MO-OLS (model1)

	Mean	Median	StdDev	10th percentile	90th percentile
CDD	− 0.0453**** (0.0175)	− 0.0461	0.2433	− 0.3310	0.17455
Constant	11.0845*** (1.0251)	11.0916	5.4276	− 2.0013	22.0421
R^2	0.963				
Observations	3,870				

Time and municipal fixed effects were considered in all the estimations. Standard errors are reported in parentheses and clustered at the municipal level. $p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$. MO-OLS denotes Mean observation regression

Table 5 The effect of drought on Log farm net value added per AWU based on MO-OLS (model 2)

	Mean	Median	StdDev	10th percentile	90th percentile
CDD	− 0.0490** (0.0160)	− 0.0374	0.2268	− 0.2902	0.1646
Temperature	0.3084*** (0.0524)	0.3002	0.7463	− 0.5231	1.271
Precipitation	0.0001 (0.0033)	− 0.0015	0.0448	− 0.0423	0.0461
Precipitation^2 (/10000)	− 0.0495 (0.0464)	− 0.0490	0.6329	− 0.7307	0.5563
Constant	9.9496*** (1.0251)	9.9538	14.648	− 2.0013	22.0421
R^2	0.9902				
Observations	3870				

Robust standard errors are reported in parentheses and clustered at the municipal level. $p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$. MO-OLS denotes Mean observation regression

Table 6 The effect of temperature on drought or CDD

	FE-OLS	MO-OLS
Temperature	0.7456*** (0.027)	0.9637*** (0.1247)
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R^2	0.201	0.960
Observations	3870. 3,870	

Robust standard errors are reported in parentheses and clustered at the municipal level. $p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

Table 7 The effect of precipitation on drought or CDD

	FE-OLS		MO-OLS	
Precipitation	− 0.0125*** (0.0003)	− 0.0533** (0.0031)	− 0.0381*** (0.0039)	− 0.0245*** (0.0058)
Precipitation squared	–	0.5496*** (0.0410)	–	− 0.2113*** (0.0742)
Municipal fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
R^2	0.574	0.364	0.987	0.985
Observations	3870			

Robust standard errors are reported in parentheses and clustered at the municipal level. $p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

Table 8 The effect of drought on Log farm net value added per AWU using the Mean-group estimator (MG-OLS)

	(1)	(2)
CDD	− 0.0519**	− 0.0660***
	(0.0184)	(0.0168)
Controls		
Municipal fixed effects	No	Yes
Time fixed effects	Yes	Yes
Quadratic time trend	Yes	Yes
R^2	0.962	0.979
observations	3,870	3,870

Standard errors are reported in parentheses and clustered at the municipal level. *$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$. The control includes temperature, precipitation and its squared

Table 9 The effect of drought on Log farm net value added per AWU using Interactive fixed effects method

	(1)	(2)
CDD	− 0.0310***	− 0.0390***
	(0.0120)	(0.0190)
Controls	No	Yes
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
observations	3,870	3,870

Robust standard errors are reported in parentheses and clustered at the municipality level.*$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

Table 10 Effect of drought on farm net value added per AWU using a dynamic space–time autoregressive model

τY_{t-1}	0.5525*** (0.0144)		
ρW_t	0.1495*** (0.0609)		
$\eta W Y_{t-1}$	– 0.1751*** (0.0705)		
CDD	– 0.0216*** (0.0070)		
R^2	0.244		
Log-likelihood	– 143.517		
Short-run	Direct	Indirect	Total effect
CDD	– 0.0209** (0.0084)	– 0.0209 – (0.0083)	0.0246*** (0.0010)
Long-run			
CDD	– 0.0469*** (0.0019)	0.0025 (0.0078)	0.0444*** (0.0186)
Observation	3870		

Robust standard errors in parentheses are clustered at the municipal level.* p > 0.1, ** p > 0.05 and *** p. We also accounted for both municipal and time fixed effects in the model estimation. It is worth noting that $\tau + \rho + \eta<1$, indicating that our model is stationary or stable. We followed the recommendation of Lesage (2014) in choosing the appropriate model specification

Table 11 The effect of dry condition on Log farm net value added per AWU

	FE-OLS	MO-OLS
Extremely dry	0.006 (0.017)	– 0.0490*** (0.020)
Drier than usual, but not extreme	0.010 (0.018)	– 0.018 (0.027)
Wetter than normal	– 0.002 (0.014)	– 0.039* (0.020)
Extremely wet	– 0.037 (0.031)	– 0.059*** (0.021)
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R^2	0.450	0.970
observations	3,870	3,870

Robust standard errors are reported in parentheses and clustered at the municipality level..*$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$. The base comparison is normal rainfall. Due to the small sample decile ranges, we classified the rainfall decile as follows: deciles 1 and 2 = extremely dry, deciles 3 and 4 = drier than usual, but not extreme, deciles 5 and 6 = normal rain, deciles 7 and 8 = wetter than normal, and deciles 9 and 10 = extremely wet

Table 12 The effect of drought on Log farm net value added per hectare

	FE-OLS	MO-OLS
CDD	− 0.0133***	− 0.0485***
	(0.0037)	(0.0182)
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R^2	0.574	0.985
observations	3,870	3,870

Robust standard errors are reported in parentheses and clustered at the municipality level..*$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

Table 13 The effect of drought on Log farm net value added

	FE-OLS	MO-OLS
CDD	− 0.218***	− 0.0623***
	(0.0037)	(0.0184)
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R^2	0.119	0.960
observations	3,870	3,870

Robust standard errors are reported in parentheses and clustered at the municipality level..*$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

Table 14 The effect of drought on farm resource use efficiency (VA/GVP)

	FE-OLS	MO-OLS
CDD	− 0.0081***	− 0.0117***
	(0.0007)	(0.0032)
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R^2	0.029	0.943
	3,870	3,870

Robust standard errors are reported in parentheses and clustered at the municipality level..*$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$. Farm resource use efficiency is calculated as farm value added (VA) divided by gross value of total production (GVP)

Table 15 The effect of drought on farm net value per AWU

	FE-0LS	MO-OLS
CDD	– 0.0753***	– 0.0499***
	(0.0109)	(0.0143)
Log intermediate input costs	0.1862***	0.1115***
	(0.0287)	(0.0298)
Log capital	0.2660***	0.1931***
	(0.0549)	(0.0289)
Subsidies	0.0007	0.0025
	(0.0004)	(0.0020)
Labour	0.0131*	– 0.0855**
	(0.0071)	(0.0310)
Log farm size	0.4004***	0.5277***
	(0.0544)	(0.0331)
Temperature	0.0639	– 0.0884**
	(0.0514)	(0.0499)
Precipitation	– 0.0006	– 0.0020
	(0.0013)	(0.0017)
Municipal fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
R^2	0.0828	0.9201
Observations	3,870	

Standard errors are reported in parentheses and clustered at the municipal level. *$p > 0.1$, ** $p > 0.05$ and *** $p > 0.001$

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