


12-2021

Comparing Organic and Conventional Yield Responses to Climate Variations

Joost Wilken Meyer
University of Arkansas, Fayetteville

Follow this and additional works at: <https://scholarworks.uark.edu/etd>

 Part of the [Agricultural Economics Commons](#), [Agricultural Science Commons](#), [Agronomy and Crop Sciences Commons](#), [Botany Commons](#), and the [Horticulture Commons](#)

Citation

Meyer, J. W. (2021). Comparing Organic and Conventional Yield Responses to Climate Variations. *Graduate Theses and Dissertations* Retrieved from <https://scholarworks.uark.edu/etd/4269>

This Thesis is brought to you for free and open access by ScholarWorks@UARK. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of ScholarWorks@UARK. For more information, please contact uarepos@uark.edu.

Comparing Organic And Conventional Yield Responses To Climate Variations

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Agriculture Economics

by

Joost Wilken Meyer
University of Sustainable Development Eberswalde
Bachelor of Science in Organic Agriculture and Marketing, 2019

December 2021
University of Arkansas

This thesis is approved for recommendation to the Graduate Council.

Qiuqiong Huang, Ph.D.
Thesis Director

Stijn Speelman, Ph.D.
Committee Member

Song Feng, Ph.D.
Committee Member

Abstract

This thesis compares the responses of organic yields and conventional yields towards climate variations. To achieve this objective, weather variables such as growing season weather conditions (average temperature, precipitation, cloud cover, relative humidity, drought index), weather anomalies, the occurrence of severe or extreme droughts and excessive rainfalls, are combined with 23 data sets gathered from previous studies that compare organic and conventional yields from the same location and time periods. To narrow the scope, the thesis focuses on soybean, maize, and wheat production in Europe and North America. Study-level fixed-effects models are used to control for any time-invariant factors such as soil characteristics management practices and operator knowledge. For all three crops studied (maize, soybean, wheat), the estimated coefficients of most weather variables from the organic yield model and the conventional yield model have the same signs. This indicates organic and conventional yields respond to variations in most climatic factors in the same way. The results also reveal some differences in the yield responses between organic and conventional crops. For example, excessive rainfall events seem to have less negative effects on organic yields. The differences may vary across crop. For example, although the growing seasons of maize and soybean largely overlap, organic and conventional soybeans differ in their yield responses to more weather factors than maize. The differences may vary between different months. For example, excessive rainfalls in June decreased organic soybean yields but boosted both organic and conventional soybean yields in August. For most cases when the yield responses are different, the magnitudes of coefficients are larger for organic yields than for conventional yields. This indicates that organic yield responds more to climate variations. Therefore,

empirical evidence from this thesis would not support the argument that organic agriculture can be more resilient to climate variations. This is an important consideration to take into account when policy makers promote organic agriculture.

Keywords: organic; conventional; maize; soybean; wheat; climate variations; yield gap; drought; excessive rainfall

©2021 by Joost Wilken Meyer
All Rights Reserved

Acknowledgements

This thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Agricultural Economics issued by the University of Arkansas (United States of America) and the joint academic degree of International Master of Science in Rural Development from Ghent University (Belgium), Agrocampus Ovest (France), Humboldt University of Berlin (Germany), Slovak University of Agriculture in Nitra (Slovakia), University of Pisa (Italy) and University of Córdoba (Spain) in collaboration with Can Tho University (Vietnam), Escuela Superior Politécnica del Litoral (Ecuador), Nanjing Agricultural University (China), University of Agricultural Science Bengaluru (India), University of Pretoria (South-Africa) and University of Arkansas (United States of America).

This thesis was elaborated and defended at the University of Arkansas within the framework of the European Erasmus Mundus Joint Master Degree International Master of Science in Rural Development (Course N° 2019 - 1507 / 001 - 001) and the EU-US Cooperation Programme in Higher Education and Vocational Training (Transatlantic Degree Consortia Projects) nr. 2008-1745/001 – 001 CPT-USTRAN and the Fund for the Improvement of Postsecondary Education (EU-US Atlantis Program grant P116J080034, U.S. Department of Education). However, the contents of the thesis do not necessarily represent the policy of the supporting agencies, and you should not assume endorsement by the supporting agencies.

I would like to address my special thanks and gratefulness to Dr. Huang, the main advisor of my thesis, for her able guidance and support in this research. Besides, to my co-promoters of

Ghent University and the University of Arkansas, Dr. Speelman and Dr. Feng, thank you for your invaluable contribution to my work. Furthermore, I thank my fellow student Eva Stephani Caroline, and the research assistants Heather Arielle Snell and Shelby Tyler Rider for their worthy contributions. Moreover, I would like to express my appreciation to those who enabled my studies in Atlantis Program: Alicia Minden, Dr. Ahrendsen, Dr. Rainey, and Jarre Lafort.

Table of Contents

Introduction	1
Data sources.....	8
Statistical Methods	12
Results.....	16
References	23
Appendix section.....	33
Table 1. Included studies	33
Table 2. Fixed effects model of maize yields, Specifications 1 and 2	34
Table 3. Fixed effects model of maize yields, Specifications 3 and 4	35
Table 4. Fixed effects model of soybean yields, Specifications 1 and 2	37
Table 5. Fixed effects model of soybean yields, Specifications 3 and 4	38
Table 6. Fixed effects model of wheat yields, Specifications 1 and 2	40

Introduction

Organic agriculture (OA) has attracted the attention of both researchers and policymakers as an alternative to conventional agriculture (CA). Generally, OA is described as a reduced-input agriculture system (e.g., Seufert, Ramankutty, and Foley 2012; FAO 1999). Most organic producers apply labels such as “European Union Organic” or “USDA Organic” to indicate the use of certified organic farming practices (EU, 2007; USDA, 2011). In most countries, organic certification requires the avoidance of synthetic chemical inputs such as herbicides, fungicides, insecticides, or chemical fertilizers.¹ The use of GMO seeds is also prohibited. “(...) *agronomic, biological, and mechanical methods, as opposed to using synthetic materials(...)*” (FAO, 1999) are widely adopted in organic farming. For example, practices such as wide crop rotations, mechanical weed management, soil enhancement, planting cover crops, and nitrogen-fixing crops such as clover are often used on organic farms (IFOAM, 2013).

OA has been one of the fastest growing agricultural sectors. Consumers’ demand for organic products is increasing rapidly (Du, Bartels, Reinders, & Sen, 2017). Globally, the area of organically managed land increased from 11 million ha in 1999 to 43.1 million ha in 2013 to 72.3 million ha in 2019. Out of this, 5 % are located in Northern America, and 22.9 % are located in Europe (Lernoud & Willer, 2015; Willer, Trávníček, Meier, & Schlatter, 2021). The European

¹ The concept of OA did not originate from sound scientific arguments. Steiner (1924) argued that the quality of food products would degenerate with the use of synthetic fertilizers. Balfour (1943) stated that synthetic fertilization would significantly reduce the organic matter in the soil. Rusch (1978) argued that synthetic fertilizers would not lead to normal plant physiology and consequently reduce the nutritiousness of crops. All of these arguments have been proven wrong (Kirchman et al. 2019).

Union plans to expand OA to 25 % of its agriculturally used land by 2030 (European Commission, 2021).

One of the rationales used to support the development of OA are the potential ecological benefits such as higher biodiversity, improved soil organics, improved groundwater quality, and lower greenhouse gas (GHG) emissions. Management practices such as wide crop rotations with a broader spectrum of crops and a higher non-crop flora such as nitrogen-fixing clover (Hald, 1999) increase biodiversity on organically cultivated land (Hole et al., 2005). The more diverse agricultural landscapes on organic farms make them suitable habitats for a broader range of wildlife (Fuller et al., 2005; Krebs, Wilson, Bradbury, & Siriwardena, 1999). Specifically, a higher abundance of insects and birds has been observed on organic farms (Feber, Bell, Johnson, Firbank, & Macdonald, 1998; Feber, Firbank, Johnson, & Macdonald, 1997; Fuller et al., 2005; Hutton & Giller, 2003). The avoidance of chemical fertilizers and pesticides could potentially reduce surface water and groundwater pollution (Hansen, Thorling, Schullehner, Termansen, & Dalgaard, 2017; Thieu, Billen, Garnier, & Benoît, 2011). This benefit is partially offset by the observation that organic systems appear to have higher nitrogen leaching into groundwater than conventional systems (Dahan, Babad, Lazarovitch, Russak, & Kurtzman, 2014). The more frequent use of management practices such as wide crop rotations, green manure, organic fertilizers, and more crop residues being retained on fields on organic farms increases soil organic matter. These practices also often result in more carbon sequestered in the soil (Cooper, Butler, and Leifert 2011; Niggli et al. 2009; Scialabba and Müller-Lindenlauf 2010; Squalli and Adamkiewicz 2018). Hence, GHG emission is reduced (Stolze & Lampkin, 2009).

The potential benefits of OA, however, come at the price of reduced yields. The existing literature on organic versus conventional agriculture yield comparisons has established that most organic crops produce lower yields than conventional ones (Badgley et al., 2007; de Ponti, Rijk, & van Ittersum, 2012; Hossard et al., 2016; Kniss, Savage, & Jabbour, 2016; Kravchenko, Snapp, & Robertson, 2017; Meemken & Qaim, 2018; Ponisio et al., 2015; Seufert, Ramankutty, & Foley, 2012; O. M. Smith et al., 2019). Meta-analyses conducted by de Ponti, Rijk, and van Ittersum (2012), Seufert, Ramankutty, and Foley (2012), and Ponisio et al. (2015) revealed a 19-25% yield gap between the two cropping systems. The yield gaps also vary across crops. Different authors present different yield gaps (Wilbois & Schmidt, 2019). Ponisio et al. (2015) reported 15.5-22.9% yield gaps for all crops with no significant difference between legumes and non-legumes. Meemken and Qaim (2008), on the other hand, reported that yield gaps are larger for cereal crops (22-26%) than for legumes (10-15%). The lower yields often observed in OA can be largely attributed to reduced inputs, which lead to nitrogen and phosphorus deficiencies (Berry P. M. et al., 2002; Oehl et al., 2002). Other differences between OA and CA such as crop rotations, soil management, weed management, pest management, and irrigation management, however, can play a role in narrowing the yield gap (Pandey, Li, Askegaard, & Olesen, 2017; Rasmussen, 2004).

The lower yields often associated with OA may also alter the evaluation results of OA in its capacity of providing environmental benefits. If environmental effects were measured per unit of land, OA would generate lower GHG emissions and lower nitrate leaching (Mondelaers, Aertsens, & van Huylenbroeck, 2009; Tuomisto, Hodge, Riordan, & Macdonald, 2012). OA

would also bring higher biodiversity (Bengtsson, Ahnström, & Weibull, 2005; Crowder, Northfield, Strand, & Snyder, 2010; Tuck et al., 2014). However, when environmental effects were measured per unit of output, the reduction in GHG emissions was much smaller (Clark & Tilman, 2017; Mondelaers et al., 2009; Treu et al., 2017; Tuomisto et al., 2012). Nitrate leaching would be higher under OA in the EU (Clark & Tilman, 2017; Dahan et al., 2014; Tuomisto et al., 2012), and biodiversity loss may actually occur on some organic farms (Meemken & Qaim, 2018; Tuck et al., 2014). The changes in environmental effects arise from the yield gaps between OA and CA. To produce the same amount of output as CA, OA would need to use more land to grow not only the intended crops but also other crops such as cover crops (Tuck et al., 2014). The environmental costs associated with increased land use would partially outweigh or completely wipe out any environmental benefits OA could bring (Mondelaers et al., 2009; Reganold & Wachter, 2016; Skinner et al., 2014; Treu et al., 2017). The back-of-envelope calculation by Kirchmann (2019) shows that proportionally land use under OA would need to increase more than the yield gap. For example, given a 35% yield gap, OA would need to cultivate 1.54 ha to produce the same amount of output as a 1-ha CA would, which is a 54% increase in land use. If indirect land use for crop rotations or cover crops were taken into account, land use under OA would be even higher.

Despite a relatively large amount literature on yield gaps, the comparisons between OA and CA in other aspects such as the stability of yield are less studied (e.g., Knapp and van der Heijden, 2018; Smith, Menalled and Robertson, 2007). Yield stability is an important consideration because it influences the degree of the reliability of food access by consumers (Müller et al.,

2018; Schmidhuber & Tubiello, 2007) as well as the extent of income stability producers can obtain (Harkness et al., 2021).

One of the main risks in agriculture production is weather shocks, which is a large contributor to yield variability. Climate change will most likely result in more volatility in precipitation and temperature as well as more frequent extreme weather events such as droughts and floods (Hall, Stuntz, & Abrams, 2011; Rosegrant, Ringler, & Zhu, 2014) and thus agriculture will be challenged to upkeep its productivity (Ortiz-Bobea, Ault, Carrillo, Chambers, & Lobell, 2021). In the environment of such climate trends, it is important to assess the resilience to increased climate variations when evaluating any food system. The reduced-input nature of OA makes it more vulnerable to the consequences of negative climate trends. Deutsch et al. (2018) estimated that a warming climate would increase both population growth and metabolic rates of insect pests in temperate regions including North America and Europe. Higher CO₂ level, elevated temperature, and more variable rainfall and drought spells are all likely to increase weed competitiveness (Ramesh, Matloob, Aslam, Florentine, & Chauhan, 2017). Organic farmers may suffer more crop losses since they cannot resort to pesticides or herbicides to alleviate pest or weed pressure associated with climate change (Gregory et al. 2009).

Core practices of organic agriculture, however, may increase OA's resilience to climatic variations. Higher agro-biodiversity under OA systems, fostered through more diverse crops and wider crop rotations, make them more resilient to failures of a single crop due to climate risks (Barbieri, Pellerin, & Nesme, 2017). Practices often used on organic farms, such as

improved crop varieties, wide crop rotations with grass-clover or legume, planting green manure and cover crops, and the use of organic fertilizer such as compost, have enhanced organic carbon stocks in soil (Müller et al. 2012). Since soil organic matter helps soils retain moisture, organically managed soils are often found to have a higher water-holding capacity (e.g., Lotter, Seidel, & Liebhardt, 2003). Several studies (e.g., Lotter et al., 2003; Scialabba & Müller-Lindenlauf, 2010b) have argued that this is the main mechanism increasing the drought tolerance of organic systems. OA may fare better than CA during excessive rainfall events as well. Organically managed soil can absorb more water than conventional ones through higher water infiltration rates and more percolation (Lotter et al., 2003). The enhanced drainage capacity reduces the risk of flood (Scialabba & Müller-Lindenlauf, 2010b). Organic management of soils also helps mitigate soil erosion, another negative consequence of excessive rainfall (Rounsevell, Evans, & Bullock, 1999). This is because higher soil organic matter and other soil improvements make organically managed soil more resistant to water erosion (Lotter et al., 2003).

The main objective of this study is to compare the yield responses to climate variations and extreme weather events under organic and conventional agriculture. The conjecture that OA may be more resilient has been made in several previous studies (Pimentel & Burgess, 2014; Rodale Institute, 2014) but only a few have provided empirical evidence (e.g., Lotter, Seidel, and Liebhardt 2003). This thesis contributes to the literature in several important ways. First, this thesis analyzes how yields respond to average weather conditions during the growing seasons, weather anomalies, and extreme weather events, including excessive rainfall and

droughts. Although including climatic factors is routine in analyzing crop yields, not many studies that compare OA and CA have done so. The research findings from this thesis will help policy makers assess how OA and CA would perform in the context of climate change. Second, data collection and estimation methods are conducted in order to ensure that differences in the yield responses to climate variations can be mostly attributable to differences between OA and CA practices. Only studies that have recorded organic and conventional yields from the same or neighboring fields and from the same years are included. Therefore, the yield differences are not driven by differences in field conditions (such as soil characteristics) or farm operator characteristics such as farming skills. Most of the studies included also provide yield comparisons from multiple years. Therefore, a fixed-effects model can be used to remove the influence of any time invariant factors.

The rest of this paper is organized as follows. The second section documents sources of yields data and weather data. The third section describes the method used for the statistical analysis. The next section reports regression results. The final section concludes and draws policy implications.

Data sources

Comparing the yield responses of OA and CA to climate variations requires data that cover long time periods and broad geographic regions to capture sufficient variations in climatic conditions. In order to find such data sets, five most cited meta-analysis studies are identified: de Ponti et al. (2012); Hossard et al. (2016); Ponisio et al. (2015); Seufert et al. (2012); Smith et al. (2019). All five studies used similar keywords in their literature search of peer-reviewed studies on the comparisons of organic and conventional yields. Search engines such as Academic Complete Search, Google Scholar and Web of Science were used. de Ponti et al. (2012) include 156 studies published between 1989 and 2010. Seufert, Ramankutty, and Foley (2012) include 66 studies published between 1980 and 2010. Ponisio et al. (2015) includes 115 studies published between 1977 and 2012. Hossard et al. (2016) only include 15 studies published between 1994 and 2015 but all studies are on wheat and maize. Smith et al. (2019) include 398 studies published between 1978 and 2017. There are overlap of studies between these five meta-data sets. For example, all 66 papers from Seufert, Ramankutty, and Foley (2012) are included in Ponisio et al. (2015). Smith et al. (2019) include 90 studies from Ponisio et al. (2015) and 40 studies from de Ponti (2015). In total, all five meta-data sets include 525 studies published between 1977 and 2017.

In order to narrow the scope, this thesis only focuses wheat, soybean, and maize yield comparisons in North America or Europe. This excludes 422 studies that are on other crops such fruits or vegetables, or animals (such as bird or beetle) or in other regions such as Australia. This is done, partly to enable larger sample size and partly to raise the comparability

of agronomic factors, such as farm management practices, that are most similar in between North America and Europe. Of the remaining 103 studies, 81 studies are excluded because of the following reasons: research focus was on other issues (e.g., tillage method, profitability or soil quality) so yields were not reported (32 studies); yield data were reported in aggregated format (e.g., mean over time) or in graphs and original yields were not available even after authors were contacted (33 studies); a study used the same data set as in other studies (11 studies); organic yields and conventional yields were not from the same location (2 studies); organic matters instead of yields were reported (3 studies). Thus, the data collection results in 23 different studies that contain both organic and conventional yields from the same year and the same location (Table 1). It is a mixed dataset of farm data and trial stations. One important data set, which provides 28% of the sample data, comes from the Kellogg Biological research station (KBS), which conducted OA and CA comparisons in multiple locations (Long term ecological research (Lter)). We include Lter's dataset, because it was used by various authors (Kellogg Biological Station, 2021).

In total 472 organic-conventional yield comparisons are obtained from 23 different studies. More than half, 251 comparisons are for maize (53.18 % of the sample), 126 for soybean (26.69 % of the sample), and 95 for wheat (20.13 % of the sample). 45 from Europe and 427 for North America. The data collected show that organic maize yields are on average 12% lower than those under conventional systems. Organic yield reduction is 17% for soybean, and 21% for wheat. The yield gaps calculated from the sample data are consistent with findings from

previous studies. For example, McBride et al. (2015) reported that the yield penalty associated with organic farming was about 27% for maize, 35% for soybeans and 32% for wheat.

Weather data were accessed using Climate Explorer (www.climexp.knmi.nl) managed by the Royal Netherlands Meteorological Institute (Trouet & Van Oldenborgh, 2013). Gridded and interpolated monthly data including temperature, precipitation, cloud cover and vapor pressure produced by the Climate Research Unit (CRU) were downloaded at the resolution of $0.5^\circ \times 0.5^\circ$ grids. CRU self-calibrating Palmer Drought Severity Index (scPDSI) (Wells, Goddard, & Hayes, 2004), a variant on the original scPDSI of Palmer (1965), was also downloaded at the same resolution. Version 4.04 of the CRU Times Series dataset is used (Mitchell & Jones, 2005).

Cloud cover, relative humidity, and potential evaporation are included as explorative variables. So far, less focus has been put on these variables. However, since relative humidity and potential evaporation are highly related, multicollinearity problems arise. Hence, potential evaporation is excluded from this study.

Vapor pressure is used to derive relative humidity. Saturation vapor pressure is calculated using formula 4.B.3. in Annex 4.B. from World Meteorological Organization WMO (2018): $e = 6.112 \exp[22.46T/(272.62+T)]$, where e is saturation vapor pressure and T is temperature. An alternative formula provided by National Weather Service (n.d.): $e = 6.11 \times 10^{\left(\frac{7.5 \times T}{237.3 + T}\right)}$ is also tried. Saturation vapor pressure measures from the two formulae are highly correlated. The

formula from WMO (2018) is used since it is widely accepted. The relative humidity is then calculated as the ratio of vapor pressure to saturation vapor pressure.

Statistical Methods

The relationship between crop yields and relevant factors can be expressed as:

$$\ln y_{it} = \alpha + \nu_i + \mathbf{x}_{it}\boldsymbol{\beta} + \epsilon_{it} \quad (1)$$

The dependent variable, $\ln y_{it}$, can be the log of organic yield in year t from study site i . It can also be the log of conventional yield in year t from study site i , or the log of the ratio of organic to conventional yields. The log is used, being a solution for different units, in that yields are presented in the dataset. Furthermore, the log was used by previous researchers on yield gap.

The parameters associated with the independent variables, \mathbf{x}_{it} , are in the vector $\boldsymbol{\beta}$ and ϵ_{it} is the error term.

Study-level fixed-effects models are used to control for any time-invariant site-specific factor that may be relevant in equation (1). Examples of such factors include soil conditions, irrigation, and characteristics of farm operators (such as farming skills and risk preferences). One set of important factors are the management practices used on the farm. The study-level fixed effects can capture management practices that are used consistently in each year and thus can be considered time-invariant. Data on some of these factors are not available. The fixed effects model finds a way to integrate these not available farm management factors: In equation (1), the use of study-level fixed effects is denoted by the term ν_i . It captures any time-invariant study-level characteristics. A brief explanation of a study-level fixed effects model is as follows. Averaging equation (1) over time generates equation (1a)

$$\overline{\ln y_i} = \alpha + \nu_i + \bar{\mathbf{x}}_i \boldsymbol{\beta} + \bar{\epsilon}_i \quad (1a)$$

where $\overline{\ln y_i} = \sum_t \ln y_{it} / T_i$, $\bar{\mathbf{x}}_i = \sum_t \mathbf{x}_{it} / T_i$, and $\bar{\epsilon}_i = \sum_t \epsilon_{it} / T_i$. Notice the time average of ν_i is itself because it is time-invariant. Subtracting (1a) from (1) generates equation (1b)

$$(\ln y_{it} - \overline{\ln y_i}) = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i) \boldsymbol{\beta} + (\epsilon_{it} - \bar{\epsilon}_i) \quad (1b)$$

The term ν_i disappears in equation (1b) after the subtraction. Estimating equation (1b) will generate consistent estimates of $\boldsymbol{\beta}$ in equation (1) without the need to include all possible observed and unobserved time-invariant factors at the study level.

The key variables of interest in \mathbf{x}_{it} are the weather variables. In the empirical analysis, several groups of weather variables are used. The first group measures the average weather conditions of the whole growing season. Growing season average temperatures are obtained by averaging monthly mean temperatures for all months during the growing season. Growing season average cloud cover and relative humidity are obtained in the same fashion. Since higher moisture (or humidity) could increase pest pressure (e.g. Lacey, Bateman, and Mirocha 1999), relative humidity may be an important climatic factor to include. Cloud cover is used to approximate solar radiation. The total precipitation of the growing season is used. Growing seasons are defined by crop and by region. For example, the growing season for wheat generally spans from October of the previous year to July of the current year.

The second group measures how much the weather conditions during the growing season deviate from the historical averages (weather anomaly). Weather variables (monthly mean temperature, monthly total precipitation, monthly mean cloud cover and monthly mean relative humidity) are measured as:

$$Dev_{W_{it}} = \frac{(W_{it} - (1/30) \sum_{t-31}^{t-1} W_{is})}{\sigma_{it}} \quad (2)$$

where W_{it} is the weather at location i and in year t . The term, $(1/30) \sum_{t-31}^{t-1} W_{is}$, calculates the mean of W_{it} in the previous 30 years. The standard deviation of W_{it} in the previous 30 years is noted by σ_{it} . Then $Dev_{W_{it}}$ is the deviation W_{it} of from the historical mean, measured in standard deviations (σ_{it}).

The third group measures the occurrence of extreme events, in particular, drought and excessive precipitation events. Following Osborn et al. (2016, 2017), extreme droughts occurred in months with values of self-calibrating Palmer Drought Severity Indices (scPDSI) below -4. Severe droughts occurred in months with values of scPDSI below -3. This thesis follows the approach of Li et al. (2019) and use standardized precipitation anomalies (as in equation 2 above) to define excessive precipitation events. Excessive precipitation months are defined as those with precipitation anomalies larger than 2.5 standard deviations. The thresholds of 3 standard deviations are also used but only accounted for less than 1% of the sites and years.

Several other variables are also included in \mathbf{x}_{it} to control for differences between organic and conventional systems among the studies. Two dummy variables are used to indicate if cover crops and legume precrops are planted in conventional systems and two more dummy

variables are used for organic systems. Two variables are added to measure the length of rotation in years under OA and CA. One more variable is added to indicate if no-till is used in CA. This variable is added for CA only because no-till is not a common practice in OA. The year variable is added to control for trends.

Results

The results of estimating equation (1) with fixed effects models are reported in Tables 2-6.

Tables 2 and 4 report the results for maize. Tables 4 and 5 report the results soybean, and Table 6 for wheat. Four specifications are used. Specification 1 (Tables 2, 4, 6, columns 1-3) uses weather variables that measure the conditions of the whole growing season such as average temperature, total precipitation, average relative humidity and average cloud cover.

Specification 2 (Tables 2, 4, 6, columns 4-6) adds a set of variables to measure the occurrence of excessive rainfall and droughts. Specification 3 (Tables 4 and 5, columns 1-3) includes monthly standardized weather anomalies as calculated in equation 2. For example, the average temperatures of April, June, and August are standardized using corresponding historical means and standard deviations. The excluded month are also of interest. Nonetheless, not all month within the growing season are included so as to avoid multicollinearity problems. The squared terms of these monthly weather anomalies also included. In Specification 4 (Tables 3 and 5, columns 4-6), the squared terms are excluded. Instead, the occurrence of excessive rainfall and droughts are included. In each specification, the first column reports estimates where the log of the ratio of organic to conventional yield is the dependent variable. The second column reports estimates where the log of organic yield is the dependent variable. The third column reports estimates where the log of conventional yield is the dependent variable. The estimated coefficients of the same variables are consistent across different specifications in terms of signs and magnitudes. Using the Akaike information criterion (AIC), Specification 4 is the preferred model for maize since it has the smallest AIC. This is true regardless of which dependent variable is used (log of yield ratio, log of organic yield or log of conventional yield). For soybean,

Specification 3 generates smallest AIC for most models. Values of AIC are close between Specifications 3 and 4. This section will focus mainly on Specification 4 but also report results on other specifications. Since Specifications 3 and 4 include a larger number of independent variables and there are only 95 observations on wheat, results for Specifications 3 and 4 fixed effects models for wheat are not reported. The Cumby-Huizinga test (Cumby & Huizinga, 1990, 1992) is performed and the result fails to reject the null hypothesis of no serial correlation in the data with a p -value of 0.15.

Results on standardized weather anomalies do not reveal any striking differences in yield responses to climate variations between organic and conventional maize (Table 3, columns 4-6). Except for a few variables (e.g., standardized April cloud cover), the estimated coefficients for organic maize (column 5) and conventional maize (column 6) have the same signs and are within the same order of magnitudes. The dependent variable in column 4 is the difference between that of column 5 and column 6, that is, $\log(\text{ratio of organic to conventional yields}) = \log(\text{organic yield}) - \log(\text{conventional yield})$. In addition, the same set independent variables are included in columns 4, 5 and 6. Then for any independent variable, the estimated coefficient in column 4 is the difference between that of column 5 and column 6. Therefore, estimating the model in column 4 allows directly testing of the difference between coefficients of columns 5 and 6 are statistically significant. Only the coefficients of standardized August relative humidity and standardized April precipitation are statistically significant (column 4). Higher relative humidity in August increases both organic maize yield and conventional maize yield (columns 5 and 6) but the positive effect is larger for organic maize. Similarly, higher precipitation in April

also benefits organic maize more than conventional maize. The results of Specification 1 (Table 2), however, show that growing season average relative humidity is more likely to reduce both organic and conventional maize yields and the negative effect is likely to be higher on organic maize. Since higher moisture (or humidity) increases pest pressure (e.g. Lacey, Bateman, and Mirocha 1999) and organic farming bans the use of chemical pesticide use, a higher relative humidity may have a larger impact on organic yields.

Results on extreme weather events show some differences in yield responses to excessive rainfalls (Table 3). Excessive rainfall events are defined as levels of precipitation higher than 2.5 standard deviations above 30-year historical mean. The coefficient of excessive rainfall in August is positive and statistically significant in column 4. Columns 5 and 6 results show that excessive rainfall in August benefits organic maize yield but reduces conventional maize yield. The difference is statistically significant (column 4). None of the coefficients of the drought variables came out statistically significant (column 4).

Fixed effects models for soybean use the same four specifications as maize (Tables 4 and 5). Compared to maize, organic and conventional soybeans differ more in their yield response to standardized weather anomalies (Table 5, column 4). Higher relative humidity in August, higher precipitation in April or June, and more cloud cover in August all positively affect organic and conventional soybean yields. However, the positive effects are higher for organic soybeans. The difference also is statistically significant for standardized April scPDSI with a positive coefficient for organic soybean and a negative coefficient for conventional soybean. Specification 1 (Table

4, columns 1-3) shows that growing season average relative humidity tends to reduce both organic and conventional soybean yields and the negative effect is higher on organic soybean. This echoes the findings of maize for the same variable.

Results on extreme weather events show some differences in yield responses to excessive rainfalls and droughts between organic and conventional soybeans (Table 5, column 4). Excessive rainfalls in June decreases organic soybean yields but affects conventional soybean yields to a much smaller extent. This results in a statistically significant difference in yield responses to excessive rainfalls in June. The effects of excessive rainfalls, however, change in August. It boosts both organic and conventional soybean yields. The positive effect is higher for organic soybean and the difference is statistically significant. Some previous studies (such as Gattinger et al. 2012; Kravchenko, Snapp, and Robertson 2017; Lotter, Seidel, and Liebhardt 2003) have either provided empirical evidence or argued that OA may be more robust towards extreme precipitation events. The coefficient of severe or extreme drought in May is negative and statistically significant in the yield ratio model (column 4). This difference is driven by a much larger negative effect on organic soybean than on conventional soybean.

Results for Specifications 1 and 2 of fixed effects model of wheat yields are reported in Table 6. Since the growing seasons for wheat are different, different months are included. In addition, the drought variables are excluded since the occurrence of extreme droughts in the growing season of wheat is infrequent. A higher growing season average scPDSI reduces organic wheat yield but does not affect conventional wheat yield, which results in a statistically significant

difference. Excessive rainfall in April has a negative effect on both organic and conventional wheat yields, but the effect on conventional wheat yield is much larger and statistically significant.

Results on other variables are also of interest. The positive and statistically significant coefficients of year indicate a positive time trend for both organic and conventional maize yields (Table 3, columns 5 and 6). In an alternative specification (not reported for the sake of brevity), instead of year, an index variable is used to indicate the temporal order, e.g., the first year of the experiment, the second year of the experiment. The coefficient of this variable is not statistically significant for the regression on the log of yield ration, indicating that the yield gap between organic and conventional maize does not change as the years of organic farming increase. Aforementioned is equivalent to the findings of soybean and wheat. Using cover crops does boost organic maize significantly. Organic wheat yield also increase with the use of cover crops. Longer rotation does boost organic maize yields, which was expected. This is also valid for organic soybean and wheat yields.

Conclusion

This study compares the responses of organic yields and conventional yields towards climate variations. For all three crops studied (maize, soybean, wheat), the estimated coefficients of most weather variables from the organic yield model and the conventional yield model have the same signs. This indicates organic and conventional yields respond to variations in most climatic factors in the same way. The results show that there are some differences in OA's and CA's responses to climatic variations. For example, excessive rainfall events seem to have less negative effects on organic yields. The differences may vary across crop. For example, although the growing seasons of maize and soybean largely overlap, organic and conventional soybeans differ in their yield responses to more weather factors than maize. The differences may vary between different months. For example, excessive rainfalls in June decreased organic soybean yields but boosted both organic and conventional soybean yields in August.

Looking across all results, for most cases when the yield responses are different, the magnitudes of coefficients are larger for organic yields than for conventional yields. This indicates that organic yield responds more to climate variations. Therefore, empirical evidence from this thesis would not support the argument that organic agriculture can be more resilient to climate variations. This is an important consideration to take into account when policy makers promote organic agriculture. Policymaking should be evidence based. If changing to a resilient cropping system towards more volatile climate conditions is the aim, rapid changes to different cropping methods may not be the way to go. Policies such as the European green deal (European Commission, 2019) which promotes to put at least 25 % of its agriculturally used

land under organic production (European Commission, 2021) should be re-evaluated. Research finding from this thesis suggests slowing down the speed of transitioning to OA, because the higher land use of OA abolished the positive environmental impact of OA, that is often illustrated. Therefore, incentives to transition shift towards organic production should be lowered. The focus should only be implementation of OA in areas that benefit most such as swamps or habitats of rare species.

Our study also points to some directions of future research. First, more climatic factors should be included. Relative humidity (derived from vapor pressure) and cloud cover are not usually included in previous studies, even though they are used in many crop simulation models (Van Wart et al. 2013). The results show that variations in these weather variables do affect crop yields. Second, policy efforts should be put on making more data available. One limitation of this thesis is that only 23 different data sets are obtained after a lot of efforts put in pursuing data when previous studies do not provide the original yield data. Authors of 35 studies were contacted because either their studies only reported aggregated yields such as mean yield averaged over years or across fields or yields were summarized in graphs. Only authors of two studies responded with data requested. Making more data available would improve the quality of research on evaluating organic versus conventional agriculture and thus provide sound scientific support for policy making.

References

- Arncken, C. M., Mäder, P., Mayer, J., & Weibel, F. P. (2012). Sensory, yield and quality differences between organically and conventionally grown winter wheat. *Journal of the Science of Food and Agriculture*. <https://doi.org/10.1002/jsfa.5784>
- Badgley, C., Moghtader, J., Quintero, E., Zakem, E., Chappell, M. J., Avilés-Vázquez, K., ... Perfecto, I. (2007). Organic agriculture and the global food supply. *Renewable Agriculture and Food Systems*, 22(2), 86–108. <https://doi.org/10.1017/S1742170507001640>
- Balfour, E. (1943). *The Living Soil: Evidence of the Importance to Human Health of Soil Vitality, with Special Reference to Post-war Planning*. London: Faber & Faber Ltd.
- Barbieri, P., Pellerin, S., & Nesme, T. (2017). Comparing crop rotations between organic and conventional farming. *Scientific Reports*, 7(13761), 1–10. <https://doi.org/10.1038/s41598-017-14271-6>
- Bengtsson, J., Ahnström, J., & Weibull, A.-C. (2005). The effects of organic agriculture on biodiversity and abundance: a meta-analysis. *Journal of Applied Ecology*, 42(2), 261–269.
- Berry P. M., Sylvester-Bradley, R., Philipps, L., Hatch, D. J., Cuttle, S. P., Rayns, F. W., & Gosling, P. (2002). Is the productivity of organic farms restricted by the supply of available nitrogen? *Soil Use and Management*, 18, 248–255. <https://doi.org/10.1079/sum2002129>
- Bilsborrow, P., Cooper, J., Tétard-Jones, C., Średnicka-Tober, D., Barański, M., Eyre, M., ... Wilcockson, S. (2013). The effect of organic and conventional management on the yield and quality of wheat grown in a long-term field trial. *European Journal of Agronomy*, 51, 71–80. <https://doi.org/10.1016/j.eja.2013.06.003>
- Campiglia, E., Mancinelli, R., De Stefanis, E., Pucciarmati, S., & Radicetti, E. (2015). The long-term effects of conventional and organic cropping systems, tillage managements and weather conditions on yield and grain quality of durum wheat (*Triticum durum* Desf.) in the Mediterranean environment of Central Italy. *Field Crops Research*, 176, 34–44. <https://doi.org/10.1016/j.fcr.2015.02.021>
- Cavigelli, M. A., Teasdale, J. R., & Conklin, A. E. (2008). Long-term agronomic performance of organic and conventional field crops in the mid-Atlantic region. *Agronomy Journal*, 100(3), 785–794. <https://doi.org/10.2134/agronj2006.0373>
- Chirinda, N. Olesen, J. E. and Porter, J. R. (2008). Effects of organic matter input on soil microbial properties and crop yields in conventional and organic cropping systems. *16th IFOAM Organic World Congress, Modena, Italy, June 16-20, 2008*, 2–5.

- Clark, M., & Tilman, D. (2017). Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. *Environmental Research Letters*, *12*. <https://doi.org/10.1088/1748-9326/aa6cd5>
- Cooper, J. M., Butler, G., & Leifert, C. (2011). Life cycle analysis of greenhouse gas emissions from organic and conventional food production systems, with and without bio-energy options. *NJAS - Wageningen Journal of Life Sciences*, *58*, 185–192. <https://doi.org/10.1016/j.njas.2011.05.002>
- Crowder, D. W., Northfield, T. D., Strand, M. R., & Snyder, W. E. (2010). Organic agriculture promotes evenness and natural pest control. *Nature*, *466*, 109–112. <https://doi.org/10.1038/nature09183>
- Cumby, R. E., & Huizinga, J. (1990). *Testing the Autocorrelation Structure of Disturbances in Ordinary Least Squares and Instrumental Variables Regressions*. Cambridge, MA.
- Cumby, R. E., & Huizinga, J. (1992). Testing the Autocorrelation Structure of Disturbances in Ordinary Least Squares and Instrumental Variables Regressions. *Econometrica*, *60*(1), 185–195. <https://doi.org/10.2307/2951684>
- Dahan, O., Babad, A., Lazarovitch, N., Russak, E. E., & Kurtzman, D. (2014). Nitrate leaching from intensive organic farms to groundwater. *Hydrology and Earth System Sciences*, *18*, 333–341. <https://doi.org/10.5194/hess-18-333-2014>
- de Ponti, T., Rijk, B., & van Ittersum, M. K. (2012). The crop yield gap between organic and conventional agriculture. *Agricultural Systems*, *108*, 1–9. <https://doi.org/10.1016/j.agsy.2011.12.004>
- Delate, K., & Cambardella, C. A. (2004). Agroecosystem performance during transition to certified organic grain production. *Agronomy Journal*, *96*, 1288–1298. <https://doi.org/10.2134/agronj2004.1288>
- Delbridge, T. A., Coulter, J. A., King, R. P., Sheaffer, C. C., & Wyse, D. L. (2011). Economic performance of long-term organic and conventional cropping systems in Minnesota. *Agronomy Journal*, *103*(5), 1372–1382. <https://doi.org/10.2134/agronj2011.0371>
- Deutsch, C. A., Tewksbury, J. J., Tigchelaar, M., Battisti, D. S., Merrill, S. C., Huey, R. B., & Naylor, R. L. (2018). Increase in crop losses to insect pests in a warming climate. *Science*, *361*, 916–919. <https://doi.org/10.1126/science.aat3466>
- Dobbs, T. L., & Smolik, J. D. (1997). Productivity and Profitability of Conventional and Alternative Farming Systems: A Long-Term On-Farm Paired Comparison. *Journal of Sustainable Agriculture*, *9*(1), 63–79. https://doi.org/10.1300/J064v09n01_06

- Du, S., Bartels, J., Reinders, M., & Sen, S. (2017). Organic consumption behavior: A social identification perspective. *Food Quality and Preference*.
<https://doi.org/10.1016/j.foodqual.2017.07.009>
- EU. (2007). Council Directive 834/2007 on organic production and labelling of organic products. *Official Journal of the European Union*, L189(2).
- European Commission. The European Green Deal. , European Commission § (2019).
- European Commission. (2021). COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS ON AN ACTION PLAN FOR THE DEVELOPMENT OF ORGANIC PRODUCTION. *Journal of Chemical Information and Modeling*.
- FAO. (1999). Definition of organic agriculture. Retrieved from
<http://www.fao.org/unfao/bodies/coag/coag15/x0075e.htm>
- Feber, R. E., Bell, J., Johnson, P. J., Firbank, L. G., & Macdonald, D. W. (1998). The effects of organic farming on surface-active spider (Araneae) assemblages in wheat in Southern England, UK. *Journal of Arachnology*, 26, 190–202. <https://doi.org/10.2307/3706158>
- Feber, R. E., Firbank, L. G., Johnson, P. J., & Macdonald, D. W. (1997). The effects of organic farming on pest and non-pest butterfly abundance. *Agriculture, Ecosystems and Environment*, 64, 133–139. [https://doi.org/10.1016/S0167-8809\(97\)00031-5](https://doi.org/10.1016/S0167-8809(97)00031-5)
- Fuller, R. J., Norton, L. R., Feber, R. E., Johnson, P. J., Chamberlain, D. E., Joys, A. C., ... Firbank, L. G. (2005). Benefits of organic farming to biodiversity vary among taxa. *Biology Letters*, 431–434. <https://doi.org/10.1098/rsbl.2005.0357>
- Gattinger, A., Muller, A., Haeni, M., Skinner, C., Fliessbach, A., Buchmann, N., ... Niggli, U. (2012). Enhanced top soil carbon stocks under organic farming. *Proceedings of the National Academy of Sciences of the United States of America*, 109(44), 18226–18231. <https://doi.org/10.1073/pnas.1209429109>
- Gregory, P. J., Johnson, S. N., Newton, A. C., & Ingram, J. S. I. (2009). Integrating pests and pathogens into the climate change/food security debate. *Journal of Experimental Botany*, 60(10), 2827–2838. <https://doi.org/10.1093/jxb/erp080>
- Hald, A. B. (1999). Weed vegetation (wild flora) of long established organic versus conventional cereal fields in Denmark. *Annals of Applied Biology*, 134, 307–314. <https://doi.org/10.1111/j.1744-7348.1999.tb05269.x>
- Hall, N., Stuntz, B., & Abrams, R. (2011). Climate change and freshwater resources. *Natural Resource & Environment*, 22(3), 30–35. <https://doi.org/10.4337/9781849809665.00011>

- Hansen, B., Thorling, L., Schullehner, J., Termansen, M., & Dalgaard, T. (2017). Groundwater nitrate response to sustainable nitrogen management. *Scientific Reports*, *7*, 1–12. <https://doi.org/10.1038/s41598-017-07147-2>
- Harkness, C., Areal, F. J., Semenov, M. A., Senapati, N., Shield, I. F., & Bishop, J. (2021). Stability of farm income: The role of agricultural diversity and agri-environment scheme payments. *Agricultural Systems*, *187*, 1–13. <https://doi.org/10.1016/j.agsy.2020.103009>
- Helmers, G. A., Langemeier, M. R., & Atwood, J. (1986). An economic analysis of alternative cropping systems for east-central Nebraska. *American Journal of Alternative Agriculture*, *1*(4), 153–158. <https://doi.org/10.1017/S0889189300001223>
- Hole, D. G., Perkins, A. J., Wilson, J. D., Alexander, I. H., Grice, P. V., & Evans, A. D. (2005). Does organic farming benefit biodiversity? *Biological Conservation*, *122*, 113–130. <https://doi.org/10.1016/j.biocon.2004.07.018>
- Hossard, L., Archer, D. W., Bertrand, M., Colnenne-David, C., Debaeke, P., Ernfors, M., ... Makowski, D. (2016). A meta-analysis of maize and wheat yields in low-input vs. conventional and organic systems. *Agronomy Journal*, *108*(3), 1155–1167. <https://doi.org/10.2134/agronj2015.0512>
- Hutton, S. A., & Giller, P. S. (2003). The effects of the intensification of agriculture on northern temperate dung beetle communities. *Journal of Applied Ecology*, *40*, 994–1007. <https://doi.org/10.1111/j.1365-2664.2003.00863.x>
- IFOAM. (2013). *Best Practice Guideline for Agriculture & Value Chains*.
- Ingver, A., Tamm, I., & Tamm, Ü. (2008). Effect of organic and conventional production on yield and the quality of spring cereals. *Agronomijas Vēstis (Latvian Journal of Agronomy)*, *11*, 61–67.
- Kaut, A. H. E. E., Mason, H. E., Navabi, A., O'Donovan, J. T., & Spaner, D. (2009). Performance and stability of performance of spring wheat variety mixtures in organic and conventional management systems in western Canada. *Journal of Agricultural Science*, *147*, 141–153. <https://doi.org/10.1017/S0021859608008319>
- Kellogg Biological Station. (2021). Long term ecological research. Retrieved from <https://lter.kbs.msu.edu>
- Kirchmann, H. (2019). Why organic farming is not the way forward. *Outlook on Agriculture*, *48*(1), 22–27. <https://doi.org/10.1177/0030727019831702>
- Kniss, A. R., Savage, S. D., & Jabbour, R. (2016). Commercial crop yields reveal strengths and

- weaknesses for organic agriculture in the United States. *PLoS ONE*, *11*(8), 1–16. <https://doi.org/10.1371/journal.pone.0161673>
- Kravchenko, A. N., Snapp, S. S., & Robertson, G. P. (2017). Field-scale experiments reveal persistent yield gaps in low-input and organic cropping systems. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(5), 926–931. <https://doi.org/10.1073/pnas.1612311114>
- Krebs, J. R., Wilson, J. D., Bradbury, R. B., & Siriwardena, G. M. (1999). The second silent spring? *Nature*, *400*, 611–612. <https://doi.org/10.1038/23127>
- L-Baekström, G., Lundegårdh, B., & Hanell, U. (2006). The interactions between nitrogen dose, year and stage of ripeness on nitrogen and trace element concentrations and seed-borne pathogens in organic and conventional wheat. *Journal of the Science of Food and Agriculture*, *86*, 2560–2578. <https://doi.org/10.1002/jsfa>
- Lacey, J., Bateman, G. L., & Mirocha, C. J. (1999). Effects of infection time and moisture on development of ear blight and deoxynivalenol production by *Fusarium* spp. in wheat. *Annals of Applied Biology*, *134*, 277–283. <https://doi.org/10.1111/j.1744-7348.1999.tb05265.x>
- Lernoud, J., & Willer, H. (2015). The World of Organic Agriculture 2015: Summary. In *The World of Organic Agriculture*. Retrieved from <https://shop.fibl.org/de/artikel/c/statistik/p/1663-organic-world-2015.html>
- Liebhardt, W. C., Andrews, R. W., Culik, M. N., Harwood, R. R., Janke, R. R., Radke, J. K., & Rieger-Schwartz, S. L. (1989). Crop Production During Conversion from Conventional to Low-Input Methods. *Agronomy Journal*, *81*, 150–159. <https://doi.org/10.2134/agronj1989.00021962008100020003x>
- Lockeretz, W., Shearer, G., Sweeney, S., Kuepper, G., Wanner, D., & Kohl, D. H. (1980). Maize Yields and Soil Nutrient Levels With and Without Pesticides and Standard Commercial Fertilizers 1. *Agronomy Journal*, *72*, 65–72. <https://doi.org/10.2134/agronj1980.00021962007200010014x>
- Lotter, D. W., Seidel, R., & Liebhardt, W. (2003). The performance of organic and conventional cropping systems in an extreme climate year. *American Journal of Alternative Agriculture*, *18*(3), 146–154. <https://doi.org/10.1079/AJAA200345>
- Mazzoncini, M., Belloni, P., Risaliti, R., An, & Tichi, D. (2007). Organic Vs Conventional Winter Wheat Quality and Organoleptic Bread Test. *3rd QLIF Congress, Hohenheim*, 1–5. Retrieved from <papers3://publication/uuid/B4C61B7E-2DF4-4AF5-BAA5-B10528FD4514%5Cpapers3://publication/uuid/C2E9D138-05C6-43EC-B8A5-7B4E65DC0448%5Cpapers3://publication/uuid/7F11512B-C880-487E-8589->

76DB708A178B%5Cnpapers3://publication/uuid/1036BC30-12DF-4194-9D74-0DF

Meemken, E. M., & Qaim, M. (2018). Organic Agriculture, Food Security, and the Environment. *Annual Review of Resource Economics*, *10*, 39–63. <https://doi.org/10.1146/annurev-resource-100517-023252>

Mitchell, T. D., & Jones, P. D. (2005). An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology*, *25*, 693–712. <https://doi.org/10.1002/joc.1181>

Mondelaers, K., Aertsens, J., & van Huylenbroeck, G. (2009). A meta-analysis of the differences in environmental impacts between organic and conventional farming. *British Food Journal*, *111*(10), 1098–1119. <https://doi.org/10.1108/00070700910992925>

Müller, C., Elliott, J., Pugh, T. A. M., Ruane, A. C., Ciais, P., Balkovic, J., ... Wang, X. (2018). Global patterns of crop yield stability under additional nutrient and water inputs. *PLoS ONE*, *13*(6), 1–14. <https://doi.org/10.1371/journal.pone.0198748>

Murphy, K. M., Campbell, K. G., Lyon, S. R., & Jones, S. S. (2007). Evidence of varietal adaptation to organic farming systems. *Field Crops Research*, *102*, 172–177. <https://doi.org/10.1016/j.fcr.2007.03.011>

National Weather Service. (n.d.). What is the formula for the vapor pressure script? Retrieved from <https://www.weather.gov/media/epz/wxcalc/vaporPressure.pdf>

Niggli, U., Fließbach, a., Hepperly, P., & Scialabba, N. (2009). Low greenhouse gas agriculture: Mitigation and adaptation potential of sustainable farming systems. *Food and Agriculture Organization of the United Nations*, 1–26. Retrieved from <http://orgprints.org/15690/1/niggli-et-al-2009-lowgreenhouse.pdf>

Oehl, F., Oberson, A., Tagmann, H. U., Besson, J. M., Dubois, D., Mäder, P., ... Frossard, E. (2002). Phosphorus budget and phosphorus availability in soils under organic and conventional farming. *Nutrient Cycling in Agroecosystems*, *62*, 25–35. <https://doi.org/10.1023/A:1015195023724>

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., & Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, *11*(4), 306–312. <https://doi.org/10.1038/s41558-021-01000-1>

Osborn, T. J., Barichivich, J., Harris, I., Schrier, G. van der, & Jones, P. D. (2016). State of the Climate in 2015, monitoring global drought using the Self-calibrating palmer drought Severity index. *Bulletin of the American Meteorological Society*, *97*(8). <https://doi.org/10.1175/2016BAMSStateoftheClimate.2>

- Osborn, T. J., Barichivich, J., Harris, I., Schrier, G. van der, & Jones, P. D. (2017). State of the Climate in 2016, monitoring global drought using the Self-calibrating palmer drought Severity index. *Bulletin of the American Meteorological Society*, 98(8).
- Pandey, A., Li, F., Askegaard, M., & Olesen, J. E. (2017). Biological nitrogen fixation in three long-term organic and conventional arable crop rotation experiments in Denmark. *European Journal of Agronomy*, 90, 87–95. <https://doi.org/10.1016/j.eja.2017.07.009>
- Pimentel, D., & Burgess, M. (2014). An environmental, energetic and economic comparison of organic and conventional farming systems. *BioScience*, 55(7), 573–582. https://doi.org/10.1007/978-94-007-7796-5_6
- Ponisio, L. C., M'gonigle, L. K., Mace, K. C., Palomino, J., Valpine, P. De, & Kremen, C. (2015). Diversification practices reduce organic to conventional yield gap. *Proceedings of the Royal Society B: Biological Sciences*, 282. <https://doi.org/10.1098/rspb.2014.1396>
- Ramesh, K., Matloob, A., Aslam, F., Florentine, S. K., & Chauhan, B. S. (2017). Weeds in a changing climate: Vulnerabilities, consequences, and implications for future weed management. *Frontiers in Plant Science*, 8, 1–12. <https://doi.org/10.3389/fpls.2017.00095>
- Rasmussen, I. A. (2004). The effect of sowing date, stale seedbed, row width and mechanical weed control on weeds and yields of organic winter wheat. *Weed Research*, 44, 12–20. <https://doi.org/10.1046/j.1365-3180.2003.00367.x>
- Reganold, J. P., Elliott, L. F., & Unger, Y. L. (1987). Long-term effects of organic and conventional farming on soil erosion. *Nature*, 330, 370–372.
- Reganold, J. P., & Wachter, J. M. (2016). Organic agriculture in the twenty-first century. *Nature Plants*, 2, 1–8. <https://doi.org/10.1038/nplants.2015.221>
- Rodale Institute. (2014). *Regenerative Organic Agriculture and Climate Change*.
- Rosegrant, M., Ringler, C., & Zhu, T. (2014). Water Markets as an Adaptive Response to Climate Change. *Global Issue in Water Policy*, 11, 35–55. <https://doi.org/10.1007/978-94-017-9081-9>
- Rounsevell, M. D. A., Evans, S. P., & Bullock, P. (1999). Climate change and agricultural soils: Impacts and adaptation. *Climatic Change*, 43, 683–709. <https://doi.org/10.1023/A:1005597216804>
- Rusch, H. (1978). *Bodenfruchtbarkeit. Eine Studie biologischen Denkens (Soil Fertility. A case of biological reasoning)*. Heidelberg: Haus Verlag, 3rd Printing.
- Sacco, D., Moretti, B., Monaco, S., & Grignani, C. (2015). Six-year transition from conventional

- to organic farming: Effects on crop production and soil quality. *European Journal of Agronomy*, 69, 10–20. <https://doi.org/10.1016/j.eja.2015.05.002>
- Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, 104, 19703–19708. <https://doi.org/10.1073/pnas.0701976104>
- Scialabba, N. E. H., & Müller-Lindenlauf, M. (2010a). Organic agriculture and climate change. *Renewable Agriculture and Food Systems*, 25(2), 158–169. <https://doi.org/10.1017/S1742170510000116>
- Scialabba, N. E. H., & Müller-Lindenlauf, M. (2010b). Organic agriculture and climate change. *Renewable Agriculture and Food Systems*, 25(2), 158–169. <https://doi.org/10.1017/S1742170510000116>
- Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, 485, 229–232. <https://doi.org/10.1038/nature11069>
- Skinner, C., Gattinger, A., Muller, A., Mäder, P., Fliebach, A., Stolze, M., ... Niggli, U. (2014). Greenhouse gas fluxes from agricultural soils under organic and non-organic management - A global meta-analysis. *Science of the Total Environment*, 468–469, 553–563. <https://doi.org/10.1016/j.scitotenv.2013.08.098>
- Smith, O. M., Cohen, A. L., Rieser, C. J., Davis, A. G., Taylor, J. M., Adesanya, A. W., ... Crowder, D. W. (2019). Organic Farming Provides Reliable Environmental Benefits but Increases Variability in Crop Yields: A Global Meta-Analysis. *Frontiers in Sustainable Food Systems*, 3(September), 1–10. <https://doi.org/10.3389/fsufs.2019.00082>
- Smith, R. G., Menalled, F. D., & Robertson, G. P. (2007). Temporal yield variability under conventional and alternative management systems. *Agronomy Journal*, 99, 1629–1634. <https://doi.org/10.2134/agronj2007.0096>
- Squalli, J., & Adamkiewicz, G. (2018). Organic farming and greenhouse gas emissions: A longitudinal U.S. state-level study. *Journal of Cleaner Production*. <https://doi.org/10.1016/j.jclepro.2018.04.160>
- Steiner, R. (1924). *Geisteswissenschaftliche Grundlagen zum Gedeihen der Landwirtschaft (Landwirtschaftlicher Kurs)*. S. 94 ff. Retrieved from <http://anthroposophie.byu.edu>
- Stolze, M., & Lampkin, N. (2009). Policy for organic farming: Rationale and concepts. *Food Policy*, 34, 237–244. <https://doi.org/10.1016/j.foodpol.2009.03.005>
- Teasdale, J. R., Coffman, C. B., & Mangum, R. W. (2007). Potential long-term benefits of no-tillage and organic cropping systems for grain production and soil improvement. *Agronomy*

- Journal*, 99, 1297–1305. <https://doi.org/10.2134/agronj2006.0362>
- Thieu, V., Billen, G., Garnier, J., & Benoît, M. (2011). Nitrogen cycling in a hypothetical scenario of generalised organic agriculture in the Seine, Somme and Scheldt watersheds. *Regional Environmental Change*, 11, 359–370. <https://doi.org/10.1007/s10113-010-0142-4>
- Treu, H., Nordborg, M., Cederberg, C., Heuer, T., Claupein, E., Hoffmann, H., & Berndes, G. (2017). Carbon footprints and land use of conventional and organic diets in Germany. *Journal of Cleaner Production*, 161, 127–142. <https://doi.org/10.1016/j.jclepro.2017.05.041>
- Trouet, V., & Van Oldenborgh, G. J. (2013). KNMI climate explorer: A web-based research tool for high-resolution paleoclimatology. *Tree-Ring Research*, 69(1), 3–13. <https://doi.org/10.3959/1536-1098-69.1.3>
- Tuck, S. L., Winqvist, C., Mota, F., Ahnström, J., Turnbull, L. A., & Bengtsson, J. (2014). Land-use intensity and the effects of organic farming on biodiversity: A hierarchical meta-analysis. *Journal of Applied Ecology*, 51, 746–755. <https://doi.org/10.1111/1365-2664.12219>
- Tuomisto, H. L., Hodge, I. D., Riordan, P., & Macdonald, D. W. (2012). Does organic farming reduce environmental impacts? - A meta-analysis of European research. *Journal of Environmental Management*, 112, 309–320. <https://doi.org/10.1016/j.jenvman.2012.08.018>
- USDA. (2011). Organic Production and Handling Standards. *Organic Production and Handling Standards*, 1–2. Retrieved from [https://www.ams.usda.gov/sites/default/files/media/Organic Production-Handling Standards.pdf](https://www.ams.usda.gov/sites/default/files/media/Organic%20Production-Handling%20Standards.pdf) www.ams.usda.gov/nop
- Van Wart, J., Grassini, P., & Cassman, K. G. (2013). Impact of derived global weather data on simulated crop yields. *Global Change Biology*, 19. <https://doi.org/10.1111/gcb.12302>
- Wells, N., Goddard, S., & Hayes, M. J. (2004). A Self-Calibrating Palmer Drought Severity Index. *Journal of Climate*, 2335–2351.
- Welsh, C., Tenuta, M., Flaten, D. N., Thiessen-Martens, J. R., & Entz, M. H. (2009). High yielding organic crop management decreases plant-available but not recalcitrant soil phosphorus. *Agronomy Journal*, 101(5), 1027–1035. <https://doi.org/10.2134/agronj2009.0043>
- Wilbois, K. P., & Schmidt, J. E. (2019). Reframing the debate surrounding the yield gap between organic and conventional farming. *Agronomy*, 9(82), 1–16. <https://doi.org/10.3390/agronomy9020082>
- Willer, H., Trávníček, J., Meier, C., & Schlatter, B. (2021). The World of Organic Agriculture. In *The World of Organic Agriculture*. Retrieved from

<https://shop.fibl.org/de/artikel/c/statistik/p/1663-organic-world-2015.html>

World Meteorological Organization. (2018). *Guide to Instruments and Methods of Observation. Volume I – Measurement of Meteorological Variables*. Geneva, Switzerland.

Wortman, S. E., Francis, C. A., Galusha, T. D., Hoagland, C., van Wart, J., Baenziger, P. S., ... Johnson, M. (2013). Evaluating cultivars for organic farming: Maize, soybean, and wheat genotype by system interactions in Eastern Nebraska. *Agroecology and Sustainable Food Systems*, 37(8), 915–932. <https://doi.org/10.1080/21683565.2013.764956>

Appendix section

Table 1. Included studies

Study/Data set	Crops	Location	Years	Pairs of organic and conventional yields
Arncken et al. (2012)	Wheat	Switzerland, Basel	2006-2009	6
Dobbs and Smolik (1997)	Maize, Soybean	USA, South Dakota, Lake county	1985-1992	16
Helmers, Langemeier, and Atwood (1986)	Maize, Soybean	USA, Nebraska, Ithaca	1978-1985	16
Ingver, Tamm, and Tamm (2008)	Spring Wheat	Estonia, Jõgeva	2005-2007	3
Kaut et al. (2009)	Wheat	Canada, Alberta, Edmonton	2003-2005	3
L-Baeckström, Lundegårdh, and Hanell (2006)	Wheat	Sweden, Kvinnersta	1999-2001	3
Liebhart et al. (1989)	Maize, Soybean	USA, Pennsylvania, Kutztown	1981-1985	13
Lockeretz et al. (1980)	Maize	USA, Iowa / Minnesota (southern third) / Nebraska (eastern third) / Illinois (northern third) / Missouri (southern third)	1975-1978	26
Mazzoncini et al. (2007)	Wheat	Italy, Pisa	2004-2005	2
Reganold, Elliott, and Unger (1987)	Wheat	USA, Washington, Spokane	1982-1986	10
Teasdale, Coffman, and Mangum (2007)	Maize, Wheat	USA, Maryland, Beltsville	1994-1998	22
Welsh et al. (2009)	Wheat	Canada, Manitoba, Glenlea	1996-2004	7
Cavigelli, Teasdale, and Conklin (2008)	Maize, Soybean, Wheat	USA, Maryland, Beltsville	1996-2005	87
Delate and Cambardella (2004)	Maize, Soybean	USA, Iowa, Greenfield	1998-2001	16
Chirinda, N. Olesen, J. E. and Porter (2008)	Wheat	Denmark, central Jutland, Foulum	2006-2007	6
Murphy et al. (2007)	Wheat	USA, Washington State	2003, 2005	5
Kellogg Biological Station (2021)	Maize, Soybean, Wheat	USA, Wisconsin, Elkhorn USA, Wisconsin, Arlington	1993-2016	134
Campiglia et al. (2015)	Wheat	Italy, Province of Viterbo	2006-2011	6
Bilsborrow et al. (2013)	Wheat	UK, Stocksfield	2004-2008	4
Sacco et al. (2015)	Maize, Soybean, Wheat	Italy, Piemonte region	2001-2006	15
Delbridge et al. (2011)	Maize	USA, Minnesota, Lamberton	1993-2010	36
Wortman et al. (2013)	Maize, Soybean, Wheat	USA, Nebraska, Mead	2004-2008	12
R. G. Smith, Menalled, and Robertson (2007)	Maize, Soybean, Wheat	USA, Minnesota, Hickory Corners	1993-2004	24

Table 2. Fixed effects model of maize yields, Specifications 1 and 2

	Specification 1			Specification 2		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
Growing season average temperature in C	-0.0353 (0.543)	0.0186 (0.807)	0.0539** (0.019)	-0.0353 (0.467)	0.00607 (0.931)	0.0414 (0.145)
Growing season total precipitation in mm	-0.000113 (0.762)	0.000203 (0.683)	0.000316 (0.303)	-0.000170 (0.788)	0.000640 (0.413)	0.000811** (0.038)
Growing season average relative humidity in %	-0.0354** (0.043)	-0.0391 (0.158)	-0.00368 (0.818)	-0.0222 (0.151)	-0.0271 (0.322)	-0.00496 (0.755)
Growing season average cloud cover in %	-3.004** (0.021)	-3.013*** (0.002)	-0.00857 (0.992)	-1.914 (0.123)	-1.588 (0.299)	0.325 (0.764)
Growing season average scPDSI index	0.0859 (0.233)	0.135 (0.186)	0.0494 (0.186)	0.0232 (0.736)	0.0309 (0.599)	0.00776 (0.725)
April precipitation 2.5 or more sd above historical mean				-0.123 (0.628)	-0.345 (0.223)	-0.222** (0.046)
June precipitation 2.5 or more sd above historical mean				0.0631 (0.730)	-0.576 (0.148)	-0.639** (0.012)
August precipitation 2.5 or more sd above historical mean				0.852*** (0.007)	0.569** (0.044)	-0.282* (0.071)
Severe or extreme drought in May				-0.697 (0.229)	-0.599 (0.296)	0.0983 (0.394)
Severe or extreme drought in June				-0.0674 (0.888)	-0.242 (0.616)	-0.174* (0.063)
Severe or extreme drought in August				0.0131 (0.980)	-0.347 (0.551)	-0.360* (0.087)
Year	-0.00162 (0.819)	0.00969 (0.352)	0.0113* (0.083)	-0.00422 (0.689)	0.00613 (0.534)	0.0104 (0.141)
Used legume precrops in organic system	-0.353*** (0.000)	-0.0349 (0.864)	0.318* (0.080)	-0.512*** (0.000)	-0.266 (0.256)	0.246 (0.203)
Used legume precrops in conventional system	-0.173** (0.024)	-0.00979 (0.874)	0.163 (0.193)	-0.205*** (0.009)	-0.00427 (0.962)	0.200 (0.154)
Used cover crops in organic system	0.378*** (0.000)	0.309 (0.233)	-0.0690 (0.745)	0.535*** (0.000)	0.432** (0.017)	-0.103 (0.576)
Used cover crops in conventional system	0.148 (0.245)	-0.0101 (0.777)	-0.158 (0.305)	0.0900 (0.400)	-0.0554 (0.640)	-0.145 (0.495)
No-till used in conventional system	0.102 (0.230)	0.00850 (0.722)	-0.0934 (0.365)	0.0664 (0.210)	-0.0605 (0.403)	-0.127 (0.293)
Rotation length in years in organic system	0.0786*** (0.002)	0.144** (0.021)	0.0652 (0.192)	0.00611 (0.846)	0.0477 (0.595)	0.0416 (0.503)
Rotation length in years in conventional system	-0.00925 (0.832)	0.0539** (0.013)	0.0631 (0.175)	0.0124 (0.688)	0.0543 (0.371)	0.0419 (0.585)
Constant	7.281 (0.590)	-13.46 (0.468)	-20.74* (0.096)	11.47 (0.570)	-7.273 (0.674)	-18.75 (0.180)
Observations	251	251	251	251	251	251
AIC	316.5	423.8	250.4	268.1	366.4	218.5
BIC	355.3	462.6	289.1	306.9	405.2	257.2

Note: Standard errors clustered at the study level and p -values are reported in parentheses; * indicates significant at 10% (p -values are between 5% and 10%); **significant at 5% (p -values are between 1% and 5%), ***significant at 1% (p -values are less than 1%).

Table 3. Fixed effects model of maize yields, Specifications 3 and 4

	Specification 3			Specification 4		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
Standardized April average temperature	-0.0185 (0.603)	0.0734 (0.300)	0.0919** (0.040)	-0.0526 (0.231)	0.0295 (0.622)	0.0821*** (0.008)
Squared	-0.0477 (0.288)	-0.0821 (0.141)	-0.0344 (0.138)			
Standardized June average temperature	-0.00983 (0.848)	0.0551 (0.325)	0.0649 (0.265)	0.00897 (0.771)	0.0857* (0.086)	0.0767 (0.107)
Squared	-0.00239 (0.943)	0.000512 (0.988)	0.00290 (0.910)			
Standardized August average temperature	0.0534 (0.446)	0.105 (0.169)	0.0520 (0.313)	0.0443 (0.350)	0.114*** (0.010)	0.0698 (0.115)
Squared	-0.0409 (0.219)	-0.0294 (0.298)	0.0115 (0.622)			
Standardized April relative humidity	-0.0692 (0.326)	-0.0917 (0.345)	-0.0225 (0.551)	-0.0681 (0.215)	-0.125 (0.144)	-0.0567 (0.210)
Squared	0.0972* (0.063)	0.150** (0.024)	0.0524** (0.024)			
Standardized June relative humidity	-0.0989 (0.230)	-0.180** (0.048)	-0.0812* (0.062)	-0.0216 (0.592)	-0.0425 (0.499)	-0.0210 (0.640)
Squared	0.0341 (0.567)	0.0562 (0.363)	0.0221 (0.397)			
Standardized August relative humidity	0.0957* (0.094)	0.263** (0.013)	0.168** (0.020)	0.0926** (0.032)	0.292*** (0.007)	0.200*** (0.010)
Squared	-0.0193 (0.672)	-0.0445 (0.511)	-0.0252 (0.402)			
Standardized April Precip	-0.0248 (0.782)	-0.0601 (0.265)	-0.0353 (0.608)	0.0615 (0.258)	0.0762* (0.057)	0.0147 (0.818)
Squared	0.00490 (0.864)	0.0317 (0.242)	0.0268** (0.011)			
Standardized June Precip	0.0628 (0.667)	0.0394 (0.808)	-0.0234 (0.686)	0.0191 (0.752)	-0.0542 (0.124)	-0.0732 (0.139)
Squared	-0.0263 (0.689)	-0.0295 (0.766)	-0.00319 (0.945)			
Standardized August Precip	-0.00282 (0.969)	0.0649 (0.133)	0.0677 (0.117)	-0.00101 (0.990)	0.0344 (0.667)	0.0354 (0.396)
Squared	0.0759* (0.097)	0.0699** (0.045)	-0.00603 (0.709)			
Standardized April cloud cover in %	-0.0265 (0.649)	-0.0222 (0.732)	0.00431 (0.920)	-0.0574 (0.197)	-0.0527 (0.392)	0.00470 (0.918)
Squared	-0.0185 (0.675)	-0.0411 (0.506)	-0.0226 (0.377)			
Standardized June cloud cover in %	0.0661 (0.505)	0.242** (0.040)	0.176*** (0.004)	-0.0277 (0.663)	0.117* (0.069)	0.145** (0.018)
Squared	-0.0293 (0.512)	-0.0598 (0.121)	-0.0305 (0.272)			
Standardized August cloud cover in %	-0.185* (0.050)	-0.411** (0.022)	-0.226** (0.016)	-0.0154 (0.840)	-0.155* (0.076)	-0.140*** (0.006)
Squared	0.0743* (0.071)	0.108* (0.060)	0.0335 (0.135)			
Standardized April scPDSI	0.191 (0.264)	0.200 (0.129)	0.00912 (0.901)	0.0793** (0.028)	0.0874 (0.143)	0.00813 (0.893)
Squared	-0.0286 (0.665)	0.0587 (0.205)	0.0873 (0.181)			
Standardized June scPDSI	0.0806 (0.458)	0.0779 (0.399)	-0.00270 (0.973)	-0.0776 (0.346)	-0.120* (0.087)	-0.0423 (0.567)
Squared	-0.0860 (0.136)	-0.173** (0.029)	-0.0866 (0.206)			
Standardized August scPDSI	-0.105 (0.285)	0.0351 (0.740)	0.140*** (0.009)	-0.0745* (0.073)	0.0214 (0.735)	0.0958 (0.154)
Squared	0.00943	-0.0171	-0.0265			

Table 3. Fixed effects model of maize yields, Specifications 3 and 4

	Specification 3			Specification 4		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
	(0.824)	(0.683)	(0.166)			
April precipitation 2.5 or more sd above historical mean				-0.148 (0.628)	-0.308 (0.307)	-0.160 (0.382)
June precipitation 2.5 or more sd above historical mean				0.0682 (0.794)	-0.441 (0.157)	-0.509*** (0.000)
August precipitation 2.5 or more sd above historical mean				0.706* (0.072)	0.491 (0.258)	-0.215 (0.309)
Severe or extreme drought in May				-0.612 (0.352)	-0.498 (0.304)	0.114 (0.676)
Severe or extreme drought in June				-0.262 (0.652)	-0.687 (0.179)	-0.425 (0.225)
Severe or extreme drought in August				0.145 (0.731)	0.0384 (0.942)	-0.107 (0.738)
Year	-0.00950 (0.398)	0.0171 (0.101)	* (0.000)	-0.00516 (0.653)	0.0221*** (0.005)	0.0273*** (0.001)
Used legume precrops in organic system	-0.365*** (0.000)	-0.0736 (0.700)	0.291 (0.104)	-0.534*** (0.000)	-0.250* (0.051)	0.284** (0.049)
Used legume precrops in conventional system	-0.146* (0.098)	0.0419 (0.474)	0.188 (0.153)	-0.194** (0.017)	-0.0180 (0.748)	0.176* (0.090)
Used cover crops in organic system	0.427*** (0.002)	0.336 (0.148)	-0.0907 (0.651)	0.584*** (0.000)	0.541*** (0.004)	-0.0431 (0.799)
Used cover crops in conventional system	0.186 (0.109)	0.157*** (0.005)	-0.0288 (0.810)	0.115 (0.313)	0.0407 (0.490)	-0.0746 (0.586)
No-till used in conventional system	0.105 (0.113)	0.0990** (0.017)	-0.00546 (0.944)	0.0872 (0.134)	0.0329 (0.312)	-0.0543 (0.496)
Rotation length in years in organic system	0.0766*** (0.010)	0.163*** (0.001)	* (0.004)	0.00655 (0.764)	0.0994*** (0.006)	0.0929*** (0.000)
Rotation length in years in conventional system	-0.0304 (0.496)	-0.0182 (0.532)	0.0121 (0.804)	0.00140 (0.963)	0.0271 (0.479)	0.0257 (0.618)
Constant	18.69 (0.405)	-31.50 (0.126)	50.19*** (0.001)	10.28 (0.655)	-41.38*** (0.008)	-51.67*** (0.001)
Observations	251	251	251	251	251	251
AIC	269.5	310.2	160.7	264.6	296.3	153.5
BIC	308.2	348.9	199.5	303.4	335.1	192.3

Note: Standard errors clustered at the study level and p -values are reported in parentheses; * indicates significant at 10% (p -values are between 5% and 10%); **significant at 5% (p -values are between 1% and 5%), ***significant at 1% (p -values are less than 1%).

Table 4. Fixed effects model of soybean yields, Specifications 1 and 2

	Specification 1			Specification 2		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
Growing season average temperature in C	-0.0135 (0.539)	-0.0240 (0.655)	-0.0105 (0.768)	-0.0169 (0.470)	-0.0232 (0.618)	-0.00631 (0.800)
Growing season total precipitation in mm	-0.0000662 (0.837)	-0.000104 (0.860)	-0.000038 (0.910)	0.0000542 (0.863)	0.000235 (0.705)	0.000181 (0.632)
Growing season average relative humidity in %	-0.0287*** (0.005)	-0.0511** (0.024)	-0.0224 (0.117)	-0.0274*** (0.005)	-0.0468** (0.015)	-0.0194 (0.152)
Growing season average cloud cover in %	1.213 (0.568)	0.206 (0.953)	-1.006 (0.650)	1.546 (0.404)	0.703 (0.845)	-0.843 (0.723)
Growing season average scPDSI index	0.0641** (0.016)	0.125 (0.112)	0.0604 (0.258)	0.0387** (0.021)	0.0472* (0.082)	0.00847 (0.596)
April precipitation 2.5 or more sd above historical mean				0.172 (0.128)	-0.0635 (0.868)	-0.235 (0.415)
June precipitation 2.5 or more sd above historical mean				-0.0624 (0.416)	-0.0502 (0.613)	0.0122 (0.724)
August precipitation 2.5 or more sd above historical mean				0.161*** (0.000)	0.453*** (0.000)	0.292*** (0.000)
Severe or extreme drought in May				-0.411** (0.035)	-0.654* (0.093)	-0.243 (0.223)
Severe or extreme drought in June				0.466 (0.135)	0.557 (0.230)	0.0909 (0.588)
Severe or extreme drought in August				-0.279 (0.197)	-0.608 (0.134)	-0.329 (0.137)
Year	-0.0107** (0.021)	-0.00735 (0.502)	0.00339 (0.665)	-0.0138** (0.049)	-0.0150 (0.249)	-0.00116 (0.865)
No-till used in conventional system	-0.0479* (0.080)	-0.041*** (0.004)	0.00686 (0.844)	-0.0470* (0.092)	-0.039*** (0.006)	0.00805 (0.822)
Rotation length in years in organic system	0.0735*** (0.000)	0.115*** (0.000)	0.0415*** (0.000)	0.0727*** (0.000)	0.113*** (0.000)	0.0404*** (0.000)
Constant	22.13** (0.018)	19.71 (0.324)	-2.416 (0.859)	28.06** (0.044)	34.36 (0.173)	6.293 (0.622)
Observations	126	126	126	126	126	126
AIC	-31.09	87.29	-2.689	-41.50	60.93	-30.05
BIC	-8.401	110.0	20.00	-15.97	86.46	-4.524

Note: Standard errors clustered at the study level. P values are reported in parentheses; * indicates significant at 10% (p values are between 5% and 10%); **significant at 5% (p values are between 1% and 5%), ***significant at 1% (p values are less than 1%).

Table 5. Fixed effects model of soybean yields, Specifications 3 and 4

	Specification 3			Specification 4		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
Standardized April average temperature	-0.0130 (0.536)	-0.00382 (0.936)	0.00915 (0.798)	-0.0347 (0.196)	-0.0391 (0.547)	-0.00440 (0.917)
Squared	-0.0487 (0.105)	-0.0695 (0.127)	-0.0207 (0.357)			
Standardized June average temperature	0.0441 (0.373)	0.0768 (0.185)	0.0327 (0.215)	0.0433 (0.484)	0.111 (0.122)	0.0679** (0.021)
Squared	-0.0359** (0.042)	-0.0301 (0.294)	0.00578 (0.739)			
Standardized August average temperature	0.0677*** (0.003)	0.121*** (0.008)	0.0533 (0.163)	0.0396* (0.050)	0.0758* (0.062)	0.0362 (0.323)
Squared	-0.00341 (0.834)	0.00948 (0.607)	0.0129 (0.379)			
Standardized April relative humidity	-0.0103 (0.805)	-0.0146 (0.807)	-0.00435 (0.879)	-0.0121 (0.616)	-0.0431 (0.521)	-0.0310 (0.506)
Squared	0.00781 (0.688)	0.0812*** (0.004)	0.0734*** (0.000)			
Standardized June relative humidity	-0.0817 (0.298)	-0.120 (0.145)	-0.0387 (0.502)	-0.0574 (0.467)	-0.0460 (0.548)	0.0113 (0.836)
Squared	0.0285 (0.139)	0.0445 (0.119)	0.0160 (0.523)			
Standardized August relative humidity	0.121*** (0.000)	0.196** (0.032)	0.0746 (0.303)	0.0781*** (0.001)	0.142* (0.093)	0.0639 (0.339)
Squared	-0.0150 (0.143)	-0.0380 (0.161)	-0.0230 (0.230)			
Standardized April Precip	0.0400 (0.182)	0.0394 (0.422)	-0.000575 (0.984)	0.0424** (0.027)	0.0744 (0.122)	0.0320 (0.328)
Squared	-0.0102 (0.252)	-0.00908 (0.654)	0.00109 (0.952)			
Standardized June Precip	0.0680*** (0.002)	0.124** (0.022)	0.0561 (0.196)	0.0808** (0.026)	0.111* (0.079)	0.0305 (0.339)
Squared	-0.0420 (0.130)	-0.0511 (0.391)	-0.00912 (0.796)			
Standardized August Precip	-0.0535 (0.137)	-0.00151 (0.982)	0.0520 (0.224)	-0.0299 (0.293)	-0.0562 (0.309)	-0.0263 (0.519)
Squared	0.0615** (0.022)	0.0312 (0.240)	-0.0303 (0.424)			
Standardized April cloud cover in %	-0.0755** (0.012)	-0.135** (0.034)	-0.0600 (0.144)	-0.0257 (0.281)	-0.130** (0.039)	-0.104* (0.051)
Squared	-0.00533 (0.765)	-0.0116 (0.719)	-0.00630 (0.806)			
Standardized June cloud cover in %	0.0391 (0.341)	0.0712* (0.063)	0.0321 (0.496)	0.00328 (0.875)	-0.0307 (0.571)	-0.0339 (0.580)
Squared	0.0182 (0.189)	-0.0220 (0.255)	-0.0402*** (0.006)			
Standardized August cloud cover in %	0.0384 (0.344)	-0.000240 (0.997)	-0.0386 (0.456)	0.0770** (0.010)	0.140*** (0.004)	0.0628** (0.018)
Squared	-0.00721 (0.694)	0.0273 (0.466)	0.0345 (0.176)			
Standardized April scPDSI	0.140*** (0.009)	0.0934 (0.103)	-0.0467** (0.037)	0.112** (0.034)	0.103 (0.114)	-0.00899 (0.808)
Squared	-0.0124 (0.706)	0.0233 (0.661)	0.0356 (0.191)			
Standardized June scPDSI	-0.0315 (0.756)	0.0593 (0.773)	0.0907 (0.500)	-0.0790 (0.453)	-0.0976 (0.484)	-0.0186 (0.724)
Squared	-0.0141 (0.676)	-0.0878 (0.231)	-0.0737 (0.183)			
Standardized August scPDSI	-0.0405	-0.0331	0.00736	-0.0163	0.0114	0.0278

Table 5. Fixed effects model of soybean yields, Specifications 3 and 4

	Specification 3			Specification 4		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
	(0.586)	(0.816)	(0.935)	(0.761)	(0.858)	(0.474)
Squared	0.0332 (0.326)	0.0391 (0.492)	0.00593 (0.852)			
April precipitation 2.5 or more sd above historical mean				0.0725 (0.205)	-0.192 (0.449)	-0.264 (0.217)
June precipitation 2.5 or more sd above historical mean				-0.288***	-0.356**	-0.0679
August precipitation 2.5 or more sd above historical mean				0.229* (0.060)	0.566** (0.015)	0.337** (0.014)
Severe or extreme drought in May				-0.358*** (0.003)	-0.356 (0.156)	0.00206 (0.991)
Severe or extreme drought in June				0.445 (0.156)	0.331 (0.527)	-0.115 (0.621)
Severe or extreme drought in August				-0.266 (0.252)	-0.506 (0.189)	-0.240 (0.219)
Year	-0.000783 (0.892)	0.00938 (0.155)	0.0102*** (0.005)	-0.00271 (0.615)	0.00777 (0.203)	0.0105*** (0.003)
No-till used in conventional system	-0.0500 (0.102)	-0.0378*** (0.004)	0.0122 (0.749)	-0.0496* (0.086)	-0.0389*** (0.005)	0.0107 (0.770)
Rotation length in years in organic system	0.0753*** (0.000)	0.112*** (0.000)	0.0369*** (0.000)	0.0750*** (0.000)	0.113*** (0.000)	0.0381*** (0.000)
Constant	1.088 (0.925)	-16.90 (0.194)	-17.99*** (0.009)	4.900 (0.648)	-13.71 (0.256)	-18.61*** (0.006)
Observations	126	126	126	126	126	126
AIC	-95.62	-1.239	-86.72	-76.85	8.359	-71.18
BIC	-70.09	24.29	-61.19	-51.32	33.89	-45.65

Note: Standard errors clustered at the study level and p -values are reported in parentheses; * indicates significant at 10% (p -values are between 5% and 10%); **significant at 5% (p -values are between 1% and 5%), ***significant at 1% (p -values are less than 1%).

Table 6. Fixed effects model of wheat yields, Specifications 1 and 2

	Specification 1			Specification 2		
	(1) ln(OA/CA)	(2) OA	(3) CA	(4) ln(OA/CA)	(5) OA	(6) CA
Growing season average temperature in °C	-0.116* (0.071)	-0.156 (0.114)	-0.0393 (0.345)	-0.109 (0.121)	-0.163 (0.115)	-0.0534 (0.196)
Growing season total precipitation in mm	0.000799* (0.088)	0.000628 (0.303)	-0.000171 (0.419)	0.000652 (0.162)	0.000770 (0.266)	0.000117 (0.656)
Growing season average relative humidity in %	-0.0491 (0.117)	-0.0813 (0.133)	-0.0322 (0.239)	-0.0484 (0.132)	-0.0822 (0.133)	-0.0337 (0.192)
Growing season average cloud cover in %	-1.273 (0.521)	-1.807 (0.610)	-0.535 (0.815)	-1.896 (0.374)	-1.235 (0.712)	0.661 (0.707)
Growing season average scPDSI index	-0.135*** (0.002)	-0.133** (0.011)	0.00241 (0.914)	-0.128*** (0.002)	-0.139** (0.012)	-0.0114 (0.571)
March precipitation 2.5 or more sd above historical mean				0.202 (0.229)	-0.203 (0.455)	-0.404* (0.074)
April precipitation 2.5 sd or more above historical mean				0.244*** (0.008)	-0.166 (0.189)	-0.410*** (0.000)
Year	0.0118 (0.520)	0.0132 (0.729)	0.00139 (0.956)	0.00968 (0.650)	0.0158 (0.658)	0.00615 (0.705)
Used legume precrops in organic system	-0.662** (0.032)	-0.956** (0.013)	-0.294*** (0.002)	-0.644** (0.048)	-0.977** (0.015)	-0.333*** (0.000)
Used legume precrops in conventional system	0.240 (0.410)	0.384 (0.285)	0.144* (0.089)	0.247 (0.410)	0.380 (0.295)	0.133* (0.069)
Used cover crops in organic system	0.103*** (0.000)	0.103*** (0.000)	0 (1.000)	0.103*** (0.000)	0.103*** (0.000)	2.37e-18 (0.934)
Used cover crops in conventional system	-0.289*** (0.006)	0.0402 (0.697)	0.330*** (0.000)	-0.244** (0.023)	-0.00567 (0.963)	0.239*** (0.001)
No-till used in conventional system	0.0569*** (0.000)	0.0174 (0.414)	-0.0395 (0.105)	0.0554*** (0.000)	0.0190 (0.258)	-0.0364** (0.039)
Rotation length of organic system in years	0.160*** (0.000)	0.153*** (0.004)	-0.00672 (0.805)	0.175*** (0.000)	0.137*** (0.004)	-0.0381 (0.467)
Constant	-19.57 (0.574)	-16.46 (0.825)	3.115 (0.950)	-15.09 (0.713)	-21.97 (0.751)	-6.876 (0.829)
Observations	95	95	95	95	95	95
AIC	-32.97	13.21	-65.90	-35.20	12.95	-88.67
BIC	-9.984	36.19	-42.92	-9.658	38.49	-63.13

Note: Standard errors clustered at the study level and p -values are reported in parentheses; * indicates significant at 10% (p -values are between 5% and 10%); **significant at 5% (p -values are between 1% and 5%), ***significant at 1% (p -values are less than 1%).