Weather and Climate Extremes 12 (2016) 69–79

Contents lists available at ScienceDirect

Weather and Climate Extremes

journal homepage: www.elsevier.com/locate/wace

Measuring the effects of extreme weather events on yields

J.P. Powell*, S. Reinhard

LEI, Wageningen University and Research Centre, The Netherlands

ARTICLE INFO

Article history:
Received 6 August 2015
Received in revised form
21 February 2016
Accepted 22 February 2016
Available online 23 February 2016

Keywords:
Extreme climate events
Wheat yields
Panel data
Netherlands

ABSTRACT

Extreme weather events are expected to increase worldwide, therefore, anticipating and calculating their effects on crop yields is important for topics ranging from food security to the economic viability of biomass products. Given the local nature of weather, particularly precipitation, effects are best measured at a local level. This paper analyzes weather events at the level of the farm for a specific crop, winter wheat. Once it has been established that extreme events are expected to continue occurring at historically high levels for farming locations throughout the Netherlands, the effects of those events on wheat yields are estimated while controlling for the other major input factors affecting yields. Econometric techniques are applied to an unbalanced panel data set of 334 farms for a period of up to 12 years. Analyzes show that the number of days with extreme high temperatures in Dutch wheat growing regions has significantly increased since the early 1900s, while the number of extreme low temperature events has fallen over that same period. The effects of weather events on wheat yields were found to be time specific in that the week in which an event occurred determined its effect on yields. High temperature events and precipitation events were found to significantly decrease yields.

1. Introduction

1. 1. Introduction

Weather, whether in terms of averages or events, is an important determinant of yields. Extreme weather events are expected to increase worldwide, therefore, anticipating and calculating their effects on crop yields is important for topics ranging from food security to the economic viability of biomass products. The latest IPCC report, confirming previous findings, attaches high confidence to the probability that extreme weather events will reduce food production (Field et al., 2012; Porter et al., 2014). Extreme events are expected to effect the volatility of yields and are seen as the principle immediate threat to global crop production (Meehl et al., 2000; Rosenzweig et al., 2001; Olesen et al., 2007; Urban et al., 2012; Min et al., 2011; Lobell et al., 2013). A natural question that arises is how to measure their effects on yields. We know from the above and other studies that variations in weather events are geographically specific, thereby implying that effects need to be examined at a correspondingly low level of analysis. An analysis of short-term weather events requires detailed time series data on weather variables at low spatial and temporal levels and corresponding data for all of other primary factors influencing yields. The approach taken in this paper is to examine the effects of uncommon precipitation and temperatures events of short duration on winter wheat yields. By precisely analyzing the effects of observed events over a relatively short time span it become possible to anticipate the effects similar such events will have in the future when their occurrence is expected to increase.

The paper consists of two main threads: first, the increasing occurrence of extreme weather events, formally defined below, is established in order to motivate the relevance of the topic. Daily time series analyses using data from up to 100 years are used to establish and forecast the development of extreme precipitation and temperatures events for over thirty regions in the Netherlands. Once the case has been made that the number of such events is either increasing and will continue to do so into the future, then the potential of extreme weather events to alter wheat yields is calculated using econometric techniques. In order to econometrically ascertain their specific, marginal, effects on yields, it is necessary to include all major inputs needed to produce winter wheat into the econometric model. In short, the specific effects of weather events on yields can only be correctly isolated once the effects of other production factors, including unobserved factors, have been filtered out or controlled for in a model. In this analysis, we combine production input data used of winter wheat, e.g., labor, capital and land, for over three hundred farms in the Netherlands from 2002 to 2013 with daily precipitation, temperature and evapotranspiration (ET) data measured at the local

* Corresponding author.
E-mail addresses: jparkerpowell@gmail.com (J.P. Powell), Stijn.Reinhard@wur.nl (S. Reinhard).

http://dx.doi.org/10.1016/j.wace.2016.02.003
2212-0947/

level. We test whether all of these various types of data are necessary in order to isolate the effects of extreme weather events on yields.

1.2. Literature review

The impact of weather on yields has been analyzed in relation to several objectives. Traditionally, crop growth models attempt to simulate average crop growth while econometric approaches are used to link inter-annual variation in weather with yields. For example, inter-annual variation in yields has been estimated using experimental plots resulting from the weather conditions in a particular year (Oskam and Reinhard, 1992). That study included data on weather and nitrogen fertilizer over the period 1948–1964 and divided the Netherlands in five regions based on location and soil type. Other studies have estimated inter-annual variation in yields of winter wheat, sugar beets, and starch potatoes using farm level panel data including nitrogen fertilizer and the acreage planted (Leneman et al., 1999). In that study, weather effects, both direct and indirect, were captured by including year dummies (1975–1996) in the regressions.

The last decade has seen a variety of techniques applied at farm and regional levels which have begun to map the effects of climate change at a local level. A meta-analysis of crop yields for several crops under climate change conditions concluded that the inter-annual variability of mean yields is likely to increase and the consensus in the literature is that yield changes will be negative beginning in 2030 (Challinor et al., 2014). Recent studies of extreme events in Europe point to an increase in the number of warm days and nights, and a decrease of the number of cold days and nights (Porter et al., 2014). Several studies also indicate general increases in the intensity and frequency of extreme precipitation events particularly in winter months during the last four decades, however, inconsistencies between studies, regions and seasons are reported (Hirschi et al., 2011; Vautard et al., 2007; Seneviratne et al., 2010; Berrang-Ford et al., 2014; Yamamoto et al., 2014; Sugiyama et al., 2014; Moriondo et al., 2011; Calzadilla et al., 2013).

The diverse nature of prolonged drought and excess precipitation was found to effect specific aspects of the growth cycle of a given crop and associated field management. Extreme weather events can directly impact the physiological processes of a crop through physical damage, but can also affect the timing and conditions of field operations. Due to differences in growth patterns among crops the impact of warming temperatures and weather extremes is crop dependent (van der Velde et al., 2012). A study at the global level used various weather scenarios to measure the effects of extreme weather events on agricultural regions with diverse crops and found that higher temperatures and events may lead to significant reductions in crop yields (Rosenzweig et al., 2001). Insect, pest, and plant diseases may exacerbate those reductions. Another study used a model based on daily weather data to simulate yields under climate scenarios and concluded that the impact of climate changes on sunflower yields will be larger than that of winter wheat (Moriondo et al., 2011). Similarly, a wheat simulation model combined with local scale climate scenarios predicted that yield losses from drought will fall, but the yield losses due to heat stress will substantially increase (Semenov and Shewry, 2011).

Previous micro-level studies, including crop models, have shown that weather events affect yields. However, few of those models have included a complete set of the most important production factors affecting yields. That qualification aside, the net effects of extreme weather events have been shown to damage most crops, an observation that has most commonly been made in relation to rice yields (Wassmann et al., 2009; Welch et al., 2010). In general, extremely high daytime temperatures are damaging and occasionally lethal to crops (Schlenker and Roberts, 2009; Porter and Gawith, 1999). However, there is debate within the climate change literature in regards to the point at which temperatures begin to negatively affect yields (Porter et al., 2014). For instance, some statistical studies find a positive effect of daytime warming on yields when extremes are infrequently realized (Welch et al., 2010). Rice yields in some regions of China have been found to be positively correlated with higher temperatures, while other regions show negative correlations (Zhang et al., 2010). Another study found that the availability of smaller spatial-scale yield data may allow for improvements in the empirical relation between hot days, precipitation and yields (Hawkins et al., 2013).

The non-inclusion of important variables affecting yields leads to omitted variable bias, an irrecoverable problem affecting all model estimates (Greene, 2012, e.g.,). In addition, the local nature of weather, particularly precipitation, favors low level spatial studies, indeed, there appears to be a trend towards review studies in which conclusions from various micro-level studies are systematically extended to higher levels of aggregation (Porter et al., 2014, Chap. 7). For example, a recent study using a crop model to calculate the effect of multiple weather stress occurrences on wheat yields across fourteen European locations found that for all sites the overall adverse event frequency is much more likely to increase than to decrease (Trnka et al., 2014). Further points of comparison for the current study are briefly reviewed by country of analysis. Articles about the effects of climate change variables on Chinese agricultural production include articles by Tao et al. (2006), Wang et al. (2008) and Chen et al. (2010). The articles are principally phenological studies of the effects of climate change on agriculture production, including winter wheat, and use both panels and data analyzes techniques Tao et al. (2009, 2014). In particular, Tao et al. (2014) regress weather variables to explain wheat growth in China; You et al. (2009) conduct a similar study for China as the one proposed in this paper but at a higher level of aggregation and not specifically focused on extreme weather events. For India, Pathak et al. (2003) use a simulation model to examine the effects of weather variables on rice and wheat yields, however, no other production variables were included in their model. A study by Auffhammer et al. (2012), which analyzes rice yields in India, takes a very similar approach to the current study except that it uses a much higher level of time and spatial aggregation. Kucharik and Serbin (2008) and Lobell et al. (2005) conduct statistical analyses for, respectively, the United States and Mexico, but do not include production variables in their analyzes. Brisson et al. (2010) provides a comprehensive analysis, including time series and simulation models, of the variables that have led to stagnating yields in France, yet at a higher level of aggregation then the one we propose. Licker et al. (2013) use times series weather variables to examine changes in wheat yields in Picardy, France and Rostov, Russia. Gregory and Marshall (2012) using a physiological based model, report potato yield increases for Scotland as a result of warming temperatures. Finally, Ludwig et al. (2009) use a model to show that despite decreasing rainfall in Western Australia, simulated yields based on actual weather data did not fall. This paper contributes to the literature by including a comprehensive set of microeconomic data and weather variables at a very low level of aggregation to examine the marginal effects of weather events on yields.

The remainder of this paper consists of two parts. The first presents the case that extreme weather events have steadily increased in the Netherlands for more than a century. If the argument is accepted that such events are real phenomena that will persist and perhaps increase in the future, then it is worthwhile to establish whether and to what extent they will affect yields. The second part of the paper does so by estimating the net effects of extreme events on winter wheat farmers in the Netherlands for the period 2002–2013.

2. Dutch long-term weather trends

The following section describes the data and methods used to identify long-term weather trends in the Netherlands and assess the likelihood that those trends will continue into the future.

2.1. Weather trends data and methods

The concept behind the approach used to identify events, whether for the long or short term, was to record the number of days for which measures exceeded a specific threshold. Two general methods were used to identify events, the first method is a relative method comparing, for example, the high daily temperature for a specific day in a year with the high temperature for that same day across all years in the sample. The second method used an absolute scale which identified, for instance, the number of days in a week equal to or above 32 °C. Both the relative and absolute methods were used to identify event trends and included in panel regressions during the model selection phase, however, given their high correlation with one another only the relative results are presented in the trend section.

The relative method is an adaptation of the methodology presented in (Klein Tank et al. (2009). Data used to identify long-term trends has been collected for many years by the Royal Dutch Weather Institute (KNMI) at its primer weather station, station 260, which is located near the center of the country. Station 260 was chosen because it has the longest series of readily available data and the data has been homogenized. Four types of extremes were identified, daily high temperatures, daily low temperatures, precipitation, and the reference evapotranspiration (a measure of the potential water loss which is often used as a proxy for crop growth potential). The identical methodology was used to identify the extremes for each variable examined, however we describe the methodology only for the maximum temperature variable.

Daily maximum temperature data for each day in a given year was compared to data for that specific day across all years available. Temperature values above the 95% quantile were selected as extreme events. For instance, for a given day in a year there are 109 observations corresponding to the number of years in the data set; those days with temperatures above the 95% quantile were identified as extreme events. The 95% quantile is a somewhat arbitrary choice, the intention was to select very rare events, but still have enough of them to be able to draw statistically meaningful conclusions. Similarly, those days with temperatures below the 5% quantile for a given day across all years were selected as extreme minimum temperature events. Precipitation and evapotranspiration events were similarly identified. Evapotranspiration is calculated by the KNMI using the Makkink method (Hooghart, 1987).

Several alternative aggregation methods were tested in order to determine their effect on the number of events identified. The method described above takes a day as the unit of comparison, we also calculated events based on weeks and months. The methodology, take for example high temperatures and months, sums the number days with temperatures above the 95% quantile for a particular week or month in a year. The appropriate level of aggregation to use in the econometric analyses depends on the sensitivity of winter wheat across a time span for the event measured. For example, aggregating over months rather than a specific day produces more observations, but did not significantly affect the conclusions drawn. The choice of which aggregation level to use depends on the amount of data and the question at hand. An example might help to illustrate the issue. For winter wheat, the precise day a high temperature event occurs is probably not critical. For instance, whether an event occurs on July 24th or July 25th will make little difference to the overall yields realized on a farm and so those two events could be aggregated, stronger still, it is probably inappropriate to assume that events on the 24th are significantly different than events occurring on the 25th in terms of wheat production. However, the further apart two events are, the more likely they will be to have different effects on yields; events in early August will certainly affect yields more than events in late August because by late August the crop is harvested, therefore monthly aggregation is less appropriate. The testing several different aggregations and expert knowledge lead to the conclusion that a weekly aggregation is best.

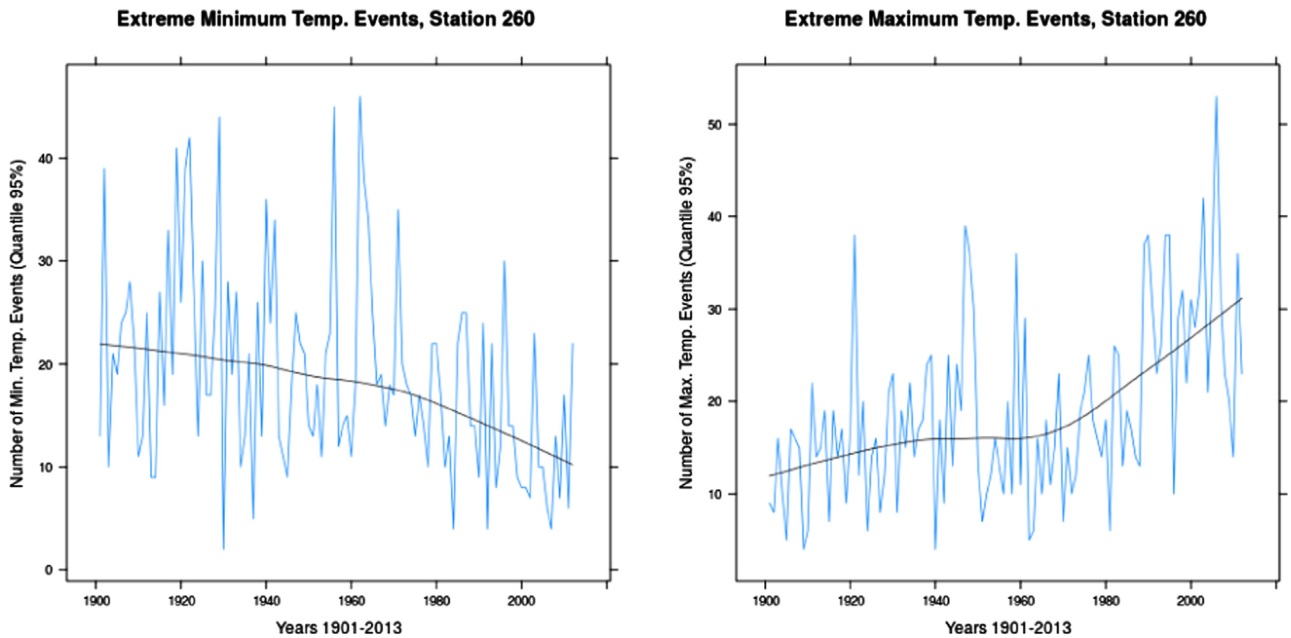
2.2. Weather trends results

This section first presents the changes in weather patterns that have occurred in the Netherlands. Both extreme events and average weather events are plotted through time in order to identify trends. Unless otherwise noted, figures were made using weekly aggregated data. All of the weather used in the paper were collected and disseminated by Royal Dutch Weather Institute (KNMI).

Fig. 1a shows that the number of yearly extreme low temperature events has decreased over the period from 1901 to 2013. The line near the center of the figure is a LOESS regression line showing, essentially, a locally weighted moving average trend line; its purpose is to help the reader to identify trends in the data. A Chow test was used to test where there was a structural break in the data in the 1970s, as the figures suggests but was rejected as was evidence of structural breaks in all other events analyzed. In short, there is no evidence that the number of events switched to another slope in the 1970s despite appearances in the figure. The slope across the entire data set is highly significant (t-value$=-3.64$), meaning that we can be confident that the trend is not a result of chance. An auto-regressive, integrated, moving average (ARIMA) model was used to fit and forecast weather event data. As necessary, the data has been differenced in order to transform non-stationary data to stationary data. The mean of the point forecasts of the fitted ARIMA(3,1,1) model over the period 2014–2023 was 12.6, indicating that the number of extreme low temperature events will remain low compared to the historical average of 18.8 over the entire sample. These point forecasts should be read with caution, Fig. 1a shows, and the ARIMA forecast confirms, that the amount of variation in the data is large; only the AR(2) and MA(1) approach significance (z values$=1.77$ and 22 respectively). This holds true for all of the extreme ARIMA regressions. The regressions are meant to be an aid to identifying general trends visible in the figures.

Fig. 1b plots the number of yearly extreme high temperature events from 1901 to 2013. The slope is again highly significant (t-value$=5.56$) and an ARIMA(0,1,1) model forecasts an average of 30.6 such events over the period 2014–2023, indicating that the relatively high number of extreme high temperature events are likely to continue compared to the historical number of yearly high temperature events of 18.8. The moving average term was found to be highly significant with a z value of over 17 while the trend was nearly significant ($z=1.72$). The findings for low and high temperature events correspond to those found in the most recent IPCC report, specifically, the occurrence of more warm days and nights compared to the historical average. The findings reinforce the importance of measuring the effects of those events on yields in anticipation of more such events in the future.

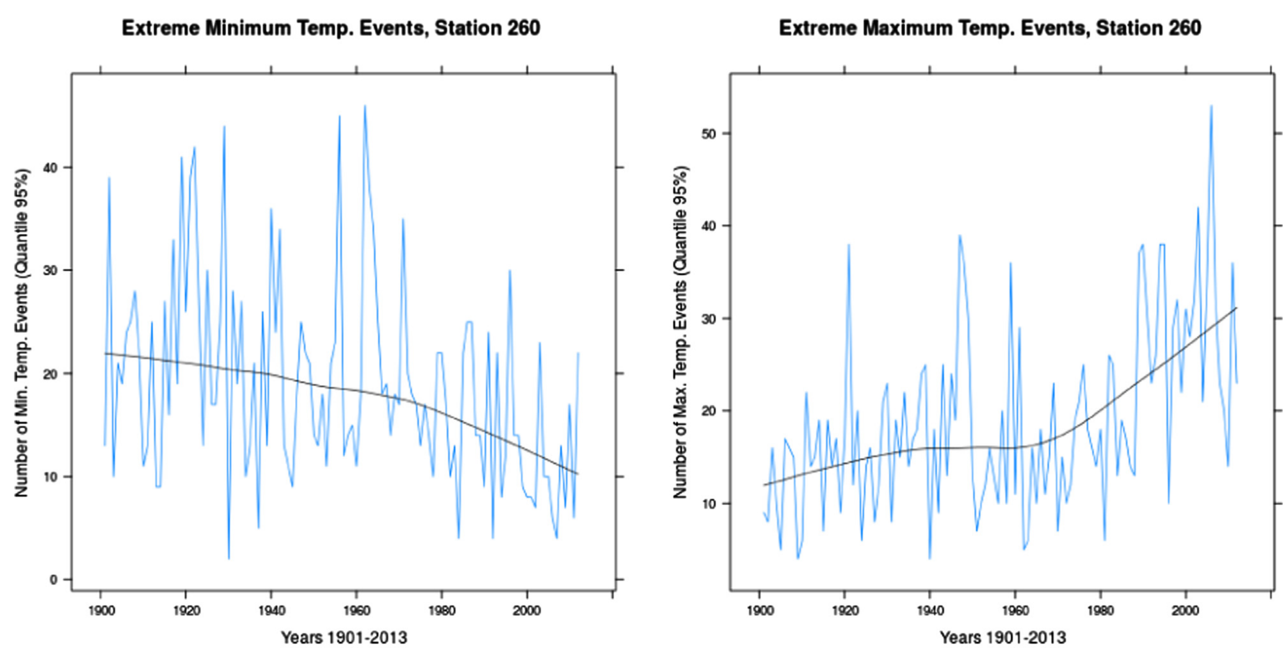
Fig. 2a shows that the number of days with extremely high amounts of precipitation has increased, a similar figure, not included, for days with no precipitation shows a strong decreasing trend. Given the historical trend, the Netherlands can expect to



(a) Extreme minimum temp. events.

(b) Extreme maximum temp. events

Fig. 1. Extreme temperature events, source original data: (Koninklijk Nederlands Meteorologisch Instituut (KNMI): Royal Dutch Meteorological Institute, 2014). (a) Extreme minimum temp. events. (b) Extreme maximum temp. events.



(a) Extreme precipitation events.

(b) Extreme evapotranspiration events.

Fig. 2. Precipitation and evapotranspiration events per month (Koninklijk Nederlands Meteorologisch Instituut (KNMI): Royal Dutch Meteorological Institute, 2014). (a) Extreme precipitation events. (b) Extreme evapotranspiration events.

experience more periods with heavy rains given that the regression slope is significant (t-value = 3.75). ARIMA results forecast an average of 23.4 events over the period 2014–2023. Fig. 2b shows that number of evapotranspiration events since 1957, the first year for which data is available, has been steadily decreasing. The t-value is significant (-2.45) and the ARIMA(2,1,1) model forecasts and average of 35 such events over the period 2014–2023, about the same as the historical average of 34.6 events. Nearly all of the AR (z values of 1.71, 1.98) and MA (49) terms are significant as was the trend (4.14).

The data presented in Fig. 4b is designed to show yearly changes in maximum temperatures, but with the data partitioned by month to keep the figure readable. The plotted lines are the LOESS regression lines of average high temperatures per month. The general trend across the entire period for all months is for a slight increase in maximum temperatures, particularly in the latter decades. Regressions against time show that April, July, August, October, November, and December have significant, positive, slope coefficients. A similar figure, not included, of minimum temperatures across all months shows a significant (t-value = 6.04), steadily increasing trend from 1902 to 2013. Temperatures, both the maximum highs and lows, appear to be increasing in the Netherlands although the changes vary by month.

The graphical and accompanying statistical evidence presented provide convincing evidence that high temperatures and precipitation events are occurring in historically high numbers; while low temperature and evapotranspiration events and are occurring in decreasing number. The results are robust, with similar patterns appearing across different time aggregations and definitions of weather events. ARIMA forecasts suggest that the number of events will either stabilize or continue to increase thereby all of which motivates the following section which estimate the impacts of events on yields.

3. Estimating effects of weather events on yields

Estimating the effects of weather events on yields requires specifying a suitable model. Given the number of potential variables in the data set, model selection involves a systematic removal of variables that are either redundant in terms of the information they convey or do not significantly add to the explanatory power of the model. The econometric method allows us to test the influence of extreme events and other inputs on yields. If an extreme event has no impact then that lack of influence should, ideally, be reflected in the econometric results, namely, the estimate for that variable should be insignificant. Ultimately, we are looking for measures that are highly correlated with and explain yearly changes in yields. Before turning to model specification, the primary potential model variables are described.

3.1. Weather in regressions

In addition to the relative event measures used to identify trends, absolute measures were defined for the same weather variables previously presented. In contrast to the relative measures which were identified using quantiles, absolute measures are a matter of choosing a threshold, for instance, daily measurements above or below a particular benchmark are identified as events. Choosing a good benchmark is crop, geographic, and time specific in the sense that crops in different regions are vulnerable to events at particular times during their development (van der Velde et al., 2012; Rosenzweig et al., 2001; Moriondo et al., 2011). In a sense, the term absolute is a misnomer in that farmers adapt their behavior to expected conditions where they are located and for the crops they farm. The term as used here primarily refers to events that are extraordinary for a given time in the Dutch winter wheat production cycle. Important months for the yields of winter wheat in the Netherlands are July and August when the kernel is forming, therefore weekly extremes were chosen with reference to those months (see Kennisakker (2014) and University of Kentucky (2014) for details). We are not claiming that only the weeks in those months are important for yields, for instance, during the winter months freezing temperatures are necessary for crop development. Rather, the focus of our study is on events that effect yields at one particularly vulnerable time in their development.

The thresholds of thirty-two degrees Celsius and above and ten degrees Celsius and below were identified as extremes for the weeks in our study. Thirty-two degrees was chosen because temperatures above thirty degrees are defined as tropical or extreme by the KNMI. Both benchmarks were chosen with reference to the data presented in Table 1 which shows that the benchmarks chosen are above and below their respective quantiles for given

Table 1
Data description.

Variable	Mean	Standard deviation	10% Quant.	90% Quant.
Yields kg/ha	8144.82	1988.54	5386.80	10392.44
Pesticides euros/ha	177.91	84.85	62.87	274.23
Fertilizers euros/ha	138.31	80.63	34.55	237.98
Farm size ha	85.59	69.10	21.61	162.78
Land euros/ha	221.80	838.00	17.55	377.55
Capital euros/ha	268.41	1556.92	8.34	354.51
Labor euros/ha	438.74	1926.75	18.79	638.05
Precip. Evt. Abs. Week 26	158.52	141.99	0.05	338.05
Precip. Evt. Abs. Week 32	192.27	148.75	27.05	398.61
Avg. Week Max Temp. Week 26	216.13	28.21	179.86	255.43
Avg. Week Max Temp. Week 32	222.01	29.90	197.57	258.57
Avg. Week Min Temp. Week 26	120.50	18.15	96.86	145.00
Avg. Week Min Temp. Week 32	133.83	20.07	108.57	163.14
Avg. Week Evap. Week 26	34.40	6.60	25.86	44.00
Avg. Week Evap. Week 32	27.00	4.65	21.57	32.34
Precip. Evt. Abs. Week 26	0.46	0.69	0.00	1.00
Precip. Evt. Abs. Week 32	0.54	0.65	0.00	1.00
Max Temp. Evt. Abs. Week 26	0.07	0.29	0.00	0.00
Max Temp. Evt. Abs. Week 32	0.22	0.85	0.00	0.00
Min Temp. Evt. Abs. Week 26	1.68	1.68	0.00	4.00
Min Temp. Evt. Abs. Week 32	0.90	1.17	0.00	3.00
Evap. Evt. Abs. Week 26	0.33	0.52	0.00	1.00
Evap. Evt. Abs. Week 32	0.32	0.55	0.00	1.00
Conseq. Days Precip. Week 26	0.46	0.69	0.00	1.00
Conseq. Days Precip. Week 32	0.54	0.65	0.00	1.00
Precip. Evt. Quantile Week 26	0.35	0.55	0.00	1.00
Precip. Evt. Quantile Week 32	0.37	0.54	0.00	1.00
Max Temp. Evt. Quantile Week 26	0.41	0.74	0.00	2.00
Max Temp. Evt. Quantile Week 32	0.34	1.05	0.00	1.00
Min Temp. Evt. Quantile Week 26	0.24	0.52	0.00	1.00
Min Temp. Evt. Quantile Week 32	0.29	0.59	0.00	1.00
Evap. Evnt. Quantile Week 26	0.43	0.58	0.00	1.00
Evap. Evnt. Quantile Week 32	0.42	0.59	0.00	1.00

Note: data is for all years across all farms. Original data: (LEI, 2014a, 2014b).

weeks of the year. Similarly, days with precipitation above 10 mm and evapotranspiration above 5 mm were flagged as events. Other measures include a measure of the number of consecutive days with precipitation above 10 mm.

In addition to including extreme events in regressions, average weekly daily temperatures and precipitation amounts were considered for inclusion in the regressions. These variables, when falling within normal ranges, are expected inputs into the wheat production process and therefore should be included in the regressions along with other inputs. These weather data represent the general underlying trends, as opposed to disruptive events. Another reason for considering their inclusion is that doing so allows us to measure the effects of extreme events net of the effects of their expected, normal, values.

As opposed to the weather data used in the trend analysis section, weather data used in current section consists of data collected for 35 weather stations located throughout the Netherlands of which 29 or 30, depending on the weather variable measured, are used in the analyses. Weather data from 2002 to 2013 is used and matched with farm data which is only available over the same period.

Although the Netherlands is a small country (41,543 km^2), there is a great deal of variation in weather across the country on any given day. This variation across space effectively multiplies the number daily observations. For example, instead of one temperature observation per day there are effectively 30 different, although correlated, observations, one for each weather station and associated farms in the data set. The weather data for a particular station was assigned to a farm based its proximity, with the station closest determining the events for a particular farm.

Critical weeks for winter wheat yields in the Netherlands are in the last weeks before harvest when the wheat is ripening. In general, harvest begins somewhere in the second half of July in the southern provinces and gradually extends to the northern provinces. Both drought and dampness can affect winter wheat yields in these periods. In order to avoid the problems of damaged kernels and germination, an acute problem in wet circumstances, harvest has to begin at the right moment. Timing of the harvest is largely dependent on the dampness of the kernel with the ideal dampness at harvest at around 15–16% in the kernel. Too damp and the wheat cannot be stored for long, particularly if the temperature is above 15 °C. Dampness can also increase the likelihood of fungus infections. Kernels are also susceptible to damage if too dry. Tropical temperatures, defined as temperatures over 30 °C as defined by the KNMI, can damage wheat in this period. However, enough rain and dampness in the ground can prevent high temperature damage.

3.2. Farm data and method

Farm level data used in the analysis is collected by LEI (LEI, 2014a). LEI, a part of the Wageningen University and Research Centre, the leading agricultural research institute in the country, is responsible for, among other activities, collecting, analyzing and disseminating agricultural data to national and international organizations.

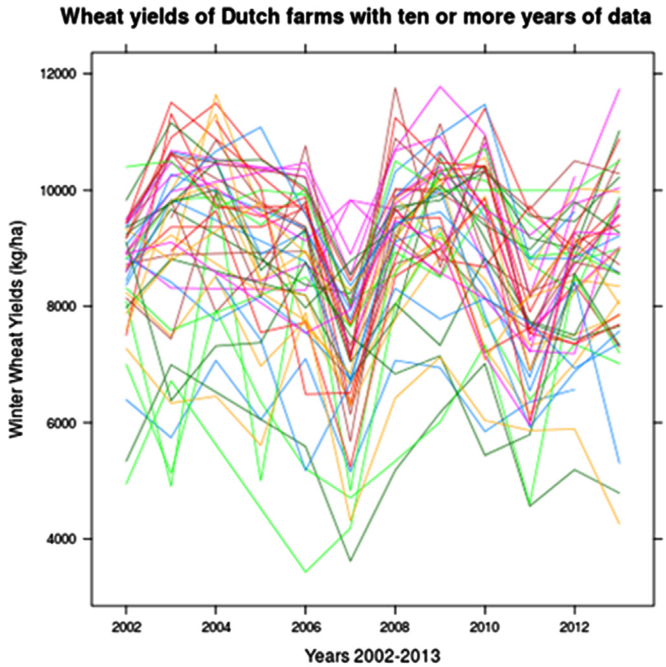
The initial economic data set considered for inclusion in the analyzes to follow consists of the main inputs used to produce winter wheat on 334 farms over the period 2002–2013 throughout the Netherlands. Winter wheat is the most important grain grown in the Netherlands and the country enjoys one of the highest wheat yields in the world. The main inputs are: fertilizers, pesticides, energy, labor, capital, a catch-all account called other inputs, and four soil types. Data are converted to their per hectare equivalents. The econometric method prizes parsimony as one element of a model and it is the reason why it is common to report the adjusted R-squared instead of the R-squared. Adjusted R-squared, like other econometric measures of comparison such as the Akaike information criterion and Baysian information criterion (Greene, 2012), penalize the addition of explanatory variables. In short, a model with fewer exogenous variables and the same explanatory power will be preferred to models with the same explanatory power and more variables. Variables that are highly correlated with one another are candidates for removal for reasons of parsimony, but also to avoid the problem of multicollinearity. This is not to say that the variables removed from the model are unimportant, only that their effects are already incorporated within the model by the included variables.

Dutch farms generally produce several different crops in a given year, therefore it is necessary to apportion the share of a farm's total productive resources to the share that is used to produce winter wheat. The method used here was based on the portion of profits derived from winter wheat in a farm's total yearly profits. For instance, if 50% of a farm's costs before tax profits came from winter wheat in a given year, then 50% of the total energy of a farm for that year were assigned to wheat. This is not a perfect methodology, for instance, some crops use more energy than others, but it is an economically sound approximation given that the costs that a farmer is willing to incur to produce a product are likely to reflect the relative profitability of that crop. Other apportionment methods were tried such as apportioning based on the area of a farm devoted to the production of winter wheat relative to the total size of a farm, but no appreciable differences were observed in the results. Similarly, the panel models were run using the quantities of variables used rather than their value in euros, again, no appreciable differences were noted in either the relative importance of estimates or their significance.

Indicators presented in Table 1 show the means, standard deviations, and 10% and 90% quantiles of the economic and weather variables used in the panel regressions. A feature of the data is the large standard deviations for the economic data, this implies a great deal of variation across Dutch farms in terms of the amounts of inputs they use per acre. This variation is important in the analysis; econometric methods depend upon such variation in order to calculate statistically meaningful results. It is this variation across time and across farms which makes the panel method employed effective. It allows us, essentially, to multiply the number of observations in the analysis and cover a wide range of differing input combinations and weather events.

Capital costs are based on yearly depreciation expenses. Labor costs are the total wages paid to all labor employed in the production process including an estimate of the value of the farmer's own labor. Energy includes both diesel and electricity costs. The costs of land are represented the mortgage paid for farm land. In addition to the land costs, we also include the area of land to test for the returns of additional land. Fertilizers include costs for both nitrogen and phosphate, while pesticides include all inputs used to protect plants. Other variables were tested, in addition to using quantities, we tried: including nitrogen and phosphate as separate explanatory variables; using only the active pesticides rather than all inputs used to protect plants; including electricity and diesel as separate regressors, and; using only the wages of permanent farm employees by excluding the wages of temporary workers. However, none of these variations led to notable changes in the general conclusions which could be drawn from the final model.

The type of soil used to grow winter wheat greatly effects yields. There are ten relevant soil types in the Netherlands, these were consolidated into five major categories: sand, peat, loess, clay and mixed soil types. Peat is a spongy soil type that forms at the bottom of swamps and is found in the northern and western Netherlands; it tends to retain water. Loess is a rich soil primarily composed of sand and/or silt and to a lesser extent clay; it, like



(a) Production for farms with data for all eleven years in the study.

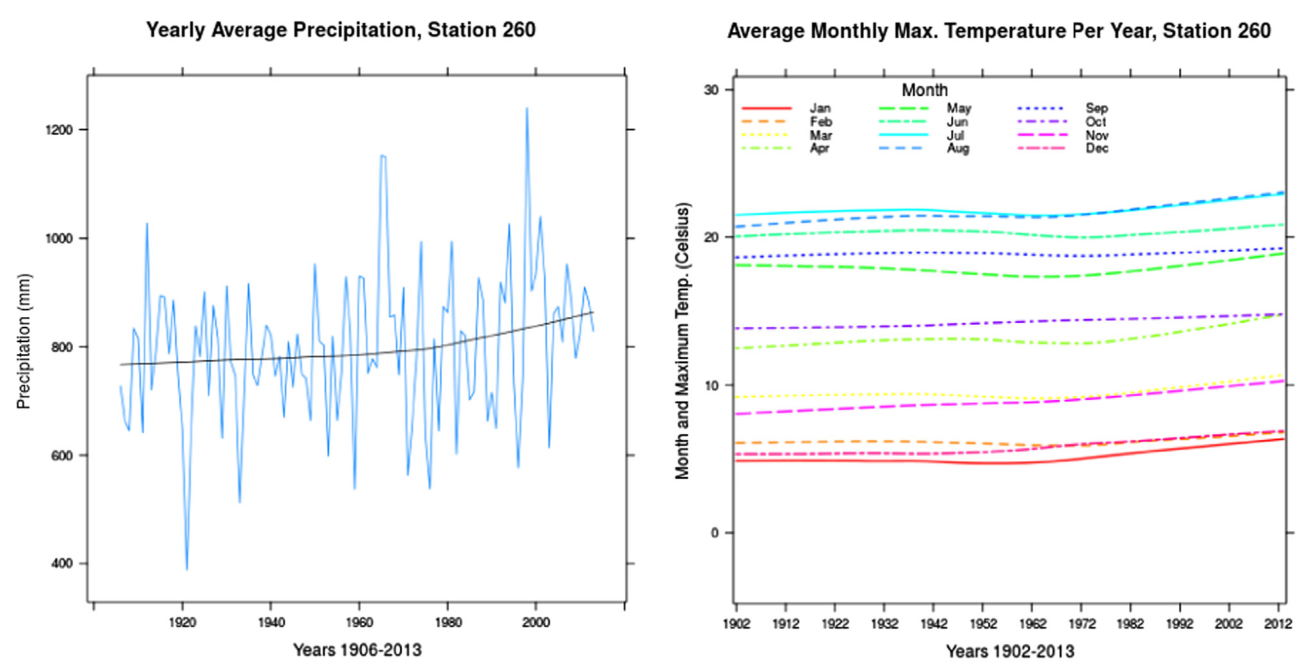
Fig. 3. Yields and average precipitation amounts (mm) in across important wheat growing months (Koninklijk Nederlands Meteorologisch Instituut (KNMI): Royal Dutch Meteorological Institute, 2014). (a) Production for farms with data for all eleven years in the study.

sand, has good drainage. Clay naturally tends to trap water which can damage wheat in periods of heavy rains, however, it is the most commonly taken to be the most productive soil type.

Fig. 3a shows wheat yields for a representative subset of the farms in the data set over the period 2002–2013. While there is a great deal of variation across farms, yields tend to move in the same direction and in response, presumably, to similar underlying disturbances. In short, there appears to be enough variation and yet enough similarity between farms in the Netherlands to make statistical analyses meaningful (Fig. 4).

3.3. Model specification

Model specification concerns which variables to include in the model and in which form. There is a high degree of correlation between many of the weather variables and a few of the economic variables; the question is whether to remove one of the correlated variables and, if so, which one to remove. Using weekly weather data and absolute and relative measures of weather events results in a hundreds of potential weather variables. That number was substantially reduced by concentrating the analyses on the weeks in July and August. The number of variables was further reduced by using a combination of statistical tools and expert knowledge. The first step was to run a basic linear regression model using all of the presumably relevant variables, and then use variance inflation factor (VIF) analysis to identify highly correlated variables. The VIF is a standard econometric technique used to quantify multicollinearity in an ordinary least squares regression analyses (Studenmund, 2006). The simple correlations of variables identified as problematic by VIF were then used to remove highly correlated variables from consideration in the regressions. For instance, high correlation was identified between the number of consecutive days with precipitation over 10 mm, absolute precipitation events, and the total number amount of rain in a given week, indicating that perhaps any one of these indicators could be used as a proxy for the others and that only one of them should be included in the model. Similar high correlation was observed for weekly average low and high temperatures and their corresponding weekly events. Finally, high correlation between measures of absolute and relative events was identified as a potential problem.



(a) Sum of monthly precipitation per year. per year.

(b) Average monthly temperatures

Fig. 4. Time series Dutch of precipitation and temperatures. Source original data: (Koninklijk Nederlands Meteorologisch Instituut (KNMI): Royal Dutch Meteorological Institute, 2014). Station 260 is located in Utrecht, close to the center of the Netherlands. (a) Sum of monthly precipitation per year. (b) Average monthly temperatures per year.

The degree of correlation between two or more variables is only an indicator of whether to remove a variable from a regression, if, with the exception of extremely high correlation which results in multicollinearity, there is a good economic or another reason to include a variable in a regression despite high correlation with other variables, then it should be included. That said, the decision was made to include only absolute measures rather than relative measures for consideration because some absolute measures have a recognized phenological effect on wheat whereas relative measures do not. In addition, high correlation between the absolute and relative measures indicate that these measures are identifying exceptional events.

Finally, the decision was made to include both high temperatures and evapotranspiration rates for consideration in the model. These two variables capture different processes, in particular, the evapotranspiration variable captures potential interactions between precipitation and high temperatures (Hiemstra and Sluiter, 2011). We follow convention by including typical inputs into the farm production function: fertilizers, pesticides, energy, labor, capital and other costs. In addition, farm size was included to capture the effects of scale on the production process. Only the costs of land per ha were removed because of its very high correlation with capital and labor costs.

Even after the problem of correlation was addressed, the potential number of variables was still large. While the decision to include only absolute measures of weather effectively halved the number of weather variables, each of these variables, precipitation, high and low temperatures and evapotranspiration, included seven weeks of data covering the period from the beginning of July to middle August. Given the exploratory nature of the study, a final selection of variables was made using measures of best fit. The procedure used was to include permutations of all of the remaining potential variables in regressions and choosing the best model based on the adjusted R-squared. The variables finally selected are those found in Table 1.

The data were then used to run a series of panel regressions with wheat yields as the endogenous variable and the other variables, including a measure of the effects of time, as explanatory or exogenous variables. It is common practice to include time effects in panel regressions to account for changes through time not otherwise identified (Baltagi, 2008). Results for three models are reported in Table 2. The Complete model, which includes both the economic and weather exogenous variables, and separate models for the economic and weather variables. By comparing results across models, we will be able to draw conclusions about the importance of each group of variables in

Table 2
Panel results.

Coefficient	Complete model		Economic model		Weather model	
	Estimate	*t*-value	Estimate	*t*-value	Estimate	*t*-value
Pesticides euros/ha	12.854	8.608	12.766	8.445		
Fertilizers euros/ha	3.297	2.809	3.905	3.289		
Farm Size ha	−6.154	−1.761	−5.728	−1.617		
Capital euros/ha	0.324	4.897	0.329	4.918		
Pesticides	−0.020	−6.462	−0.020	−6.273		
Fertilizer	−0.006	−1.897	−0.006	−2.202		
Farm size	0.015	1.747	0.015	1.710		
Capital	−0.000	−4.273	−0.000	−4.376		
Soil loess	−502.641	−1.240	−668.176	−1.626		
Soil mixed	−83.427	−0.398	−94.582	−0.447		
Soil peat	−208.77	−0.549	75.084	0.201		
Soil sand	93.259	0.313	22.860	0.076		
Precip. Evt. Week 26	31.650	0.596			−15.622	−0.286
Precip. Evt. Week 27	−11.754	−0.298			−2.939	−0.072
Precip. Evt. Week 28	58.236	1.291			51.591	1.106
Precip. Evt. Week 29	−50.538	−1.012			−14.479	−0.280
Precip. Evt. Week 30	−25.549	−0.475			−26.496	−0.475
Precip. Evt. Week 31	−91.294	−2.268			−135.172	−3.254
Max. Temp. Evt. Week 27	−429.745	−4.851			−440.821	−4.797
Max. Temp. Evt. Week 29	−49.702	−0.624			−52.223	−0.633
Max. Temp. Evt. Week 30	−151.491	−1.050			−162.867	−1.087
Max. Temp. Evt. Week 32	62.689	1.296			23.765	0.478
Min. Temp. Evt. Week 26	35.209	1.238			41.566	1.409
Min. Temp. Evt. Week 27	−2.011	−0.052			0.098	0.002
Min. Temp. Evt. Week 29	−85.863	−1.954			−92.196	−2.020
Min. Temp. Evt. Week 30	−140.914	−2.787			−150.367	−2.871
Min. Temp. Evt. Week 32	111.207	3.280			97.788	2.775
Evap. Evt. Week 27	−200.450	−1.706			−209.200	−1.733
Evap. Evt. Week 27	−200.450	−1.706			−209.200	−1.733
Evap. Evt. Week 28	−148.745	−1.490			−111.177	−1.075
Evap. Evt. Week 30	76.901	0.620			−0.758	−0.006
Year 2004	418.305	2.237	458.094	3.157	363.197	1.882
Year 2007	−1675.280	−10.198	−1565.259	−16.423	−1778.394	−10.461
Year 2011	−1027.684	−4.536	−1101.385	−11.564	−995.056	−4.266
Year 2012	−573.073	−4.197	−460.655	−4.585	−376.207	−2.711
Year 2013	−508.192	−3.359	−199.596	−1.891	−320.623	−2.063

Note: the Complete model includes both the economic and weather variables, the Economic model includes only economic variables, while the Weather model consists of only the weather variables. The coefficients all three models are for the fixed effects or 'within' model and include time effects as well as individual effects. Standard tests strongly reject a common group intercept (p=3.26e-87). The F-statistic (374,1454) for the entire model is 11.89° of freedom with a corresponding p-value of less than 6.3e-267. Adjusted R-squared=0.69. A F-test (368,1460)=12.06 indicates the overall the regression is significant (p-value=9.2e-269). A F-test (333,1460) rejects an OLS model specification in favor of the within specification (p-value=1.237e-88). A Wald test Chi-squared (11)=156.25 for joint significance of time dummies for all years is reject (p-value=7.86e-28). A Hausman test favors the within over the random effects form of the model (ChiSq (35)=147.01, p-value=1.12e-15). Finally, Wald tests favor the Complete model over either the Economic or Weather models (ChiSq=0.0012 and 2.0e-11 respectively).

determining yields. In particular, the comparison is important because it allows us to determine just how wrong we might be when only regressing yields against weather variables as is common in highly aggregated studies.

The within form of the panel model was chosen over the OLS and random effects models. The within model removes the effects of both unobserved and observed variables affecting yields (Baltagi, 2008). The statistics comparing these models are reported at the end of Table 2. The essential messages of those statistics are that, on the whole, individual Dutch farms have distinguishing characteristics and should be analyzed as individuals rather than lumped together as single set of data. In addition, a Hausman test indicates that the assumptions of the random effects model are not met, and so we use the within form (Greene, 2012). A test of the joint significance of the time variables is rejected, however, individual years were found to be significant as measured by their *t*-values. In particular, the years 2004, 2007, 2011, 2012 and 2013 were found to be significant, with yields in 2004 above average and those in 2007 and 2011 below average. The effects in 2007 and 2011 are clearly visible in Fig. 3a.

The first two columns in Table 2 present results for the Complete econometric model; the model which includes both economic and weather variables. Columns three and four show results for the Economic model; only the economic variables plus soil type and time are included in the model. Columns five and six present results for the Weather model which only includes time and the weather variables. A working assumption, later statically confirmed, is that the economic and weather models are wrong to the extent that they are misspecifications, i.e., they omit important determinants of yields out of the model. They were modeled precisely for that reason, to allow us to speculate on the effects of leaving out variables given that they are frequently not available or of poor quality in more aggregated studies. As reported in Table 2, Wald tests of comparing the Complete model with the Economic model and the Complete model with the Weather model reject the nulls, i.e., the Complete model is preferred to either of those two models.

The estimate column for each of the models shows the effect of a one-unit increase in a variable on the kilograms per hectare (yield) of winter wheat produced. The *t*-value reports the statistical confidence that can be placed in the variable, by convention, an absolute *t*-value of around 1.96 or greater is considered significant. Those t-values with absolute values less than 1.96 are considered to be insignificant in the sense that their contribution to the explanatory power of the model cannot be distinguished from zero, in short, they do not help to explain changes in yields given the other variables in a model.

Pesticides, fertilizers, and capital in the Complete model are all significant and have the expected sign, i.e., the more of these inputs added to the production of wheat, all else equal, the greater the yield. The negative, significant, sign for farm size indicates that increasing the size of a farm reduces yields. Quadratic terms for each of these variables were also included in order to assess the whether diminishing returns are present. Although none of the coefficients is large, they are all significant or nearly so and have a negative sign indicating decreasing marginal productivity. The coefficients for three of the four soil types, although insignificant, are as expected in that they are all negative because they are calculated in relation to wheat grown on clay, generally regarded as the most productive of the soil types in the Netherlands. The coefficient for sand, is positive; indicating that, all else equal, it is more productive than clay (which is absorbed in the intercept term). This result could be due to the drainage properties of sand, that is confirmed in previous studies (Oskam and Reinhard, 1992).

Turning to the effects of the weather variables in the Complete model, recall that variables are categorized according to whether they are events or averages. Given that we chose to use weekly rather than, e.g., monthly data, the effects of events and average values for the same variable in a given week are naturally highly correlated; accordingly, the decision was made to only include event variables. Although quadratic terms for each of these variables were included in the model, they were all insignificant and dropped from the final specification as were interaction terms.

The model indicates that events can have either positive, negative or no effect on yields. This is unsurprising given that we know that wheat kernels can be damaged by either too wet or too dry conditions. Results in the table can be read, loosely, as the average effects of these events on yields across all farms over the period 2002–2013. The only precipitation event that has significant effect on yields, is the precipitation event in week 31. This is near the end of the harvest season, and the effect is negative. Furthermore, the significance of the other precipitation terms remained low even when evapotranspiration events were removed from the model or when only weekly sums of precipitation and low and high temperature events were included in the model.

The coefficient for high maximum temperature events in week 27 (July 1st in 2013) is significant and negative, indicating that high temperature events near the beginning of the harvest season damage crops or, perhaps, force farmers to harvest before the yield has reached its maximum. They remained so in nearly every permutation of variables tried. The estimate for week 27 tells us that one additional high temperature event will lower yields by nearly −430 kg per hectare. Given the average yield in Table 1, this represents a loss of around 5%. The effects of low temperature events were also significant and negative in the 29th and 30th week. Low temperature events in the middle and near the end of the harvest season, depending on the specific year, have negative effects on yields. The only positive effect of weather events observed is for cool days in the 32nd week near the end of the harvest season. Cooler days in that week are associated with higher yields.

The Wald-test favors the Complete model over the Economic and Weather models. Comparing the Complete model with the Economic model illustrates the importance of including weather variables. Although none of the variables that are significant in both models change signs, their magnitudes do change, in some cases substantially. A comparison of the Complete model with the Weather model indicates that a researcher would, in general, overestimate the negative effects of significant weather events, using the Weather model. Although the signs of the estimates that are significant in both models remain stable, their magnitudes are quiet different, to the degree that they might convey the wrong impression.

4. Discussion and conclusions

4.1. Discussion

The added value of the current research is a narrowly focused analysis of the net effects of weather events on winter wheat yields at a local level after having controlled for the effects of differing production inputs and hidden fixed effects. There is a tension between precision of results and general applicability. The full value of the findings presented here will be realized when they are placed in a wider context along with other micro-level studies. We measure and report the combination of direct and indirect effects of weather events on Dutch winter wheat yields. Dutch farmers are some of the most productive in the world, they have access to the latest technologies and operate in an efficient, stable, economy, and have ready access to a large market. All of which allows them a degree of flexibility in how they produce, harvest, and distribute their products, thereby affording them a degree of insulation from environmental changes. Farmers in countries without these characteristics will presumably be more susceptible to extreme weather events. In short, the findings presented here need to be combined with other micro-level economic studies. Wheat production and consumption takes place within a global market which will adjust to prices and other economic indicators. Understanding how the production and consumption of wheat and other crops will react to climate changes will require placing micro-level studies into a wider context. The trick will be to retain the information contained in low aggregation studies while scaling-up the analyzes to levels at which global policies can be influenced.

Another characteristic of using micro-level data, particularly precise weather data, is the possibility of incorporating local knowledge. Our study required us to focus on a particularly susceptible period in the development of winter wheat in the Netherlands in order to retain adequate degrees of freedom in the regression models. Although this trade-off allows us to focus analyses on events that are most likely to affect yields when they are most vulnerable, we were required to limit the time frame of the study. That said, studies using data at higher levels of aggregation run the risk of incorporate weather events that do not significantly affect yields. In contrast to the low level analysis used here, highly aggregated econometric studies cannot disentangle changes in yields attributable to changes in weather variables versus changes attributable to other inputs simply because important yield determining variables cannot reasonably be included in such models (Lobell and Field, 2007; Lobell et al., 2011).

Our Complete model is comparable with that of (Oskam and Reinhard (1992). They aggregated weather over the entire growing season using monthly temperature and sum of evapotranspiration, but they did not include weather extremes. In their model, the time trend was significantly negative for three out of five regions and follows a similar pattern to the pattern observed in this paper. Both the temperature and evapotranspiration show decreasing marginal returns in their model, indicating that excess temperature and evapotranspiration reduce yields.

Another result, using meteorological information on temperature and precipitation during the growing season at a higher level of aggregation than our study, suggests that careful consideration of nonlinear technology trends and an interaction between temperature and precipitation is essential in any empirical mode (Hawkins et al., 2013). All of our quadratic and interaction terms were found to be insignificant, perhaps, as discussed, due to the short time scale used in our analysis. Finally, a study comparing observed and modeled yields of wheat and maize in France in two years with extreme conditions, found that both years adversely affected yields (van der Velde et al., 2012). Our results confirm that yields in 2007 were extremely, negatively, affected, however, 2003 does not appear to be either a significantly good or bad year for Dutch wheat yields. This discrepancy is due to differences in weather and harvesting patterns between the two countries.

4.2. Conclusions

Dutch weather data over the period 1901–2013 show that the number of extreme high temperatures and extreme precipitation events is increasing while the number of yearly low temperatures extremes is decreasing. Our findings confirm the IPCC findings and indicate that the number of precipitation events is increasing. Most importantly, the effects of those events on winter wheat yields in the Netherlands were found to be detrimental. Our findings support the conclusions of Trnka et al. (2014) who found, using site data, that adverse effects were likely to out-number the positive effects of weather events.

Furthermore, our results indicate that a model that includes both economic and weather variables is statistically preferred to one that includes only one of the two sets of data. Although the direction of the effects of a given subset of significant exogenous economic or weather variables in comparison to a model combining these variables remains the same; the magnitude of the variables changes, thereby leading to potentially erroneous conclusions. However, if only one set of data is available, either economic or weather data, then our results show that such a model would accurately identify the direction that the included variables would have yields, but not their magnitude.

This study contributes to the literature on climate change by assessing the impact of weather extremes on winter wheat yields of a panel of Dutch farms for twelve years. Yields are examined in relation to the actual regional weather data and observed productive inputs used to grow winter wheat on a farm. While the primary goal of this paper was to measure the effects of weather events on yields in the Netherlands, the relevance of that goal depends on the expected occurrences of weather events in the Netherlands. Based on an analysis of over a hundred years of daily data, the expected patterns of the occurrence of extreme events were estimated and forecasted ten years into the future. The number of extreme high temperature and precipitation events was shown to be significantly increasing over the period while the number of minimum temperature and evapotranspiration events was found to be significantly decreasing. These results provide convincing evidence that weather events have been steadily increasing and ARIMA model results indicate that they are likely to remain at historically high levels. In addition, average rainfall and both average maximum and minimum temperatures have been increasing steadily over the last 100 years.

Given that long-term trends indicate that the number of precipitation and high temperature events will increase or remain that historically high levels, we can conclude that their impacts will be detrimental for winter wheat yields. However, given that the number of minimum temperature events is decreasing and that a decrease in the number of minimum temperature events increases yields, all else equal, that process will increase yields. However, the number of extreme minimum temperatures is approaching zero. At the point that such events become rare, the negative effects of increasing precipitation and maximum temperature events will dominate Dutch wheat production.

Studies conducted at high levels of aggregation cannot adequately account for the effects of farm and crop level characteristics influencing yields. It was argued that a low level analysis is necessary in order to isolate the effects of weather events on yields. Therefore, in addition to weather variables, economic variables, including the main factors of production, were included in a within panel model to explain yields. Results indicate the importance of both weather events on yields and the need to specify the time period over which events are measured. Weather events can have either positive or negative effects on yields depending on the week in which they occur. However, the majority of events, either precipitation, or low or high temperature events reduce yields.

References

Auffhammer, M., Ramanathan, V., Vincent, J., 2012. Climate change, the monsoon, and rice yield in India. Clim. Chang. 111 (2), 411–424.

Baltagi, B.H., 2008. Econometric Analysis of Panel Data. John Wiley and Sons, Ltd, West Sussex, UK.

Berrang-Ford, L., Ford, J.D., Lesnikowski, A., Poutiainen, C., Berrera, M., 2014. What drives national adaptation? A global assessment. Clim. Chang. . http://dx.doi.org/10.1007/s10584-014-1078-3, http://dx.doi.org/10.1007/s10584-014-1078-3

Brisson, P.G.N., Gouache, D., Charmet, G., Oury, F., Huard, F., 2010. Why are wheat yields stagnating in Europe? A comprehensive data analysis for France. Field Crops Res. 119, 201–212.

Calzadilla, A., Rehdanz, K., Betts, R., Falloon, P., Wiltshire, A., Tol, R.S., 2013. Climate change impacts on global agriculture. Clim. Chang. 120, 357–374. http://dx.doi.org/10.1007/s10584-013-0822-4.
Challinor, A.J., Watson, J., Lobell, D.B., 2014. A meta-analysis of crop yield under climate change and adaption. Nat. Clim. Chang. 4, 637–643.
Chen, C., Wang, E., Yu, Q., Zhang, Y., 2010. Quantifying the effects of climate trends in the past 43 years (1961–2003) on crop growth and water demand in the north China plain. Clim. Chang., 559–578.
In: Field, C., Barros, V. et al. (Eds.), 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK, and New York, USA.
Greene, W.H., 2012. Econometric Analysis, seventh ed. Pearson, Essex, England.
Gregory, P., Marshall, B., 2012. Attribution of climate change: a methodology to estimate the potential contribution to increases in potato yield in Scotland since 1960. Glob. Chang. Biol. 18, 1372–1388.
Hawkins, E., Fricker, T.E., Challinor, A.J., Ferro, C.A.T., Ho, C.K., Osborne, T.M., 2013. Increasing influence of heat stress on French maize yields from the 1960s to the 2030s. Glob. Chang. Biol. 19, 937–947.
Hiemstra, P., Sluiter, R., 2011. Interpolation of Makkink evaporation in the Netherlands. Royal Netherlands Meteorological Institute (KNMI), De Bilt.
Hirschi, M., Seneviratne, S., V Alexandrov, F.B., Boroneant, C., Christensen, O., Formayer, H., Orlowsky, B., Stepanek, P., 2011. Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. Nat. Geosci. 4, 17–21.
Hooghart, C., (ed), 1987. From Penman to Makkink, Vol 28, TNO committee on Hydrological Research, The Hague.
Kennisakker, 2014. Teelthandleiding Wintertarwe-groei en Ontwikkeling. Internet.
Klein Tank, A., Zwiers, F., Zhang, X., 2009. Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation, climate data and monitoring. Technical Report WCDMP-No. 72, WMO-TD No. 1500, World Meteorological Organization.
Koninklijk Nederlands Meteorologisch Instituut (KNMI): Royal Dutch Meteorological Institute, 2014. 〈https://data.knmi.nl/portal-webapp/knmi-datacentrum.html#1〉.
Kucharik, C., Serbin, S., 2008. Impacts of recent climate change on Wisconsin corn and soybean yield trends. Environ. Res. Lett. 3 (034), 003.
LEI, 2014a. 〈http://www.wageningenur.nl/en/Expertise-Services/Research-Institutes/lei.htm〉.
LEI, 2014b. 〈http://www.wageningenur.nl/nl/project/EU-Farm-Accountancy-Data-Network.htm〉 (in Dutch).
Leneman, H., Reinhard, S., Hoogeveen, M.W., 1999. Weather and yield: impact of weather on yield in arable crops, Technical reports, LEI, The Agricultural Economic Institute, (in Dutch).
Licker, R., Kucharik, C., Doré, T., Lindeman, M., Makowski, D., 2013. Climatic impacts on winter wheat yields in Picardy, France and Rostov, Russia: 1973–2010. Agric. For. Meteorol. 176, 25–37.
Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2.
Lobell, D.B., Ortiz-Monasterio, J.I., Asner, G.P., Matson, P.A., Naylor, R.L., Falcon, W.P., 2005. Analysis of wheat yield and climatic trends in Mexico. Field Crop. Res. 94, 250–256.
Lobell, D.B., Hammer, G.L., McLean, G., Messina, C., Roberts, M.J., Schlenker, W., 2013. The critical role of extreme heat for maize production in the United States. Nat. Clim. Chang. 3, 497–501.
Lobell, D., Schlenker, W., Costa-Roberts, J., 2011. Climate trends and global crop production since 1980. Science 333 (6042), 616–620.
Ludwig, F., Milroy, S., Asseng, S., 2009. Impacts of recent climate change on wheat production systems in western Australia. Clim. Chang. 92, 495–517.
Meehl, G.A., Zwiers, F., Evans, J., Knutson, T., Mearns, L., Whetton, P., 2000. Trends in extreme weather and climate events: issues related to modeling extremes in projections of future climate change. Bull. Am. Meteorol. Soc. 81 (3).
Min, S., Zhang, X., Zwiers, F., Hegerl, G., 2011. Human contribution to more-intense precipitation extremes. Nature 470, 378–381.
Moriondo, M., Giannakopoulos, C., Bindi, M., 2011. Climate change impact assessment: the role of climate extremes in crop yield simulations. Clim. Chang. 104 (3–4), 679–701. http://dx.doi.org/10.1007/s10584-010-9871-0.
Olesen, J.E., Carter, T.R., et al., 2007. Uncertainties in projected impacts of climate change on European agriculture and terrestrial ecosystems based on scenarios from regional climate models. Clim. Chang. 81, 123–143.
Oskam, A.J., Reinhard, A.J., 1992. Weather indices of agricultural production in the Netherlands 1948–1989. Neth. J. Agric. Sci. 40, 187–205.
Pathak, H., Ladha, J., Aggarwal, P., Peng, S., Das, S., Singh, Y., Singh, B., Kamra, S., Mishra, B., Sastri, A., Aggarwal, H., Das, D., Gupta, R., 2003. Trends of climatic potential and on-farm yields of rice and wheat in the indo-gangetic plains. Field Crop. Res. 8, 223–234.
Porter, J., Gawith, M., 1999. Temperatures and the growth and development of wheat: a review. Eur. J. Agron. 10, 23–36.
Porter, J.R., Xie, L., et al. 2014. Climate change 2014: impacts, adaptation, and vulnerability. Working Group II contribution to the IPCC Fifth Assessment Report. IPCC, authors include: Coordinating lead authors, lead authors, contributing authors and review editors.
Rosenzweig, C., Iglesias, A., Yang, X.B., Epstein, P.R., Chivian, E., 2001. Climate change and extreme weather events – implications for food production, plant diseases, and pests. Glob. Chang. Human Health 2 (2), 90–104.
Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc. Natl. Acad. Sci. USA 106 (37), 15594–15598 (PNAS).
Semenov, M.A., Shewry, P.R., 2011. Modelling predicts that heat stress, not drought, will increase vulnerability of wheat in Europe. Sci. Rep. 1.
Seneviratne, S., Corti, T., Davin, E., Hirschi, M., Jaeger, E., Lehner, I., Orlowsky, B., Teuling, A., 2010. Investigating soil moisture–climate interactions in a changing climate: a review. Earth-Sci. Rev. 99 (3–4), 125–161.
Studenmund, A.H., 2006. Using Econometrics: A Practical Guide, 5th ed. Pearson International, Prentice Hall, USA.
Sugiyama, M., Akashi, O., Wada, K., Kanudia, A., Li, J., Weyant, J., 2014. Energy efficiency potentials for global climate change mitigation. Clim. Chang. 123 (3–4), 397–411.
Tao, F., Yokozawa, M., Xu, Y., Zhang, Z., 2006. Climate changes and trends in phenology and yields of field crops in China, 1981–2000. Agric. For. Meteorol. 138, 82–92.
Tao, F., Zhang, Z., Liu, J., Yokozawa, M., 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis. Agric. For. Meteorol. 149, 831–850.
Tao, F., Zhang, Z., Xiao, D., Zhang, S., Rötter, R.P., Shi, W., Liu, Y., Wang, M., Liua, F., Zhang, H., 2014. Responses of wheat growth and yield to climate change in different climate zones of China, 1981–2009. Agric. For. Meteorol. 189–190, 91–104.
Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Oleson, J.E., Žalund, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. Nat. Clim. Chang.
University of Kentucky, 2014. A Comprehensive Guide to Wheat Management in Kentucky. 〈http://www2.ca.uky.edu/agc/pubs/id/id125/id125.pdfhttp://www2.ca.uky.edu/agc/pubs/id/id125/id125.pdf〉 (accessed 18. 02.16).
Urban, D., Roberts, M.J., Schlenker, W., Lobell, D.B., 2012. Projected temperature changes indicate significant increase in inter-annual variability of U.S. maize yields. Clim. Chang. 112 (2), 525–533.
van der Velde, M., Tubiello, F.N., Vrieling, A.J., Bouraoui, F., 2012. Impacts of extreme weather on wheat and maize in France: evaluating regional climate simulations against observed data. Clim. Chang. 113 (3–4), 751–765.
Vautard, R., Yiou, P., D'Andrea, F., de Noblet, N., Viovy, N., Cassou, C., Polcher, J., Ciais, P., Kageyama, M., Fan, Y., 2007. Summertime European heat and drought waves induced by wintertime Mediterranean rainfall deficit. Geophys. Res. Lett. 34 (7).
Wang, H., Gan, Y., Wang, R., Niu, J., H Zhao, Q.Y., Li, G., 2008. Phenological trends in winter wheat and spring cotton in response to climate changes in northwest China. Agric. For. Meteorol. 148, 1242–1251.
Wassmann, R., Jagadish, S., Heur, S., Ismail, A., Redona, E., Serraj, R., Singh, R., Howell, G., Pathak, H., Sumfleth, K., 2009. Climate change affecting rice production: the physiological and agronomic basis for possible adaptation strategies. Adv. Agron. 101, 59–122.
Welch, J., Vincent, J., Auffhammer, M., Moya, P., Dobermann, A., Dawe, D., 2010. Rice yields in tropical subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. Proc. Natl. Acad. Sci. 107, 14562–14567.
Yamamoto, H., Sugiyama, M., Tsutsui, J., 2014. Role of end-use technologies in long-term GHG reduction scenarios developed with the bet model. Clim. Chang. 123 (3–4), 583–596. http://dx.doi.org/10.1007/s10584-013-0938-6.
You, L., Rosegrant, M., Wood, S., Sun, D., 2009. Impact of growing season temperature on wheat productivity in China. Agric. For. Meteorol. 149, 1009–1014.
Zhang, T., Zhu, J., Wassmann, R., 2010. Responses of rice yields to recent climate change in China: an empirical assessment based on long-term observations at different spatial scales (1981–2005). Agric. For. Meteorol. 150, 1128–1137.