ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Mitigating the effects of extreme weather on crop yields: insights from farm management strategies in the Netherlands

To cite this article: S van der Veer *et al* 2024 *Environ. Res. Lett.* **19** 104042

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
10 April 2024

REVISED
14 August 2024

ACCEPTED FOR PUBLICATION
23 August 2024

PUBLISHED
6 September 2024

LETTER

Mitigating the effects of extreme weather on crop yields: insights from farm management strategies in the Netherlands

S van der Veer[1,*], R Hamed[2], H Karabiyik[3,4] and J L Roskam[1]

[1] Performance and Impact Agrosectors, Wageningen Economic Research, Droevendaalsesteeg 4, 6708 PB Wageningen, The Netherlands
[2] Institute for Environmental Studies, Vrije Universiteit, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
[3] School of Business and Economics, Vrije Universiteit, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
[4] Tinbergen Institute, Gustav Mahlerplein 117, 1082 MS Amsterdam, The Netherlands
[*] Author to whom any correspondence should be addressed.

E-mail: sinne.vanderveer@wur.nl

Keywords: extreme weather, agriculture, management practices, panel data, drought

Abstract

Weather extremes can drive substantial crop losses. Farm-level management strategies play a critical role in mitigating the impacts of and consequences for farmer livelihoods and food security. While the impacts of extreme weather on crop yields are well documented in recent studies, these predominantly focused on expansive geographical scales and commonly overlooked the critical role of management practices in modulating the dynamics of weather-crop sensitivities. We fill this gap in the literature by using a unique dataset that explores the timely relationship between extreme weather and crop yields at farm level in the Netherlands. We cover 10 types of crops and elucidate the role of soil types, irrigation and nutrient application in modulating the relationship between extreme weather and crops, by estimating fixed-effects regression models. We show substantial impacts from drought during the growing- and harvesting period and excessive precipitation during the planting- and growing period. Severe droughts show significant ($p \leqslant 0.05$) reductions in yield for all crops, and lead to yield reductions up to 24 percent relative to average yields during the growing period. Meanwhile, eight crops show significant reductions in yield due to severe water excess during the planting period, with yield reductions up to 18 percent. Soils such as sand or loess amplify the negative impact of drought on crop yield, while softening the impact of excessive precipitation. Irrigation and to a lesser extent nutrient application are shown to moderately decrease the impact of extreme weather on crop yield. Our findings contribute valuable insights to guide local adaptation priorities which are critical given the projected increase in the intensity and frequency of extreme weather under climate change.

1. Introduction

Arable crop farming is highly sensitive to variability in weather conditions and in particular to weather extremes [1]. As the climate warms, extreme wet and dry conditions are expected to increase in frequency and intensity [2]. Both excessive wetness and severe dry spells can lead to substantial crop failures, with important cascading impacts on national food production and the associated socioeconomic conditions [3–5].

Many studies have investigated the effects of climate extremes on crop yields [3, 6–10]. Most of the existing studies focus on either national, sub-national or regional levels, while only few study the effects on a farm level [11]. Furthermore, few studies control for other variables that could explain yield variability, such as soil type and irrigation [11, 12], or investigate the interaction effects of drought with variables that mitigate yield loss. However, in previous studies, it has been recommended to include additional variables such as management practices and irrigation [8, 13], and to further investigate the effects of weather extremes on crop yields on a farm or field-level scale [13, 14]. While farm-level management strategies, such as irrigation and nutrient application, have the potential to alleviate the impacts of weather extremes on crops [15, 16], these strategies have not been sufficiently incorporated into existing evaluations. To support adaptation measures that reduce the potential impacts of the future challenges on climate adaptation, it is important to acquire a comprehensive quantitative understanding of the effectiveness of existing farm-level management strategies. However, studies are often limited due to a lack of real observed data regarding the aforementioned mediating variables and statistics on a farm- or field-level scale.

This study deviates from prior research on the effects of extreme weather on crop yields by using a farm-level modeling approach instead of aggregated regional data. This method allows for a detailed examination from a farmer's perspective and the investigation of various farm management strategies. We define extreme weather as severe deviations from normal meteorological conditions that influence water stress and potentially limit crop growth. The added value of this study is to fill the explained gap in the literature using a unique dataset containing farm-level statistics on production and management practice obtained from farmers accountancy data. We aim to answer the following research question: How do climate extremes affect crop yields in the Netherlands? Based on existing literature, it is hypothesized that some crops are more affected by climate extremes than others. Crops grown on soil types such as sand and loess, which have a lower water holding capacity [17, p 48], are expected to be more affected by drought than crops grown on soil types such as clay or peat. In addition, it is assumed that the effects of drought are diminished by irrigation use and increased nutrient application. Policymakers and farm managers could use our findings to prioritize and implement targeted irrigation and nutrient application strategies to mitigate the adverse impacts of extreme weather on crop yields.

2. Material and methods

2.1. Farm data

This study uses data collected in the framework of the Dutch Minerals Policy Monitoring Program (LMM). The LMM makes as much use as possible of the data of farms that are affiliated to the Dutch Farm Accountancy Data Network (FADN), collected by Wageningen Economic Research. The FADN sample is stratified according to farm type and standard economic output (SO) [18]. In the LMM, soil type region is also included in the stratification process. Hence, additional farms are, if necessary, recruited for the LMM. Farms with less than 10 hectares are excluded from participation and therefore do not belong to the target population of the LMM. An economic size of at least EUR 25 000 SO is also required.

This dataset includes crop yields from 10 different crops. For an overview of the variables and their descriptive statistics see table A1. Besides crop yields, the data also include soil type (indicated by fraction sand or loess), irrigation quantity, nitrogen application and phosphate application (from artificial fertilizer, animal manure and other organic manure). Farm data from 2006 until 2022 are used. However, not all data are available for all farms in each year. For example, irrigation data are only available from 2010 onwards.

2.2. Weather data

Weather data, including daily precipitation and potential evapotranspiration (PET), are collected from the Royal Netherlands Meteorological Institute (KNMI)[5]. Precipitation data are sourced from 279 stations across the country, ensuring comprehensive geographic coverage, whereas PET data are obtained from 18 strategically placed weather stations, selected based on their historical reliability and geographical distribution. PET is estimated by KNMI according to the Makkink method [19]. Both variables are obtained for stations that were present during the years 1993 through 2022 and are aggregated to a monthly level. An overview of the descriptive statistics for the collected weather data are shown in table 1. Figure 1 shows the locations of the precipitation and weather stations that are used.

2.3. Estimation of climate variability

Field-level precipitation and PET are estimated by assigning each field to the k_p nearest precipitation stations and the k_w nearest weather stations. In case field-level coordinates are not available, farm coordinates are used instead. For cases where farmers cultivate a single crop on multiple fields, a weighted average of the precipitation and PET levels is calculated based on the size of the fields. This is done to be able to combine the weather data with the farm data, which are collected at the crop level and not on a field level. Subsequently, Inverse Distance Weighted Interpolation (IDWI) is used, calculating a weighted average of the climate variable based on their corresponding distances to the stations [20, pp 215–6]. Choosing appropriate values for k_p and k_w number of nearest stations is done by applying leave-one-out validation and selecting values that yield the smallest mean squared error (MSE) [21, p 30]. See tables B1 and B2, and figure B1 for outcomes of the validation procedure.

The Standardized Precipitation Evapotranspiration Index (SPEI) is used to quantify climate extremes [22]. The SPEI gives an indication of the likelihood of a weather event occurring at a certain location. The SPEI is based on the more simplistic Standardized Precipitation Index (SPI)

[5] Available via: https://www.knmi.nl/nederland-nu/klimatologie.

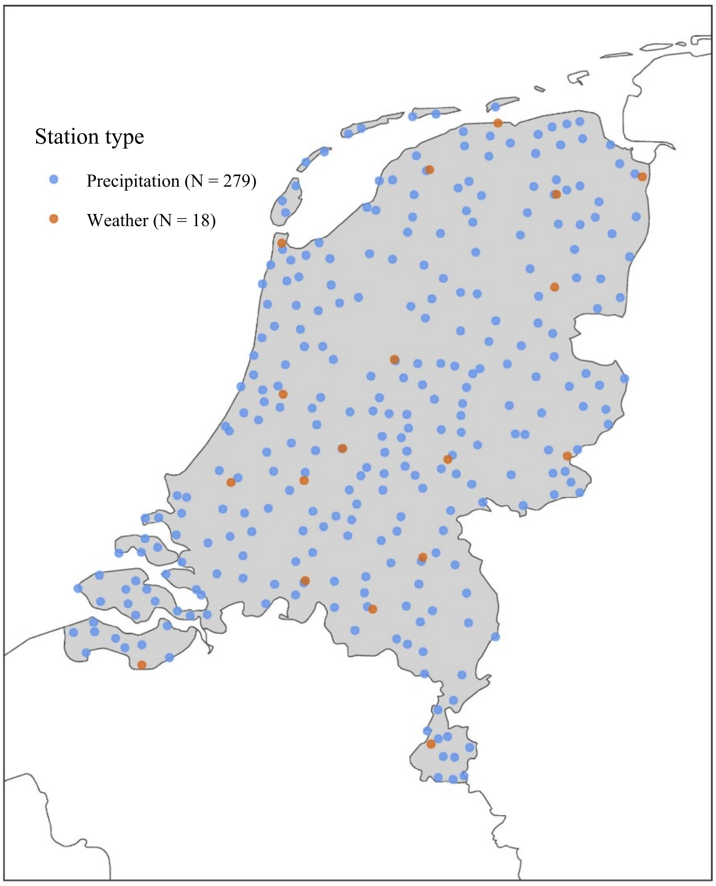


Figure 1. Map of the Netherlands, indicating the locations of the KNMI precipitation (blue) and weather (orange) stations used and the corresponding number of stations *N*.

Table 1. Descriptive statistics of KNMI weather and precipitation stations.

	Units	N Stations	Time range	Min	Median	Mean	St. Dev.	Max	Observations
PET	mm	18	1993–2022	4	44.4	49.70	35.80	140.1	6480
Precipitation	mm	279	1993–2022	0	66.9	71.93	39.62	320.0	100 440

[23]. The SPEI is chosen for its ease of interpretation and its capability to incorporate precipitation as well as temperature, solar radiation and wind speed, which determine PET, and subsequently affect crop water uptake. While the SPI is merely a standardized measure of precipitation, the SPEI considers the difference between monthly precipitation and PET, also known as a precipitation surplus or deficit, calculated by

$$D_{i,m,t} = P_{i,m,t} - PET_{i,m,t}, \tag{1}$$

where $P_{i,m,t}$ and $PET_{i,m,t}$, denote precipitation and PET for farm i, during month m, at year t, respectively. Due to the memory characteristic of extreme weather, it is important to take precipitation deficit from previous months into account. Therefore, past values of $D_{i,m,t}$ can be weighted according to a kernel function. Here, a *rectangular* kernel is used, such that all the previous months have equal weights [24]. Calculating the newly obtained variable $x^k_{i,m,t}$, where s denotes the specified time scale, then comes down to

$$x^s_{i,m,t} = s^{-1} \sum_{l=m-s+1}^{i} D_{i,l,t}. \tag{2}$$

It is suggested to use the three-parameter log-logistic probability distribution for calculation of the SPEI [22]. The parameters of this distribution are estimated using the Probability Weighted Moments (PWMs) procedure [25]. Instead of using the plotting-position method [22, 25], an unbiased version of the PWMs method is used [26], since this is favorable for computing climate extremes [27]. Subsequently, the SPEI takes on values with mean

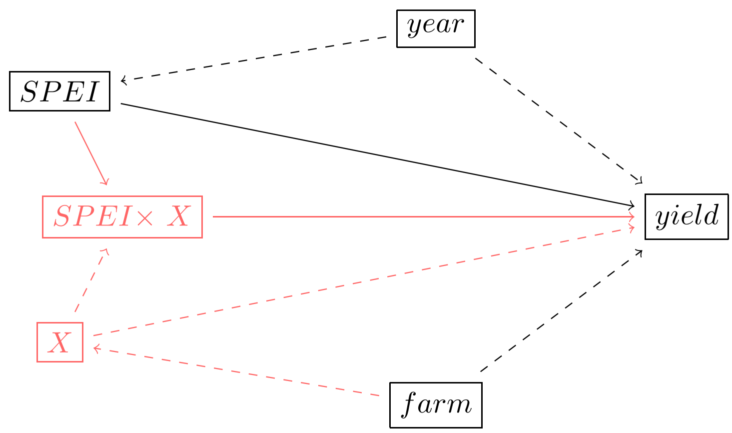


Figure 2. Diagram showing the underlying causal assumptions of the models. The solid lines indicate the causal effects of interest. The variables *year* and *farm* refer to unobserved year and farm specific variables. The variable X can be any of *soil type, irrigation, nitrogen application* or *phosphate application*. SPEI refers to the indicators used to quantify weather extremities. The red variables and lines are only relevant for estimating the interaction effects of SPEI and X on yield (equation (4)) and not for estimating the total effects of SPEI on yield (equation (3)). As can be seen from the diagram, when estimating the total effects of SPEI on yield, we need to control for the year specific effects in order to close any backdoor path that could lead to confounding. When estimating the interaction effects, we also need to control for X itself. Controlling for X closes the backdoor paths SPEI $\times X \leftarrow X \rightarrow$ yield and SPEI $\times X \leftarrow X \leftarrow$ farm $\rightarrow$ yield.

zero and standard deviation one. The SPEI is estimated using the R package **SPEI** [24].

Drought and excessive water affect crop yields differently across seasons [10, 14]. In order to capture these heterogeneous effects, the SPEI is estimated for three periods (planting, growing and harvesting) separately using time scale $s = 3$. The time periods included in the SPEI consist of March through May, June through August, and September through November. These might not correspond to the realised dates, however, they should roughly capture the planting, growing and harvesting periods, respectively, for the Netherlands. No distinction is made across crops. For some crops these dates are likely different. The selected growing period, however, largely captures the growing period for all crops.

2.4. Model

We used two regression models. Firstly, with the aim of identifying the total causal relations, we regress yields on a polynomial function of SPEI. Using a polynomial approach to model this relation allows us to account for potentially nonlinear interactions between the weather and crop yields. A graphical analysis indicated that extreme weather events, as represented by the tails of the SPEI, led to an exponential reduction in crop yields, justifying the use of a polynomial function. The regression model we adopt is

$$\begin{aligned} yield_{i,t} = &\beta_1 spei_{p,i,t} + \beta_2 spei^2_{p,i,t} + \beta_3 spei_{g,i,t} \\ &+ \beta_4 spei^2_{g,i,t} + \beta_5 spei_{h,i,t} + \beta_6 spei^2_{h,i,t} \\ &+ \mu_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $yield_{i,t}$ is the annual yield in kilograms per hectare for the corresponding crop of farm i in year t. $spei_{p,i,t}$ is the climate index of farm i in the planting season of year t. Here, the subscripts p, g and h represent the planting, growing, and harvesting periods, respectively.

The second regression model aims at uncovering the interactions between certain field characteristics and farmers' decisions. We allow for interactions between SPEI and soil type, irrigation, nitrogen application and phosphate application. The model we adopt for this purpose is

$$\begin{aligned} yield_{i,t} = &\gamma_1 spei_{p,i,t} + \gamma_2 spei^2_{p,i,t} + \gamma_3 spei_{g,i,t} \\ &+ \gamma_4 spei^2_{g,i,t} + \gamma_5 spei_{h,i,t} + \gamma_6 spei^2_{h,i,t} \\ &+ \gamma_7 X_{i,t} + \gamma_8 \left(spei_{p,i,t} \times X_{i,t}\right) \\ &+ \gamma_9 \left(spei^2_{p,i,t} \times X_{i,t}\right) + \gamma_{10} \left(spei_{g,i,t} \times X_{i,t}\right) \\ &+ \gamma_{11} \left(spei^2_{g,i,t} \times X_{i,t}\right) \\ &+ \gamma_{12} \left(spei_{h,i,t} \times X_{i,t}\right) + \gamma_{13} \left(spei^2_{h,i,t} \times X_{i,t}\right) \\ &+ \mu_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where $X_{i,t}$ represents the variable that we are testing the interactions of.

In both models, we allow for individual fixed effects, represented by μ_i, to account for time-invariant heterogeneity in crop yields across farms. Moreover, we allow for fixed time-effects, represented by δ_t to capture the common effects of unobserved shocks. Finally, $\varepsilon_{i,t}$ represent the idiosyncratic shocks. We use a two-way fixed effects approach to estimate the models. For inference, the standard errors we use are robust to potential serial correlation and heteroskedasticity in the errors [28]. For computing the robust standard errors, observations are clustered at the group level and the HC3 weighting scheme is used, which is recommended for linear regression models [29]. The causal diagram that these models assume are shown in figure 2.

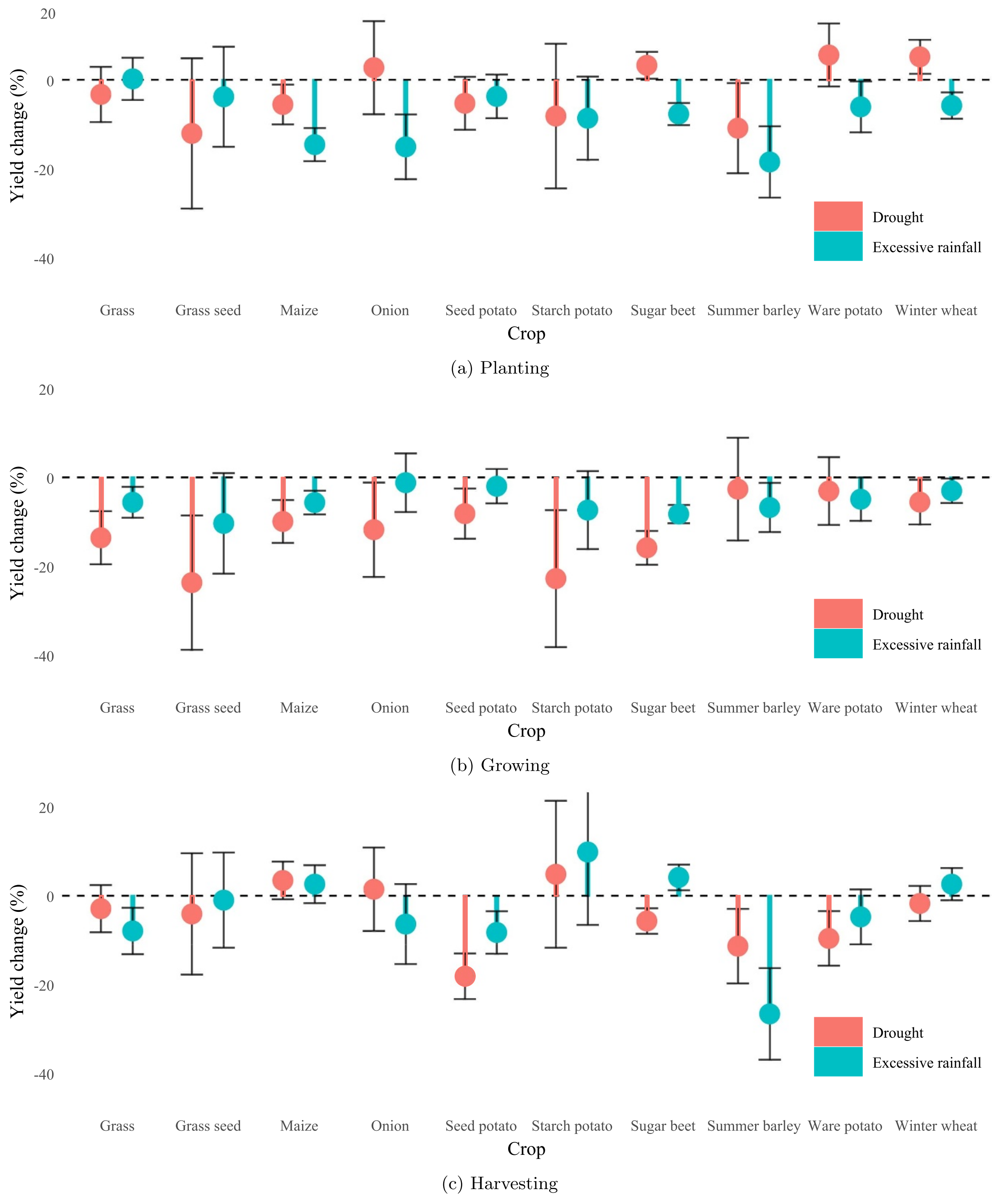


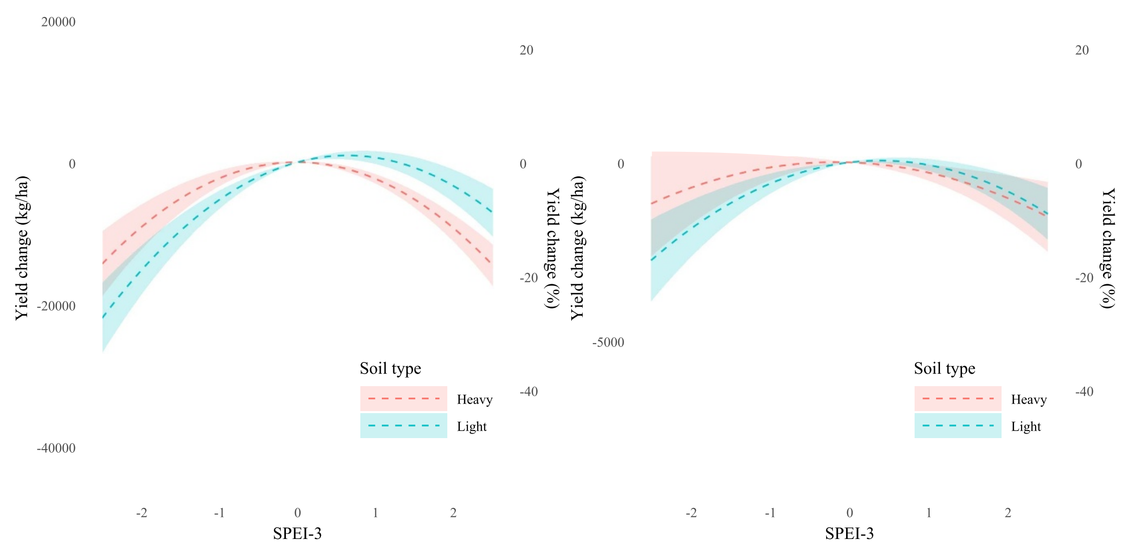
Figure 3. Predicted yield changes (% of average yield) in case of a drought (SPEI = −2; in red) and excessive rainfall (SPEI = 2; in blue) across crops (x-axis) during the planting (top), growing (middle) and harvesting (bottom) period. The whiskers show the 90% confidence interval. The predicted changes are based on the model specifications from equation (3).

3. Results

3.1. Yield reductions as a consequence of extreme weather

The fitted models from equation (3) show significant effects of extreme weather on crop yields for eight out of ten crops ($p \leqslant 0.01$). The model shows significant effects for starch potato ($p \leqslant 0.1$), while the effects are insignificant for grass seed. Notably, these two crops have the lowest number of observations. The regression coefficients can be found in tables C1 and C2. The first column of table C11 shows a joint F-test statistics on all SPEI indicator coefficients for each crop, which indicate a strong explanatory power of the model.

To better understand the implications of the results, we predict changes in crop yields for different values of the SPEI across all three periods. Figure 3 shows the predicted changes in case of a severe drought (SPEI = −2) and a severe water excess (SPEI = 2), for all ten crops. There are three main takeaways from these figures. First, during the planting period, excessive precipitation substantially reduces crop yields. Figure 3(a) show yield reductions up to



(a) Sugar beet (b) Maize

Figure 4. Predicted changes in crop yield compared to SPEI = 0 (y-axis) of sugar beet (left) and maize (right) vs. SPEI-3 (x-axis) for the growing period. The different lines indicate the effects of drought for different soil types (light soil type refers to 100% sand or loess and heavy soil type to 100% clay or peat). The shaded areas indicate a 90% confidence interval. The percentage yield change refers to the change relative to the average yield for that crop.

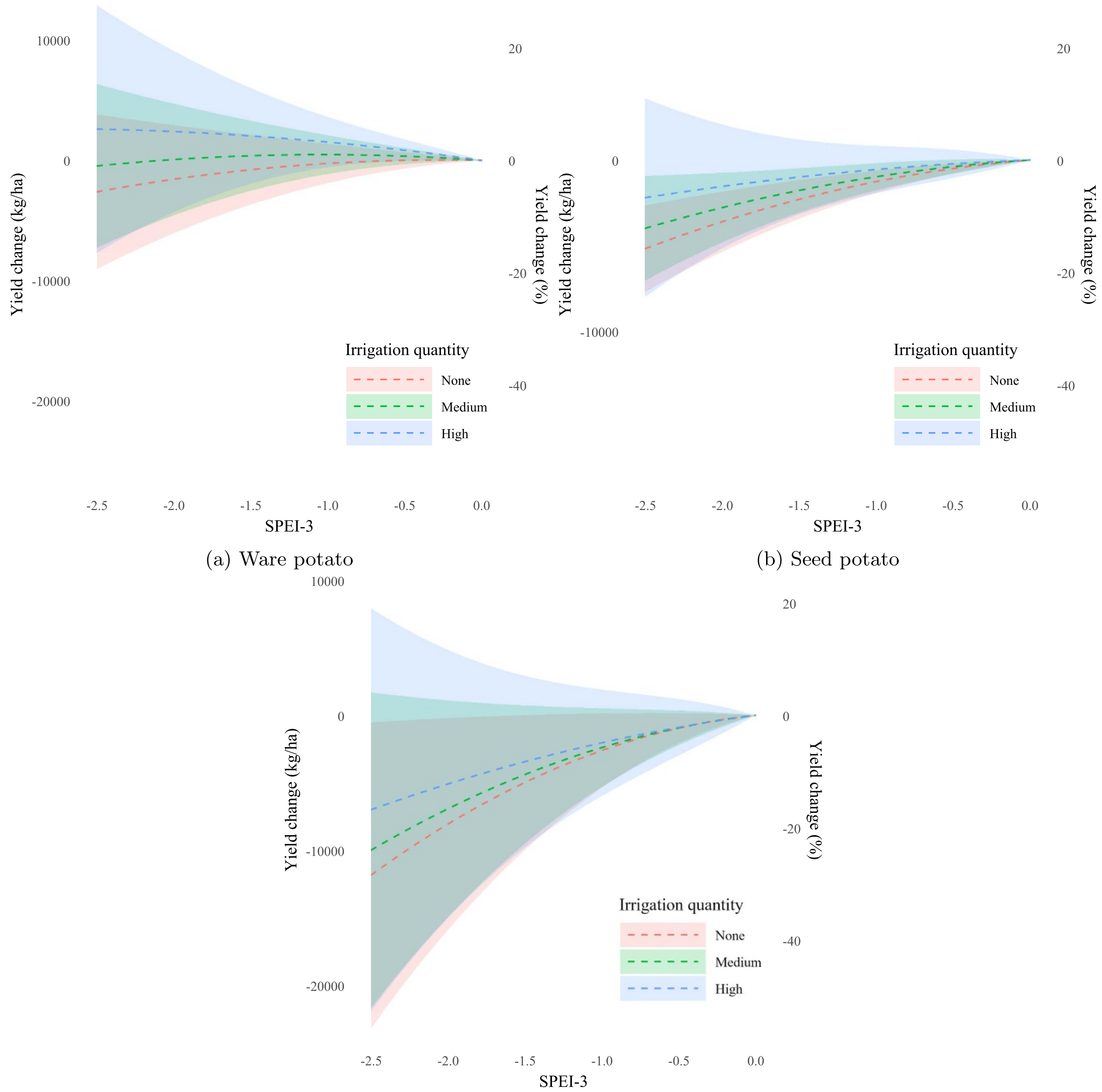
19% compared to their average yield and for six out of ten crops the predicted yield change is significantly lower than zero ($p \leqslant 0.05$). Meanwhile, drought during the planting period is not shown to have major impacts, only showing significant decrease for maize and summer barley and even showing a slight increase for sugar beet and winter wheat. Second, the most important factor reducing crop yields seems to be a dry growing period. Figure 3(b) shows that for eight out of ten crops a significant decrease in crop yields is observed with respect to the average yield. These yield reductions range from 6% to 23%. However, excessive precipitation during the growing period is also shown to significantly reduce crop yields for six different crops. For the remaining four crops, a substantial reduction is also observed, however, not statistically significant. Third, the estimated effects of extreme weather during the harvesting period show mixed results. For seed potato, sugar beet, summer barley and ware potato, dry harvesting periods significantly reduce crop yields. Conversely, for grass, seed potato and summer barley, excessive precipitation during the harvesting period significantly reduces yields.

3.2. Moderating role of soil density

The soil type on which crops are cultivated is shown to play an important role in moderating the effects of extreme weather on crop yield. Tables C3 and C4 show the regression output for the models including fraction sand/loess soil and its interaction with the SPEI variables. A joint F-test on the addition of soil type shows that the coefficients are jointly significantly different from zero for five out of ten crops at $p \leqslant 0.05$ (six at $p \leqslant 0.1$).

Heavy soils such as clay or peat are shown to be more drought resistant than lighter soils. The estimated yield reduction caused by a severe drought (SPEI $= -2$) during the growing period are lower on heavy soils than on light soils for eight out of ten crops. Although this moderating property is shown for multiple crops, the effect is most clearly illustrated for weather extremes on sugar beet and maize fields during the growing period, as shown in figure 4. The figure shows the predicted yield changes (y-axis) for different values of SPEI-3 (x-axis) during the growing period across different values of sand/loess fraction for sugar beet (left) and maize (right). Note that the direct effect of the soil type is not shown by the figures. Focusing on the left side of figure 4(a), it can be seen that for sugar beet the yield reduction during a severe drought is approximately 19% for light soil types, while approximately 11% for heavy soil types. For maize (figure 4(b)) yield reduction is predicted to be 4% on heavy soil types, while on light soil types it is predicted to decrease by about 13%. This confirms our hypothesis that heavy soil types, which have a higher water holding capacity [17, p 48], are better at mitigating the effects of drought than light soil types.

On the other hand, light soil types such as sand or loess are shown to reduce the negative impact of excessive precipitation on crop yield. The estimated yield reductions caused by severe wetness (SPEI $= 2$) during the growing period are lower on light soils than on heavy soils for eight out of ten crops. If we look at figure 4(a), we see that the sign of the moderating effect of soil type switches at SPEI $= 0$ (the 'normal' situation). The differences between estimated yield reduction on light versus heavy soil for



(a) Ware potato (b) Seed potato (c) Starch potato

Figure 5. Predicted changes in crop yield compared to SPEI = 0 (y-axis) of ware potato (top left), seed potato (top right) and starch potato (bottom) vs. SPEI-3 (x-axis) for the growing period. The different lines indicate the effects of drought for no-, medium- and high values of irrigation quantity. The medium and high values are subjective to the crop and based on the median and 90th percentile of the nonzero irrigation values, respectively. The shaded areas indicate a 90% confidence interval. The percentage yield change refers to the change relative to the average yield for that crop.

sugar beet is 8% (12%–4%). The difference for maize, however, seems to be insignificant.

3.3. Drought mitigation through irrigation

For several crops, irrigation seems to play an important role in moderating the effects of drought on crop yield. The regression output including irrigation and its interaction with the SPEI variables are shown in tables C5 and C6. F-tests for inclusion of irrigation in the model, like shown in table C11 on the third column, show that the irrigation terms are jointly significantly different from zero for four out of ten crops, with $p \leqslant 0.01$. Irrigation seems mainly relevant for onions, grass seeds, ware potatoes and starch potatoes. In figure 5 we further investigate the role of irrigation for three types of potatoes, due to their dependence on irrigation water. The figure shows the predicted yield change (y-axis) for different values of SPEI-3 (x-axis) during the growing period across different irrigation quantities for ware potato (top left), seed potato (top right) and starch potato (bottom).

From figure 5 it can be seen that for all three potato types, predicted yield losses caused by drought during the growing period are lower when irrigation quantity is higher. The differences in predicted yield losses between medium irrigation and no irrigation during an extreme drought (SPEI $= -2$) are 3% (3%$-$0%), 2% (10%$-$8%) and 2% (19%$-$17%) for ware-, seed- and starch potato, respectively. These differences do not seem substantial for any of the potato types. For high irrigation (90th percentile of nonzero values) the difference with no irrigation does seem quite substantial. Comparing high irrigation with no irrigation, the differences in crop yield loss due to a severe drought (SPEI $= -2$) during the growing period are estimated to be 8% (3%+5%), 6% (11%−5%) and 7% (19%−12%) for ware-, seed- and starch potato, respectively. However, the confidence intervals are also extremely wide, indicating that these differences are very uncertain. This could be due to a limited number of nonzero irrigation values. Another possible explanation for the high variance is that the timing and irrigation method are important factors in determining the effectiveness of irrigation.

3.4. Modulating the effects of extreme weather with fertilizer

The moderating role of nutrient application in the relationship between extreme weather and crop yield is not so evident. The regression output for the models including nitrogen and the interaction with SPEI variables are shown in tables C7 and C8, while the regression output for the phosphate models are given by tables C9 and C10. F-tests on the addition of the nitrogen variables and their interaction with the SPEI variables are significant for winter wheat, grass and maize at $p \leqslant 0.01$ and for sugar beet, grass seed and seed potato at $p \leqslant 0.1$. For the addition of phosphate, only grass and maize show significance ($p \leqslant 0.05$). A possible explanation for grass and maize mainly benefiting from fertilization in mitigating the effects of extreme weather could be that a large share of grass and maize fertilization originates from animal manure rather than artificial fertilizer. Animal manure is known to increase soil organic matter [30], which influences water holding capacity by acting as a sponge to retain water [31, 32]. On average, about 66% of nitrogen and 98% and phosphate application administered to grass are animal-based and for maize 83% and 89%, respectively. These numbers are higher for maize and grass than for the other eight crops. Since the models only show significant results for maize and grass, we will continue by focusing on these two crops. For grass we will focus on extreme weather during the growing period and for maize during the planting period, since these are the periods that have the most impact on their production as discussed in section 3.1. Figure 6 shows the predicted yield change (y-axis) for different values of SPEI-3 (x-axis) during the growing period across different nutrient application quantities for grass and maize. For grass, both the nitrogen as well as the phosphate model only show significant interaction effects of nutrient application with SPEI during the growing period. For maize, however, both models only show significant interaction terms of nutrient application with SPEI for the planting- and harvesting periods. However, no direct effects of extreme weather in the harvesting period for maize have been found. Therefore, we investigate the growing period for grass and the planting period for maize.

From figures 6(a) and (c) we can see that for grass, both nitrogen and phosphate application are able to mitigate a substantial amount of yield loss caused by excess water during the growing period. The yield change caused by severe excess water (SPEI $= 2$) is estimated to be −11% when low amount of nitrogen is applied, while it is estimated to *increase* by 1% when high amounts of nitrogen are applied. For phosphate these numbers are −8% and +1%, respectively. Yield loss caused by drought during the growing period, however, are only moderately mitigated by increased phosphate application (from 13% in case of low amounts of phosphate to 8% in case of high amounts of phosphate) and not by nitrogen. This could be related to a higher percentage of application of phosphate originating from animal manure than for nitrogen application.

The mitigating role of nutrient application in yield loss due to extreme weather during the planting period can be seen in figures 6(b) and (d). Yield loss due to a severe water excess (SPEI $= 2$) are shown to be substantially lower when high amounts of phosphate are applied (9%) compared to low amounts (20%). For high amounts of nitrogen application, however, yield loss is predicted to be 14% compared to 16% when it is low and their respective confidence bounds largely overlap, indicating no significant difference. For maize, the drought mitigating patterns of nitrogen and phosphate application during the planting period appear very similar. Yield loss in case of a severe drought (SPEI $= -2$) are predicted to be 10% for low nitrogen application compared to 3% when it is high, and 8% when phosphate application is low compared to 3% when it is high.

4. Discussion

Contrary to prior research on the effects of extreme weather on crop yields, that predominantly utilize aggregated regional data, our farm-level modeling approach provides a unique perspective into the nuanced effects of extreme weather on crop yields. This approach allows us to take on a farmer's perspective on this relationship and investigate moderating properties of several farm management strategies. Furthermore, we allow ourselves to discover variability of this relationship between farmers. For example, we find clear evidence of starch potato yield loss caused by drought, however, high unexplained variance in this relationship shows us great heterogeneity in yield response. High variance in our data also means that drawing conclusions based on significance tests becomes more difficult and, therefore, has to be compensated by a high number of observations. This stresses the importance of farm- and field-level data collection. Part of this unexplained variance can also be attributed to parameter uncertainty. Our climate estimation approach allows us to establish field-level climate indicators. Outcomes of the leave-one-out validation procedure show that the variance explained is quite high (98.1% and 99.9% for

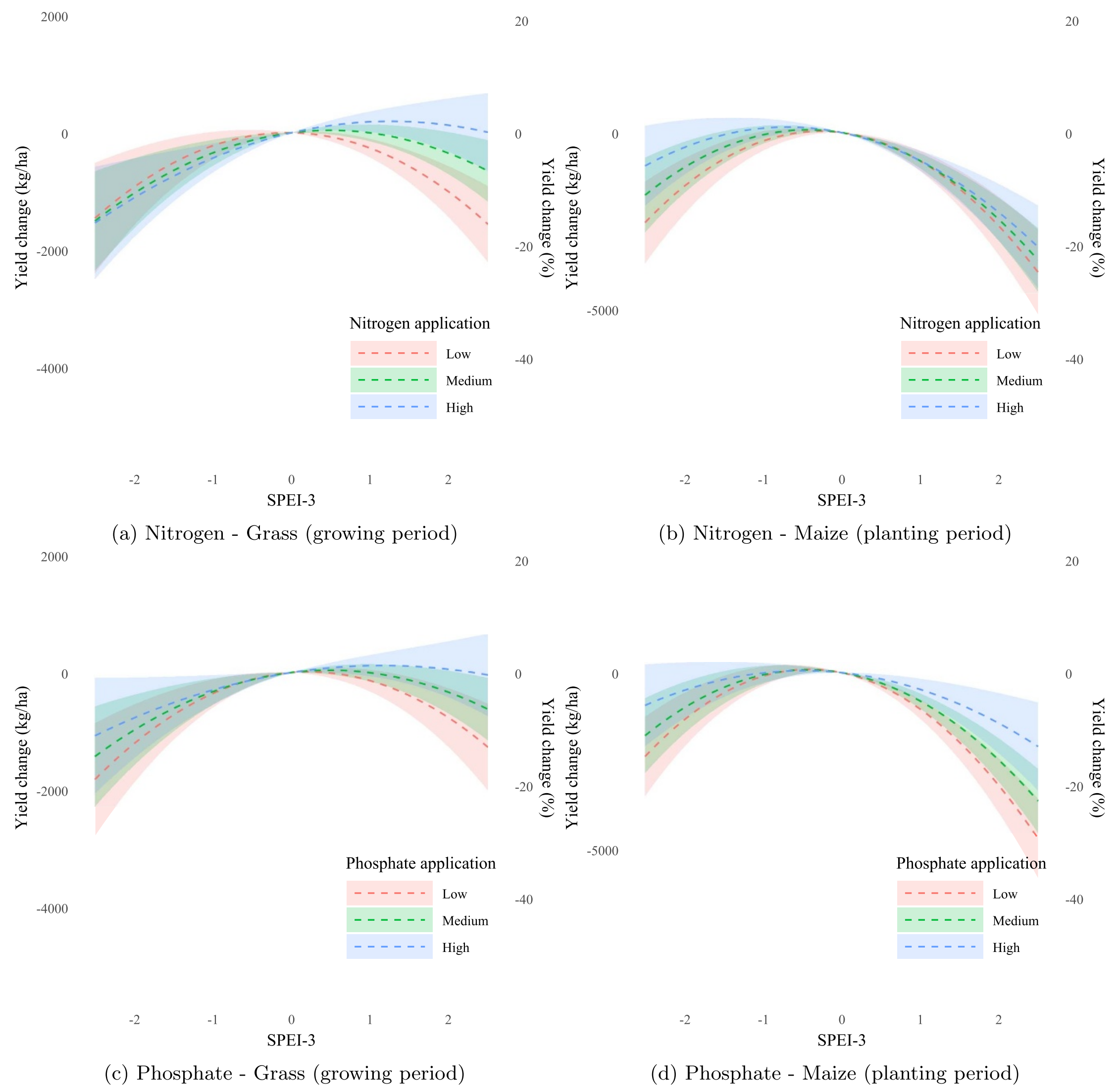


Figure 6. Predicted changes in crop yield compared to SPEI = 0 (y-axis) of grass (left) and maize (right) vs. SPEI-3 (x-axis). For grass the effects during the growing period are shown, while for maize the effects during the planting period. The different lines indicate the effects of drought for low, medium and high values of nitrogen (top) and phosphate (bottom) application, which are subjective to the crop and based on the 10th percentile, the median and the 90th percentile of nitrogen and phosphate values, respectively. The shaded areas indicate a 90% confidence interval. The percentage yield change refers to the change relative to the average yield for that crop.

precipitation and PET, respectively), however these predictions are not perfect. This means that there is some uncertainty in the variables that are used for the models.

Using the SPEI as an indicator for extreme weather seems to be widely supported in agricultural drought research [6–9]. The choice of indicator is backed by a study in which different indicators for agricultural drought are compared [33]. Using SPEI as indicator for water excess is less common. However, it is shown that the SPEI can also be used to identify agricultural water excess relevant to wheat production [3]. Furthermore, the SPEI incorporates both precipitation as well as temperature, which have shown to be jointly detrimental for determining crop yield outcomes [34]. While the SPEI seems to have good explanatory power when investigating crop yield variability, many other potential indicators are not considered in this study. One issue with our choice of indicator could be that even though we account for differences in weather extremities between planting-, growing- and harvesting period, multiple extreme weather events could happen consecutively within one of these periods. The SPEI averages these events out when two opposing events (like a flood and a short period of intense drought) occur consecutively. Several studies investigate a variety of other indicators for extreme weather in relation to crop yields [15, 35]. While these approaches could add significant explanatory power to the regression function, including more indicators hurts the causal interpretability of the model. Subsequently, we chose not to include any other climate indicators. It could be interesting to investigate these model specifications in a causal matter, for example by using recent advances in causal machine learning [36].

In this study, we solely investigate the short term effects of extreme weather, while the compound effects of prolonged drought or water excess could be highly relevant to crop yield. In 2018, a dry harvesting period following a dry growing period reduced crop yields substantially higher than predicted by our models. As frequencies of sustained periods of weather extremes increase, it is worth investigating these compound effects or even legacy effects occurring over multiple years, instead of focusing only on the harvesting year itself. This would require a dynamic modelling approach and gives rise to new issues due to movement of crop fields as consequence of crop rotation and a loss of data due to farms dropping out of the sample.

In order to compare the use of a farm-level modeling approach with regional statistics, we compare our results with other studies investigating the impacts of climate extremes in the Netherlands from 2012 [37] and 2023 [14]. First, in the 2012 study drought is not identified as an extreme weather event that causes negative potato yield anomalies in the Netherlands [37]. They suggest this is due to ample irrigation and a mild climate. This result strongly contradicts our model outcomes, which show that potato yields are significantly reduced by drought in both the growing- as well as the harvesting period. Furthermore, natural vegetation and drinking water availability might be at risk as a result of prolonged drought due to a decrease in groundwater levels [38]. This could pressure policy makers to temporarily ban irrigation in order to preserve water. Therefore, examining the effectiveness of irrigation is key to informed decision-making when it comes to drought adaptation for both farmers as well as policy makers.

The 2023 study shows that the probability of onions, ware- and seed potatoes experience extreme yield loss as a consequence to having a dry growing period is very high, while maize, winter wheat and starch potatoes were not shown to have this property. Sugar beet is shown to lie somewhere in between [14]. These findings are similar to ours, with one major difference. We show starch potato to be the most vulnerable crop to drought during the growing period. Furthermore, the 2023 study did not find a correlation between wet planting period and yield loss [14], which is contradictory to the findings in this study. Extreme water excess is shown to be especially relevant during the planting period and to a lesser extent also the growing- and harvesting periods. The difference in scale on which the studies focus could potentially explain the differences in findings, since farm specific characteristics cannot be accounted for when using aggregates and high variability among farmers is averaged out.

Improved farm management strategies improve agricultural productivity, food security and contribute to economic stability and environmental sustainability by optimizing resource use and mitigating the adverse effects of climate change on agriculture. In this study, we focus on farm management practices that use inputs like water for irrigation and fertilizer for nutrient supply in order to mitigate effects of extreme weather. Insights in the effectiveness of these practices are important, not only to boost crop production itself, but also to maximize input efficiencies. Farmers in the Netherlands have had ample access to high amounts of water for irrigation and fertilizer input for nutrient application for many years [39]. However, restrictions on these inputs in efforts to reduce agricultural emissions and protect fresh water supplies force farmers to use them more efficiently [40, 41]. Furthermore, these inputs come at an economic cost, which could diminish profits. Our results could aid in these trade-off decisions. Other than these high-input solutions to climate adaptation, low-input solutions such as diversifying crop species, soil management and changes to cultivation plans could be considered [2] and should be studied in future research.

The findings of the paper suggest that future farming policies could prioritize targeted irrigation and nutrient application strategies to mitigate the adverse impacts of extreme weather on crop yields, given that irrigation and nutrient application are shown to moderately decrease the impact of drought and excessive precipitation on crop yields. Additionally, policies might focus on soil management practices, as we show that heavy soils are more drought-resistant, and light soils are superior during excessive wetness, offering a basis for soil-specific agricultural recommendations.

5. Conclusion

Given the rising frequency of extreme weather due to climate change, its impact on arable crop yields in the Netherlands is increasingly critical. This trend poses significant challenges for future crop productivity and has broad economic implications for the nation's agricultural sector. Using a unique dataset at farm level, we show that a dry growing period has the highest impact on crop yields, followed by an extremely wet planting period. Effects of extreme weather on crop yields differ substantially across crops, with onions and potatoes belonging to the most affected group. Heavy soils are shown to be more drought resistant than light soils in terms of crop yield, while during excessive wetness light soils are proven to be superior. Irrigation and to a lesser extent nutrient application are shown to be a relevant drought mitigation strategy for some crops.

Future research should focus on obtaining a deeper understanding of climate adaptation, resilience, awareness among farmers and changes in agricultural practices induced by extreme weather. Policy makers and farmers can use this information to prepare themselves for the negative effects of climate extremes on crop production and avoid potentially great yield losses. The results of this study could help in isolating farms that are currently most vulnerable to the effects of extreme weather.

Data availability statement

The data cannot be made publicly available upon publication due to legal restrictions preventing unrestricted public distribution. The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

This research was conducted on behalf of the Dutch Ministry of Agriculture, Fisheries, Food Security and Nature, as part of the Wageningen UR project Dutch Minerals Policy Monitoring Program (LMM), with project number: BO-43-101-057. The authors thank Anne F van Loon and Lars de Graaff of the Institute for Environmental Studies at Vrije Universiteit Amsterdam, and Marga Hoogeveen of Wageningen Economic Research for their support and feedback during this study.

Appendix A. Farm descriptives

Table A1. Descriptive statistics of farm data per crop.

Crop	Variable	Min	Max	Median	Mean	St. Dev.	Unique values	Observations
Onion	Farm ID						237	1990
	Year	2006	2022	2015	2014.48	4.66	17	1990
	Yield (kg ha^{-1})	0	103 253.1	50 000	48 903.95	16 759.06	1979	1990
	Irrigation (m3 ha^{-1})	0	2000.12	0	158.82	321.32	487	1616
	Nitrogen use (kg ha^{-1})	0	432	153.91	160.9	84.23	1842	1936
	Phosphate use (kg ha^{-1}	0	246.95	33.63	46.34	50.58	1473	1960
	Sand/loess fraction	0	1	0	0.13	0.33	88	1990
Sugar beet	Farm ID						442	4157
	Year	2006	2022	2014	2013.82	4.83	17	4157
	Yield (kg ha^{-1})	0.13	136 808.5	79 937.8	80 107.06	15 114.71	4156	4157
	Irrigation (m3 ha^{-1})	0	2000.01	0	57.07	214.5	356	3150
	Nitrogen use (kg ha^{-1})	0	458.86	162.56	174.5	82.39	3932	4101
	Phosphate use (kg ha^{-1}	0	246.05	51.38	55.76	53.67	2785	4085
	Sand/loess fraction	0	1	0	0.42	0.48	335	4142
Winter wheat	Farm ID						370	2977
	Year	2006	2022	2014	2013.74	4.75	17	2977
	Yield (kg ha^{-1})	0.13	15 092.57	9047.41	8806.33	1781.4	2950	2977
	Irrigation (m3 ha^{-1})	0	1200	0	8.98	72.52	58	2268
	Nitrogen use (kg ha^{-1})	0	539.14	226.89	229.33	90.12	2826	2944
	Phosphate use (kg ha^{-1}	0	221.29	25.26	39.37	45.67	1749	2951
	Sand/loess fraction	0	1	0	0.21	0.39	269	2960
Grass seed	Farm ID						132	920
	Year	2006	2022	2014	2013.6	4.79	17	920
	Yield (kg ha^{-1})	0.24	2892.21	1414.87	1416.6	449.89	919	920
	Irrigation (m3 ha^{-1})	0	623.53	0	6.77	49.62	18	679
	Nitrogen use (kg ha^{-1})	0	504.44	169.04	187.49	96.59	853	903
	Phosphate use (kg ha^{-1}	0	265.11	0	37.8	54.42	439	912
	Sand/loess fraction	0	1	0	0.16	0.35	54	920
Ware potato	Farm ID						286	2361
	Year	2006	2022	2014	2013.89	4.72	17	2361
	Yield (kg ha^{-1})	0.28	98 374.29	48 679.27	46 731.01	13 896.17	2334	2361
	Irrigation (m3 ha^{-1})	0	2250.01	0	166.97	362.77	505	1822
	Nitrogen use (kg ha^{-1})	0	724.23	248.19	256.92	136.11	2230	2333
	Phosphate use (kg ha^{-1}	0	292.94	61.39	72.76	61.79	1930	2301
	Sand/loess fraction	0	1	0	0.3	0.44	177	2342
Summer barley	Farm ID						243	1452
	Year	2006	2022	2013	2013.3	4.83	17	1452
	Yield (kg ha^{-1})	0.23	12 722.22	6401.13	6258.01	1693.74	1441	1452
	Irrigation (m3 ha^{-1})	0	800.73	0	14.18	77.51	47	1037
	Nitrogen use (kg ha^{-1})	0	254.91	95.85	101.41	46.87	1314	1408
	Phosphate use (kg ha^{-1}	0	149.12	0	21.64	29.92	661	1428
	Sand/loess fraction	0	1	0.95	0.57	0.47	177	1452
Seed potato	Farm ID						212	2037
	Year	2006	2022	2014	2013.89	4.74	17	2037
	Yield (kg ha^{-1})	0.4	56 639.82	33 233.6	32 814.28	8033.47	1859	2037
	Irrigation (m3 ha^{-1})	0	1500.01	0	45.54	157.75	189	1568
	Nitrogen use (kg ha^{-1})	0	430	131	143.37	84.56	1910	2005
	Phosphate use (kg ha^{-1}	0	248.29	58.36	65.4	50.66	1748	1999
	Sand/loess fraction	0	1	0	0.31	0.45	117	2037

(Continued.)

Table A1. (Continued.)

Crop	Variable	Min	Max	Median	Mean	St. Dev.	Unique values	Observations
Starch potato	Farm ID						74	759
	Year	2006	2022	2014	2014.18	4.76	17	759
	Yield (kg ha^{-1})	15 367.51	61 778.9	42 070.67	41 641.15	6092.02	759	759
	Irrigation (m3 ha^{-1})	0	1025.65	0	68.35	185.23	110	597
	Nitrogen use (kg ha^{-1})	0	446.67	241.78	242.07	59.94	748	748
	Phosphate use (kg ha^{-1}	0	176.46	68.15	71.5	29.89	743	749
	Sand/loess fraction	0	1	1	0.93	0.18	180	759
Grass	Farm ID						683	5958
	Year	2006	2022	2014	2013.79	4.84	17	5958
	Yield (kg ha^{-1})	4000.73	19 873.35	9420.11	9612.05	2787.66	5956	5958
	Irrigation (m3 ha^{-1})	0	1812.98	0	50.59	182.95	552	4473
	Nitrogen use (kg ha^{-1})	0	689.66	385.38	376.93	95.04	5350	5351
	Phosphate use (kg ha^{-1}	0	158.89	82.43	82	20.66	5248	5250
	Sand/loess fraction	0	1	0.75	0.56	0.45	1656	5958
Maize	Farm ID						754	5495
	Year	2006	2022	2014	2014.07	4.75	17	5495
	Yield (kg ha^{-1})	5004.21	24 981.7	15 947.76	15 953.02	3678.05	4614	5495
	Irrigation (m3 ha^{-1})	0	1400	0	34.38	140.45	369	4271
	Nitrogen use (kg ha^{-1})	0	464.16	211.53	212.12	78.32	5267	5385
	Phosphate use (kg ha^{-1}	0	187.57	69.5	73.05	33.21	5125	5301
	Sand/loess fraction	0	1	1	0.73	0.42	664	5495

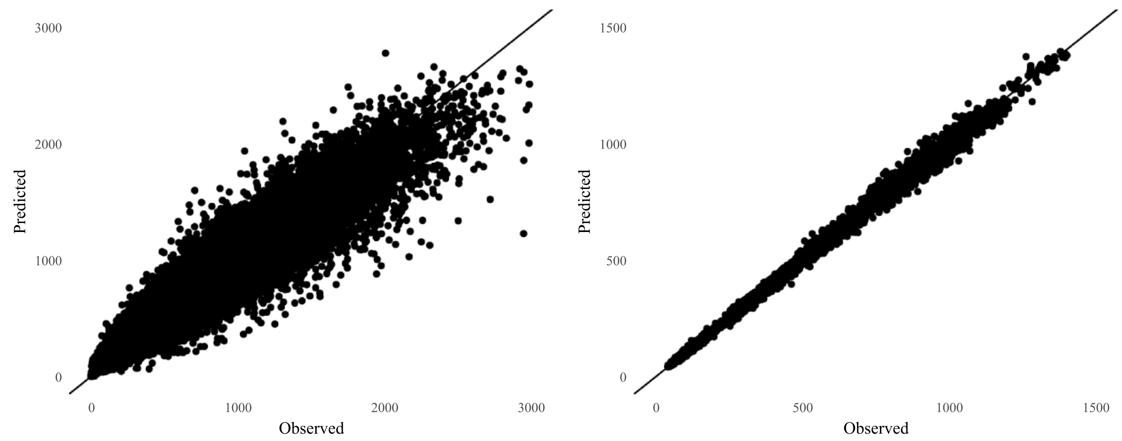
Appendix B. Validation of climate variable estimation

Table B1. Leave-one-out validation results of precipitation imputation.

	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
RMSE	130.073	121.580	117.650	115.800	114.471	113.617
MAE	88.927	83.496	81.081	79.939	79.067	78.617
R-squared	0.975	0.978	0.979	0.980	0.981	0.981

Table B2. Leave-one-out validation results of potential evapotranspiration imputation.

	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
RMSE	20.399	18.893	19.371	18.952	19.241	19.482
MAE	13.238	12.460	12.951	12.638	12.854	12.989
R-squared	0.999	0.999	0.999	0.999	0.999	0.999



(a) Precipitation (b) Potential evapotranspiration

Figure B1. Plots of predicted vs. observed values of the leave-one-out validation for both climate variables.

Appendix C. Regression output

Table C1. FE panel data regression output with robust standard errors for onion, sugar beet, winter wheat, grass seed and ware potato models, with only SPEI and SPEI^2 for each period as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Onion	Sugar beet	Winter wheat	Grass seed	Ware potato
SPEI-3 (May)	-2176.171^{***}	-2195.560^{***}	-241.128^{***}	29.198	-1362.004^{***}
	(712.043)	(336.029)	(47.115)	(29.044)	(453.917)
SPEI-3^2 (May)	−756.525	−446.835	−7.037	−28.147	−30.968
	(567.807)	(291.721)	(39.288)	(27.308)	(397.432)
SPEI-3 (Aug)	1292.037	1518.513^{***}	56.077	47.172	−214.408
	(849.739)	(477.523)	(70.413)	(37.164)	(565.068)
SPEI-3^2 (Aug)	−791.788	-2411.679^{***}	-94.265^{**}	-60.235^{***}	−466.338
	(501.541)	(286.483)	(41.298)	(21.906)	(355.679)
SPEI-3 (Nov)	−957.756	1964.288^{***}	95.524	10.979	565.425
	(950.416)	(440.656)	(66.068)	(30.557)	(587.553)
SPEI-3^2 (Nov)	−298.839	−154.312	9.784	−8.942	-836.183^{***}
	(490.933)	(273.382)	(38.418)	(21.546)	(323.940)
Observations	1990	4157	2977	920	2361
R^2	0.014	0.037	0.011	0.012	0.009
F Statistic	4.420^{***}	25.054^{***}	6.838^{***}	1.729	4.000^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C2. FE panel data regression output with robust standard errors for summer barley, seed potato, starch potato, grass and maize models, with only SPEI and SPEI^2 for each period as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Summer barley	Seed potato	Starch potato	Grass	Maize
SPEI-3 (May)	-118.907 (93.390)	127.797 (300.202)	-50.191 (1094.012)	84.170 (94.239)	-359.808^{***} (114.149)
SPEI-3^2 (May)	-229.698^{***} (73.386)	-370.839 (227.261)	-875.341 (636.687)	-37.160 (65.526)	-401.803^{***} (82.025)
SPEI-3 (Aug)	-64.676 (117.382)	506.023 (311.044)	1603.411^{**} (790.335)	191.730^{**} (95.623)	169.916 (111.749)
SPEI-3^2 (Aug)	-73.595 (63.185)	-415.936^{**} (184.681)	-1567.909^{**} (688.386)	-230.503^{***} (53.069)	-310.503^{***} (76.239)
SPEI-3 (Nov)	-238.276^{**} (106.040)	806.609^{**} (330.564)	520.271 (1613.649)	-120.533 (101.304)	-33.043 (128.770)
SPEI-3^2 (Nov)	-296.376^{***} (71.827)	-1080.061^{***} (184.143)	764.497 (659.110)	-129.760^{**} (57.904)	121.072 (80.528)
Observations	1452	2037	759	5958	5495
R^2	0.033	0.023	0.018	0.005	0.015
F Statistic	5.166^{***}	8.685^{***}	1.783^{*}	4.231^{***}	10.030^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C3. FE panel data regression output with robust standard errors for onion, sugar beet, winter wheat, grass seed and ware potato models, including SPEI and SPEI^2 for each period, as well as sand/loess fraction and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Onion	Sugar beet	Winter wheat	Grass seed	Ware potato
SPEI-3 (May)	-2087.996^{***}	-2347.271^{***}	-192.594^{***}	22.818	-1113.997^{**}
	(723.261)	(370.287)	(51.780)	(28.819)	(476.225)
SPEI-3^2 (May)	-1197.346^{**}	-453.028	-34.527	-10.637	473.706
	(580.206)	(323.262)	(41.973)	(31.453)	(438.050)
SPEI-3 (Aug)	1050.811	-39.678	21.731	50.832	-730.822
	(849.787)	(450.245)	(69.252)	(39.560)	(587.845)
SPEI-3^2 (Aug)	-1090.755^{**}	-2293.074^{***}	-138.101^{***}	-61.873^{**}	-423.242
	(519.512)	(324.287)	(45.901)	(24.107)	(371.277)
SPEI-3 (Nov)	-925.867	1382.481^{***}	113.021^{*}	18.496	95.326
	(941.818)	(466.449)	(68.055)	(32.691)	(602.110)
SPEI-3^2 (Nov)	-98.641	-160.369	22.755	-6.343	-1118.131^{***}
	(541.120)	(328.363)	(44.131)	(23.340)	(352.692)
Sand/loess fraction	1691.003	-3622.459^{*}	-479.939	-48.344	140.175
	(4837.840)	(2148.616)	(369.180)	(109.574)	(3360.714)
SPEI-3 (May):Sand/loess fraction	813.198	-34.286	-30.933	12.269	-1013.032^{*}
	(930.753)	(412.194)	(85.836)	(45.499)	(573.428)
SPEI-3^2 (May):Sand/loess fraction	1631.096	76.293	57.975	-45.557	-860.797^{**}
	(1067.975)	(330.424)	(65.882)	(32.308)	(424.219)
SPEI-3 (Aug):Sand/loess fraction	297.396	2986.845^{***}	86.681	-20.198	1199.897^{*}
	(1265.506)	(451.687)	(76.761)	(37.245)	(640.919)
SPEI-3^2 (Aug):Sand/loess fraction	1850.374	-17.497	147.067^{*}	25.239	103.676
	(1209.241)	(335.002)	(76.436)	(36.860)	(421.696)
SPEI-3 (Nov):Sand/loess fraction	-759.366	967.710^{**}	-105.041	-42.485	983.012
	(1513.378)	(409.118)	(106.765)	(40.526)	(663.953)
SPEI-3^2 (Nov):Sand/loess fraction	-1588.969	168.029	-104.111	-55.373	1349.575^{**}
	(989.813)	(438.712)	(82.937)	(49.051)	(635.258)
Observations	1990	4142	2960	920	2342
R^2	0.021	0.060	0.018	0.017	0.017
F Statistic	2.986^{***}	16.578^{***}	4.050^{***}	1.244	3.533^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C4. FE panel data regression output with robust standard errors for summer barley, seed potato, starch potato, grass and maize models, including SPEI and SPEI^2 for each period, as well as sand/loess fraction and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Summer barley	Seed potato	Starch potato	Grass	Maize
SPEI-3 (May)	−108.032 (111.843)	275.786 (320.440)	−1162.354 (2238.264)	−64.635 (110.986)	−382.365** (150.962)
SPEI-3^2 (May)	−225.050*** (78.745)	−502.501** (240.239)	−2993.097** (1417.773)	−22.786 (73.401)	−539.094*** (114.942)
SPEI-3 (Aug)	−54.328 (119.352)	553.919* (325.534)	711.386 (2354.041)	70.397 (106.038)	−72.987 (147.743)
SPEI-3^2 (Aug)	−142.790* (81.022)	−488.611** (203.322)	−273.267 (1593.839)	−254.770*** (61.707)	−213.121** (105.663)
SPEI-3 (Nov)	−253.272** (112.777)	914.269*** (347.789)	−1487.584 (2651.637)	−153.514 (105.968)	−114.278 (157.754)
SPEI-3^2 (Nov)	−185.481** (94.357)	−1194.560*** (182.049)	1987.229 (1600.037)	−58.657 (68.573)	89.097 (120.596)
Sand/loess fraction	−46.501 (332.776)	559.149 (1176.749)	2869.880 (3549.461)	133.278 (828.043)	128.254 (469.827)
SPEI-3 (May):Sand/loess fraction	6.396 (112.481)	−323.446 (283.871)	956.813 (2042.816)	231.493** (103.829)	−26.157 (139.579)
SPEI-3^2 (May):Sand/loess fraction	−10.726 (64.618)	207.007 (191.417)	2249.177 (1375.293)	−18.318 (72.899)	203.115** (103.541)
SPEI-3 (Aug):Sand/loess fraction	−63.479 (83.260)	24.078 (288.642)	997.545 (2397.669)	170.161** (77.547)	332.065*** (115.383)
SPEI-3^2 (Aug):Sand/loess fraction	155.968** (75.942)	−221.557 (199.038)	−1349.161 (1453.640)	70.324 (63.079)	−119.117 (99.172)
SPEI-3 (Nov):Sand/loess fraction	−36.917 (97.562)	−99.191 (255.824)	2097.029 (2287.740)	8.411 (87.505)	117.445 (127.056)
SPEI-3^2 (Nov):Sand/loess fraction	−199.066* (110.185)	966.219*** (312.538)	−1334.917 (1748.935)	−112.052 (86.654)	75.261 (132.582)
Observations	1452	2037	759	5958	5495
R^2	0.039	0.033	0.052	0.008	0.019
F Statistic	3.297***	6.614***	2.598***	2.988***	6.401***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C5. FE panel data regression with robust standard errors output for onion, sugar beet, winter wheat, grass seed and ware potato models, including SPEI and $SPEI^2$ for each period, as well as irrigation and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Onion	Sugar beet	Winter wheat	Grass seed	Ware potato
SPEI-3 (May)	−3077.628***	−2642.198***	−316.050***	46.951	−1611.814***
	(813.411)	(376.159)	(50.022)	(33.521)	(505.338)
SPEI-3^2 (May)	−1002.607	−276.217	−23.735	−29.448	−234.520
	(613.796)	(335.007)	(44.330)	(30.969)	(437.245)
SPEI-3 (Aug)	2319.595**	900.282	33.198	43.788	−280.688
	(982.802)	(600.579)	(71.334)	(44.531)	(695.318)
SPEI-3^2 (Aug)	−1185.453*	−2275.926***	−95.600**	−46.130*	−530.539
	(635.565)	(345.468)	(41.700)	(27.839)	(442.741)
SPEI-3 (Nov)	621.627	1415.679***	9.645	−8.440	935.248
	(1061.854)	(502.629)	(67.748)	(43.154)	(638.484)
SPEI-3^2 (Nov)	232.908	−9.998	74.690**	−9.894	−817.246**
	(556.600)	(298.797)	(37.318)	(22.640)	(372.354)
Irrigation (m3 ha^{-1})	7.673**	−0.351	−0.313	−2.575	−1.952
	(3.322)	(2.798)	(1.543)	(5.403)	(1.647)
SPEI-3 (May):Irrigation	2.035	−1.318	−4.249	−10.557*	−0.661
	(1.254)	(2.735)	(3.502)	(6.304)	(0.930)
SPEI-3^2 (May):Irrigation	−0.265	−0.666	−2.138	−4.398**	0.964
	(1.089)	(1.415)	(1.748)	(1.940)	(0.604)
SPEI-3 (Aug):Irrigation	−7.786***	1.189	−0.478	0.677	−1.281
	(2.610)	(1.770)	(0.949)	(0.636)	(0.919)
SPEI-3^2 (Aug):Irrigation	−4.301*	0.300	0.071	−0.186	0.175
	(2.312)	(1.287)	(0.878)	(0.532)	(0.878)
SPEI-3 (Nov):Irrigation	−2.816**	2.710	−1.192	1.576	0.074
	(1.434)	(1.827)	(0.814)	(0.987)	(0.823)
SPEI-3^2 (Nov):Irrigation	−1.631	1.602	0.138	1.140	1.799**
	(1.427)	(1.671)	(1.213)	(1.727)	(0.714)
Observations	1616	3150	2268	679	1822
R^2	0.046	0.036	0.028	0.053	0.043
F Statistic	4.521***	8.794***	5.029***	7.574***	4.287***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C6. FE panel data regression output with robust standard errors for summer barley, seed potato, starch potato, grass and maize models, including SPEI and SPEI^2 for each period, as well as irrigation and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Summer barley	Seed potato	Starch potato	Grass	Maize
SPEI-3 (May)	-364.155^{***} (124.246)	-295.061 (359.639)	-1109.023 (1208.536)	6.678 (103.799)	-629.118^{***} (130.217)
SPEI-3^2 (May)	-243.169^{***} (92.069)	-483.837^{**} (242.118)	-620.838 (608.464)	24.120 (76.219)	-567.116^{***} (104.955)
SPEI-3 (Aug)	-68.128 (146.560)	711.245^{**} (311.641)	1190.186 (1056.075)	338.608^{***} (106.927)	-61.620 (128.422)
SPEI-3^2 (Aug)	-33.334 (84.189)	-540.543^{***} (193.550)	-1419.971^{*} (774.260)	-236.514^{***} (60.977)	-276.395^{***} (85.399)
SPEI-3 (Nov)	-195.290 (151.173)	1287.818^{***} (338.504)	-1386.888 (1498.525)	-96.241 (117.019)	119.063 (154.672)
SPEI-3^2 (Nov)	-179.398^{**} (78.654)	-989.214^{***} (198.461)	486.877 (673.593)	-118.922^{*} (63.048)	140.585 (86.870)
Irrigation (m3 ha^{-1})	1.373 (2.583)	-0.948 (1.430)	6.350^{***} (2.340)	1.542^{**} (0.704)	0.482 (1.656)
SPEI-3 (May):Irrigation	-1.714 (3.853)	-0.333 (0.976)	0.996 (2.801)	0.266 (0.779)	0.961 (1.038)
SPEI-3^2 (May):Irrigation	-0.906 (1.459)	0.702 (0.848)	-1.374 (1.372)	-0.220 (0.416)	0.426 (0.562)
SPEI-3 (Aug):Irrigation	0.053 (0.683)	-0.509 (1.649)	0.404 (3.307)	-0.112 (0.260)	-0.157 (0.838)
SPEI-3^2 (Aug):Irrigation	0.584 (0.490)	0.429 (1.143)	1.084 (1.954)	-0.040 (0.227)	0.417 (0.531)
SPEI-3 (Nov):Irrigation	0.239 (0.900)	1.129 (0.855)	-0.854 (0.965)	-0.265 (0.387)	-0.139 (0.638)
SPEI-3^2 (Nov):Irrigation	-0.955 (0.758)	0.092 (0.903)	-1.088 (1.683)	-0.238 (0.293)	-0.311 (0.631)
Observations	1037	1568	597	4473	4271
R^2	0.048	0.033	0.068	0.010	0.026
F Statistic	3.644^{***}	4.319^{***}	3.382^{***}	2.521^{***}	5.917^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C7. FE panel data regression with robust standard errors output for onion, sugar beet, winter wheat, grass seed and ware potato models, including SPEI and SPEI^2 for each period, as well as nitrogen use and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Onion	Sugar beet	Winter wheat	Grass seed	Ware potato
SPEI-3 (May)	−2505.572*** (936.011)	−1968.120*** (527.793)	−119.813 (107.482)	88.030* (46.699)	−1730.544** (803.458)
SPEI-3^2 (May)	−606.957 (756.440)	−1027.126** (483.530)	−93.995 (84.169)	7.033 (42.849)	−238.971 (559.315)
SPEI-3 (Aug)	1467.825 (1059.996)	1330.128** (630.600)	148.991 (102.883)	17.682 (53.170)	−401.899 (854.305)
SPEI-3^2 (Aug)	−1376.399* (809.200)	−1908.518*** (473.014)	18.077 (79.597)	−27.465 (38.834)	−1057.894** (511.521)
SPEI-3 (Nov)	−1125.151 (1127.792)	2644.284*** (659.135)	116.545 (109.223)	12.587 (48.886)	492.899 (796.022)
SPEI-3^2 (Nov)	208.008 (768.831)	−295.798 (487.612)	7.287 (79.987)	−37.331 (39.416)	−777.176 (594.646)
Nitrogen use (kg ha^{-1})	13.109* (7.436)	5.340 (3.703)	1.484*** (0.576)	0.505** (0.206)	2.152 (2.753)
SPEI-3 (May):Nitrogen	2.087 (4.589)	−0.971 (2.246)	−0.512 (0.406)	−0.310 (0.201)	1.960 (2.277)
SPEI-3^2 (May):Nitrogen	0.092 (3.128)	2.869 (1.994)	0.340 (0.313)	−0.193 (0.136)	0.336 (1.365)
SPEI-3 (Aug):Nitrogen	−0.975 (4.126)	0.395 (2.556)	−0.349 (0.324)	0.125 (0.143)	0.613 (2.064)
SPEI-3^2 (Aug):Nitrogen	4.515 (3.989)	−3.324 (2.038)	−0.546* (0.279)	−0.163 (0.137)	2.549* (1.492)
SPEI-3 (Nov):Nitrogen	1.071 (3.903)	−3.365 (2.561)	−0.009 (0.333)	−0.003 (0.165)	1.430 (1.924)
SPEI-3^2 (Nov):Nitrogen	−2.834 (3.701)	0.582 (2.459)	0.032 (0.292)	0.141 (0.163)	−0.179 (2.072)
Observations	1936	4101	2944	903	2333
R^2	0.022	0.043	0.025	0.030	0.014
F Statistic	3.297***	13.049***	5.546***	2.288***	2.561***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C8. FE panel data regression output with robust standard errors for summer barley, seed potato, starch potato, grass and maize models, including SPEI and SPEI^2 for each period, as well as nitrogen use and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Summer barley	Seed potato	Starch potato	Grass	Maize
SPEI-3 (May)	−241.825 (154.875)	168.228 (372.028)	333.641 (1576.164)	−90.736 (226.698)	−161.405 (207.887)
SPEI-3^2 (May)	−265.159*** (97.697)	−92.790 (253.287)	−1165.303 (868.269)	52.208 (124.205)	−638.586*** (152.546)
SPEI-3 (Aug)	64.918 (172.447)	515.848 (396.649)	2106.619 (1344.326)	−372.988** (153.677)	372.119** (164.911)
SPEI-3^2 (Aug)	−159.133 (110.256)	−563.691** (264.764)	−1887.143* (1045.965)	−367.003*** (129.976)	−471.512*** (146.697)
SPEI-3 (Nov)	−375.163** (164.803)	1079.481*** (377.928)	206.017 (1782.986)	−220.383 (187.496)	−420.348** (201.335)
SPEI-3^2 (Nov)	−398.495*** (126.508)	−758.064*** (290.719)	721.523 (1234.628)	−21.301 (154.259)	−211.083 (168.633)
Nitrogen use (kg ha^{-1})	−1.445 (1.637)	6.065** (2.535)	−0.062 (5.598)	8.533*** (0.919)	−2.851*** (1.013)
SPEI-3 (May):Nitrogen	1.226 (1.172)	−0.051 (2.068)	−0.910 (4.175)	0.308 (0.546)	−0.962 (0.815)
SPEI-3^2 (May):Nitrogen	1.027 (0.750)	−2.322* (1.271)	1.130 (2.597)	−0.328 (0.320)	1.000* (0.581)
SPEI-3 (Aug):Nitrogen	−0.728 (0.995)	−0.325 (1.722)	−2.272 (4.349)	1.408*** (0.361)	−0.924 (0.580)
SPEI-3^2 (Aug):Nitrogen	0.453 (0.894)	0.949 (1.226)	1.650 (3.370)	0.507 (0.319)	0.698 (0.534)
SPEI-3 (Nov):Nitrogen	1.540 (1.105)	−2.210 (1.537)	0.333 (3.874)	0.374 (0.401)	1.816** (0.730)
SPEI-3^2 (Nov):Nitrogen	1.320 (1.186)	−2.294 (1.606)	2.193 (5.025)	−0.294 (0.404)	1.462** (0.668)
Observations	1408	2005	748	5351	5385
R^2	0.034	0.028	0.025	0.051	0.022
F Statistic	2.381***	5.693***	1.628*	13.076***	7.508***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C9. FE panel data regression with robust standard errors output for onion, sugar beet, winter wheat, grass seed and ware potato models, including SPEI and $SPEI^2$ for each period, as well as phosphate use and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Onion	Sugar beet	Winter wheat	Grass seed	Ware potato
SPEI-3 (May)	-2057.215^{***}	-2214.967^{***}	-247.258^{***}	36.082	-974.984
	(764.239)	(396.295)	(56.893)	(31.058)	(595.939)
$SPEI\text{-}3^2$ (May)	-886.795	-779.642^{**}	-45.850	-22.157	117.093
	(629.179)	(361.111)	(45.255)	(29.560)	(482.807)
SPEI-3 (Aug)	1563.394^{*}	1174.928^{**}	103.572	44.107	37.491
	(906.481)	(509.988)	(73.364)	(40.389)	(696.586)
$SPEI\text{-}3^2$ (Aug)	-797.199	-2416.397^{***}	-74.764	-55.009^{**}	-618.795
	(585.632)	(365.895)	(46.495)	(26.224)	(420.668)
SPEI-3 (Nov)	-1264.314	1811.523^{***}	87.891	14.776	557.672
	(989.639)	(502.224)	(79.948)	(36.225)	(669.885)
$SPEI\text{-}3^2$ (Nov)	-385.513	-346.366	-3.127	-2.494	-653.027
	(593.662)	(342.092)	(45.263)	(25.757)	(446.425)
Phosphate use (kg ha^{-1})	9.320	-0.676	0.255	0.645^{**}	7.259
	(12.460)	(7.140)	(0.953)	(0.316)	(6.029)
SPEI-3 (May):Phosphate	2.040	1.187	0.445	-0.250	-5.642
	(8.244)	(3.688)	(0.780)	(0.339)	(5.024)
$SPEI\text{-}3^2$ (May):Phosphate	4.226	5.765^{*}	0.969	-0.171	-3.988
	(5.648)	(3.259)	(0.627)	(0.226)	(3.048)
SPEI-3 (Aug):Phosphate	-3.257	4.585	-1.086^{*}	-0.023	-7.423
	(6.430)	(4.666)	(0.618)	(0.236)	(4.733)
$SPEI\text{-}3^2$ (Aug):Phosphate	1.653	-0.096	-0.641	-0.027	3.914
	(6.340)	(3.664)	(0.484)	(0.203)	(3.511)
SPEI-3 (Nov):Phosphate	8.019	3.716	0.209	-0.094	0.237
	(7.196)	(3.999)	(0.722)	(0.307)	(4.742)
$SPEI\text{-}3^2$ (Nov):Phosphate	3.680	4.522	0.364	-0.211	-2.017
	(6.988)	(4.178)	(0.590)	(0.262)	(4.655)
Observations	1960	4085	2951	912	2301
R^2	0.018	0.041	0.016	0.015	0.014
F Statistic	2.862^{***}	12.251^{***}	4.531^{***}	1.278	3.002^{***}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C10. FE panel data regression output with robust standard errors for summer barley, seed potato, starch potato, grass and maize models, including SPEI and SPEI^2 for each period, as well as phosphate use and its interaction with the SPEI variables as regressors. The R-squared and F-statistic refer to the variance explained and F-test on the explanatory variables, respectively, after demeaning the data.

	Dependent variable:				
	Yield (kg ha^{-1})				
	Summer barley	Seed potato	Starch potato	Grass	Maize
SPEI-3 (May)	−105.635	247.435	−658.377	−7.949	−577.140***
	(98.521)	(329.537)	(1494.862)	(234.095)	(182.955)
SPEI-3^2 (May)	−232.733***	−377.954	−905.008	48.508	−723.309***
	(75.167)	(237.956)	(678.007)	(160.442)	(127.913)
SPEI-3 (Aug)	−39.166	606.974*	2423.355**	3.127	207.295
	(124.210)	(352.090)	(1140.752)	(181.700)	(157.144)
SPEI-3^2 (Aug)	−96.169	−215.433	−1804.942**	−417.895***	−455.520***
	(67.522)	(223.109)	(833.261)	(144.755)	(129.077)
SPEI-3 (Nov)	−253.641**	713.536**	458.568	39.225	−355.437*
	(114.408)	(333.860)	(1762.772)	(226.123)	(188.769)
SPEI-3^2 (Nov)	−296.706***	−951.313***	1060.145	−219.940	−35.863
	(82.447)	(242.538)	(1058.767)	(185.789)	(152.156)
Phosphate use (kg ha^{-1})	−2.102	6.153	−5.696	17.031***	−6.414***
	(1.797)	(4.159)	(13.981)	(3.680)	(2.287)
SPEI-3 (May):Phosphate	−0.328	−1.007	6.216	0.409	3.011
	(1.857)	(3.561)	(10.601)	(2.449)	(1.976)
SPEI-3^2 (May):Phosphate	−0.050	−0.203	2.601	−1.581	4.208***
	(1.266)	(2.152)	(6.623)	(1.777)	(1.342)
SPEI-3 (Aug):Phosphate	0.127	−1.768	−14.029	1.903	−0.362
	(1.435)	(2.884)	(10.115)	(1.921)	(1.476)
SPEI-3^2 (Aug):Phosphate	0.427	−2.817	5.598	3.087*	1.783
	(1.251)	(2.089)	(7.544)	(1.635)	(1.265)
SPEI-3 (Nov):Phosphate	1.025	−0.560	−0.433	−1.855	4.653**
	(1.922)	(2.691)	(8.355)	(2.403)	(1.815)
SPEI-3^2 (Nov):Phosphate	−0.302	−1.502	−4.275	0.860	2.041
	(2.049)	(2.845)	(12.072)	(2.189)	(1.730)
Observations	1428	1999	749	5250	5301
R^2	0.035	0.023	0.025	0.026	0.019
F Statistic	2.591***	3.799***	1.142	6.438***	5.864***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C11. Outcomes of F-test testing the addition of variables to the basic model for each model-crop combination. For the basic model, the F-tests test the joint probability of all the SPEI coefficients to be nonzero. For the other models, it tests the joint probability of the additional coefficients to be nonzero.

	Basic	Soil	Irrigation	Nitrogen	Phosphate
Onion	4.420***	1.246	3.871***	1.615	1.188
Sugar beet	25.054***	8.619***	0.551	1.987*	1.251
Winter wheat	6.838***	2.179**	1.600	3.430***	1.224
Grass seed	1.729	0.606	8.995***	1.744*	0.619
Ware potato	4.000***	2.401**	4.777***	1.210	1.339
Summer barley	5.166***	0.850	1.608	0.782	0.374
Seed potato	8.685***	3.171***	0.578	2.013*	0.568
Starch potato	1.783*	0.925	4.466***	0.649	0.558
Grass	4.231***	1.882*	1.527	21.727***	9.289***
Maize	10.030***	2.824***	1.107	4.497***	2.387**

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ORCID iDs

S van der Veer https://orcid.org/0009-0006-4108-3406
R Hamed https://orcid.org/0000-0003-2243-3109
H Karabiyik https://orcid.org/0000-0002-4584-7526
J L Roskam https://orcid.org/0000-0002-7665-2094

References

[1] Vogel E, Donat M G, Alexander L V, Meinshausen M, Ray D K, Karoly D, Meinshausen N and Frieler K 2019 *Environ. Res. Lett.* **14** 054010
[2] Malhi G S, Kaur M and Kaushik P 2021 *Sustainability* **13** 1318
[3] Zampieri M, Ceglar A, Dentener F and Toreti A 2017 *Environ. Res. Lett.* **12** 064008
[4] Lesk C, Rowhani P and Ramankutty N 2016 *Nature* **529** 84–87
[5] Polman N, Peerlings J and van der Vat M 2019 Economische effecten van droogte voor landbouw in Nederland: samenvatting *Technical Report* (Wageningen Economic Research)
[6] Wang Q *et al* 2014 *Quat. Int.* **349** 10–21
[7] Nath R, Nath D, Li Q, Chen W and Cui X 2017 *Adv. Atmos. Sci.* **34** 335–46
[8] Yaddanapudi R and Mishra A K 2022 *Sci. Total Environ.* **807** 150801
[9] Hussain A, Jadoon K Z, Rahman K U, Shang S, Shahid M, Ejaz N and Khan H 2023 *Nat. Hazards* **115** 389–408
[10] Sumner E, Li M and Shr Y H J 2023 Is yield response enough? Drought impacts on crop acreage throughout the production cycle (available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4462721) (Accessed 29 May 2023)
[11] Leneman H, Reinhard A J and Hoogeveen M W 1999 *Weer en Gewasopbrengst; Invloed van Weer op Productie van Akkerbouwgewassen* (Landbouw-Economisch Instituut (LEI))
[12] Kuwayama Y, Thompson A, Bernknopf R, Zaitchik B and Vail P 2019 *Am. J. Agric. Econ.* **101** 193–210
[13] Mehrabi Z *et al* 2022 *One Earth* **5** 756–66
[14] van Oort P, Timmermans B, Schils R and van Eekeren N 2023 *Eur. J. Agron.* **142** 126662
[15] Troy T J, Kipgen C and Pal I 2015 *Environ. Res. Lett.* **10** 054013
[16] Smith D, Dijak M, Bulman P, Ma B and Hamel C 1999 *Barley: Physiology of Yield* (Springer) pp 67–107
[17] Fischer R, Byerlee D and Edmeades G 2014 *Crop Yields and Global Food Security* (ACIAR) pp 8–11
[18] Roskam J, van der Meer R W and van der Veen H B 2022 Sample for the Dutch FADN 2020 *Technical Report* (Wageningen Economic Research)
[19] De Bruin H and Lablans W 1998 *Hydrol. Process.* **12** 1053–62
[20] Bivand R S, Pebesma E J, Gomez-Rubio V and Pebesma E J 2008 *Applied Spatial Data Analysis With R* vol 2 (Springer)
[21] Zhou Z H 2021 *Machine Learning* (Springer)
[22] Vicente-Serrano S M, Beguería S and López-Moreno J I 2010 *J. Clim.* **23** 1696–718
[23] McKee T B, Doesken N J and Kleist J 1993 The relationship of drought frequency and duration to time scales *Proc. 8th Conf. on Applied Climatology* vol 17 (Boston) pp 179–83
[24] Beguería S and Vicente-Serrano S M 2023 Package 'SPEI' https://cran.r-project.org/web/packages/SPEI/SPEI.pdf (Accessed 22 March 2023)
[25] Singh V, Guo H and Yu F 1993 *Stoch. Hydrol. Hydraul.* **7** 163–77
[26] Hosking J R 1990 *J. R. Stat. Soc.* B **52** 105–24
[27] Beguería S, Vicente-Serrano S M, Reig F and Latorre B 2014 *Int. J. Climatol.* **34** 3001–23
[28] Arellano M 1987 *Oxford Bull. Econ. Stat.* **49** 431–4
[29] Long J S and Ervin L H 2000 *Am. Stat.* **54** 217–24
[30] Gerzabek M H, Pichlmayer F, Kirchmann H and Haberhauer G 1997 *Eur. J. Soil Sci.* **48** 273–82
[31] Bhadha J H, Capasso J M, Khatiwada R, Swanson S and LaBorde C 2021 Raising soil organic matter content to improve water holding capacity *Technical Report* (University of Florida, Institute of Food and Agricultural Sciences)
[32] Libohova Z, Seybold C, Wysocki D, Wills S, Schoeneberger P, Williams C, Lindbo D, Stott D and Owens P R 2018 *J. Soil Water Conserv.* **73** 411–21
[33] Zarei A R, Mahmoudi M R and Moghimi M M 2023 *Nat. Hazards* **115** 923–46
[34] Heino M, Kinnunen P, Anderson W, Ray D K, Puma M J, Varis O, Siebert S and Kummu M 2023 *Sci. Rep.* **13** 3583
[35] Carter E K, Melkonian J, Steinschneider S and Riha S J 2018 *Agric. Forest Meteorol.* **256** 242–52
[36] Schölkopf B 2022 Causality for machine learning *Probabilistic and Causal Inference: The Works of Judea Pearl* (ACM Books) pp 765–804
[37] Van Oort P, Timmermans B, Meinke H and Van Ittersum M 2012 *Eur. J. Agron.* **37** 11–22
[38] Gé van den E *et al* 2021 Droogte in zandgebieden van Zuid-, Midden-en Oost-Nederland: het verhaal-analyse van droogte 2018 en 2019 en bevindingen: eindrapport *Technical Report* (KnowH2O)
[39] Bos J F F P, Smit A (B) L and Schröder J J 2013 *NJAS-Wageningen J. Life Sci.* **66** 65–73
[40] Koopman J F, Kuik O, Tol R S, van der Vat M P, Hunink J C and Brouwer R 2019 *Economy-Wide Modeling of Water at Regional and Global Scales* (Springer) pp 159–92
[41] Kros H, Cals T, Gies E, Groenendijk P, Lesschen J P, Voogd J C, Hermans T and Velthof G 2024 *Sci. Total Environ.* **909** 168501