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The optimal drought index for designing weather index insurance

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Abstract

Climate change increases the need for better insurance solutions that enable farmers to cope with drought risks. We design weather index insurance using drought indices based on precipitation, soil moisture and evapotranspiration as underlying drought index and compare their risk-reducing potential for winter wheat producers in Eastern Germany. In general, we find that all drought indices can reduce financial risk exposure. However, the largest risk reduction can be achieved if the underlying drought index is tailored individually for each farm. This implies that insurers should offer insurance with farm-specific underlying drought index.

Keywords: index-based insurance, drought risks, index design, drought indices, quantile regression

JEL classification: G22, Q14, Q54

1. Introduction

Drought is a major driver of crop yield volatility and, in particular, causes low yields that can lead to substantial financial losses (Chavas et al., 2018; Webber et al., 2018). Climate change is likely to increase these financial losses in many regions and thus improved drought risk management is essential (Lobell, Schlenker and Costa-Roberts, 2011; Trnka et al., 2014; Yang et al., 2014; Pirttioja et al., 2015; Grillakis, 2019). Whilst on-farm measures, such as using drought tolerant crops, installing irrigation systems or practicing water-conserving tillage, mitigate some drought risks, they might still fail to absorb

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losses from extreme droughts (Olesen et al., 2011). Insurance solutions can therefore be a viable complementary risk management tool to compensate for the remaining downside risks and improve farmers' financial well-being (Breustedt, Bokusheva and Heidelbach, 2008; Musshoff, Odening and Xu, 2011; Di Falco et al., 2014). Weather index solutions where indemnification is based on a weather index, such as precipitation, and not on actual crop yields are particularly suitable to cope with drought risks (e.g. Turvey, 2001; Vedenov and Barnett, 2004).

In this paper, we systematically test and compare the ability of different drought indices to reduce basis risk in weather index insurance, i.e. differences between the index-dependent payout and actual losses. To achieve this, we use an empirical example of wheat production in Eastern Germany and test potential gains from farm-specific tailoring of the underlying drought index.

As weather index insurance[1] provides protection against systemic risks in particular, and at a low administrative cost, it is a complementary tool for classical indemnity insurance products (Barnett and Mahul, 2007). The amount of indemnification in weather index insurance depends on a realised value of a weather index, such as cumulative precipitation, officially reported by a weather station or other data sources (Turvey, 2001; Vedenov and Barnett, 2004). This means there is no on-field damage assessment, which allows fast payouts to farmers within the growing period. In addition, historical data of the weather index permits the calculation of farm-specific premiums and thereby mitigate adverse selection problems (Odening, Mußhoff and Xu, 2007; Barnett, Barrett and Skees, 2008). Moreover, weather index insurance can also compensate for additional expenditures, such as increased irrigation costs during drought occurrence and therefore does not distort farmers' incentives to reduce losses (Miranda and Vedenov, 2001). Basis risk, i.e. the difference between the index-dependent payout and actual losses, is a drawback as it limits the risk-reducing potential of weather index insurance (Woodard and Garcia, 2008). Therefore, it is crucial that the weather data input predicts low yields accurately to ensure optimal risk reduction.

Previous studies addressing the protection of drought risks with weather index insurance[2] have used precipitation-based indices (Martin, Barnett and Coble, 2001; Berg, Quirion and Sultan, 2009; Musshoff, Odening and Xu, 2011; Norton, Turvey and Osgood, 2012; Leblois et al., 2014a; Dalhaus and Finger, 2016), mixed indices based on precipitation and temperature (Vedenov and Barnett, 2004; Breustedt, Bokusheva and Heidelbach, 2008; Pelka and Musshoff, 2013), a soil moisture index (Kellner and Musshoff, 2011) and the water requirement satisfaction index (Meze-Hausken, Patt and Fritz, 2009; Leblois and Quirion, 2013) as well as its standardised form, the

1 Alternative terms are parametric weather insurance or weather derivative (e.g. Musshoff, Odening and Xu, 2011).

2 Note, here we focus solely on weather index insurance. Other index insurance products use area yield statistics (e.g. Skees, Black and Barnett, 1997) or vegetation health indices (Bokusheva et al., 2016) as the underlying index. See also Vroege et al. (2019) for an overview.

evaporative stress index (Enenkel et al., 2019).[3] There are also alternative drought indices that are frequently used to monitor agricultural droughts. Two prominent examples of such alternatives are the standardised precipitation index (Vicente-Serrano, Cuadrat-Prats and Romo, 2006; Okpara et al., 2017) and the standardised precipitation evapotranspiration index (Vicente-Serrano et al., 2012; Bozzola, Smale and Di Falco, 2018; Tian, Yuan and Quiring, 2018; Peña-Gallardo et al., 2019). However, these two standardised indices have not been applied to the design of weather index insurance.

We provide two key contributions to the literature. Firstly, instead of adhering rigidly to a single drought index to calculate insurance payouts, or comparing only two indices against each other, we systematically evaluate five prominently used drought indices of index insurance and relevant climate impact literature to assess their ability to reduce farmers' financial downside risk exposure. Secondly, we go a step further and identify the farm-specific 'BEST' index to maximise index insurances' risk-reducing capacity. Therefore, we extend previous literature by suggesting tailor-made weather index insurance products based on a farm-specific risk assessment rather than using the same underlying index for all insured farms.

In our analysis, we provide an ex-ante simulation of the risk-reducing capacity of weather index insurance using five prominent drought indices for 85 representative large-scale winter wheat farms in Eastern Germany. More specifically, these indices form a complexity gradient that considers further soil-plant-atmosphere interactions in the following increasing order: (i) cumulative precipitation index, (ii) standardised precipitation index, (iii) standardised precipitation evapotranspiration index, (iv) soil moisture index and (v) evaporative stress index. We test whether the risk-reducing potential of weather index insurance increases when the underlying index is tailored individually for each farm. The index design is based on the latest research, phenology data are used to tailor the optimal index measurement period and quantile regression serves to tailor payout formulas that minimise basis risk (e.g. Conradt, Finger and Bokusheva, 2015a; Dalhaus, Musshoff and Finger, 2018). This means that meteorology and phenology data are combined with unique historical yield data at the farm-level, and farm-specific downside risk removals can be simulated using risk premiums and lower partial moments. Wheat production in Eastern Germany is an excellent case study because this region is one of Europe's major breadbaskets, where farmers face comparatively high and increasing drought risks and show interest in improved risk management tools (Gornott and Wechsung, 2016; Lüttger and Feike, 2018).

We find that all of the drought indices considered here can significantly reduce farmers' financial exposure to drought risks. On average, the evaporative stress index causes the largest reduction in financial exposure to drought risks in our case study. Most importantly, our results show that 'the most

3 The study of Enenkel et al. (2019) does not design farm-specific weather index insurance contracts but they show a strong correlation between the evaporative stress index and the (lagged) NDVI. Moreover, by comparing the index to reported losses in Africa, they show that the evaporative stress index is a good indicator of low yields.

suitable' underlying drought index has not yet been identified and that each of the five drought indices can generate the largest risk reduction for at least some farms. Hence, our results indicate a need for farm-specific risk assessment and tailor-made insurance contracts for each farm.

The remainder of the paper is structured as follows. We first provide a conceptual framework for designing weather index insurance and reducing basis risk. In this section, we also introduce the five drought indices applied in the study. Next, we present the empirical risk analysis framework, followed by the presentation of our case study and data. We then put forward our results and summarise the robustness checks. This is followed by a discussion, and finally, we end this paper with concluding remarks.

2. Conceptual framework of weather index insurance and basis risk

We assume that crop yield $\tilde{y}$ is a random variable that stochastically depends on random weather conditions. The realised value of an underlying weather index, $\tilde{I}$ represents these conditions. Following Elabed et al. (2013), we further assume that $\tilde{y}$ is a function of $\tilde{I}$ whose impact is approximated with $g(\tilde{I})$ as illustrated in Equation (1). Since the measured weather $\tilde{I}$ only partly captures the general impact of weather on $\tilde{y}$, the error term $\tilde{\vartheta}$ accounts for weather induced impacts outside $\tilde{I}$. In addition, the error term $\tilde{\eta}$ represents any other random factors that are uncorrelated with $\tilde{I}$ but influence $\tilde{y}$ (e.g. weather-independent changes in management).

$$\tilde{y} = g\left(\tilde{I}\right) + \tilde{\vartheta} + \tilde{\eta} \tag{1}$$

The estimated parameters of $g\left(\tilde{I}\right)$ determine critical parameters in insurance design and both error terms together represent basis risk, whereby the approximation error $\tilde{\vartheta}$ can be reduced by improving the weather index insurance design, i.e. increasing the predictive power of $\tilde{I}$ (Conradt, Finger and Bokusheva, 2015a). More specifically, insurance design should use an estimate of $g(.)$ that is tailored to yield losses and apply an underlying index $\tilde{I}$ that best captures the yield reducing weather events.

2.1. A set of weather indices for drought insurance

In this section, we first introduce the five drought indices that serve as underlying index in this study[4] and subsequently discuss the optimal index

4 The set of indices chosen here reflects a subjective set of possibilities that are prominently used in weather index insurance and drought impact studies. Due to the large range of alternatives (e.g. Zargar et al., 2011), we do not claim that this list is complete.

measurement period to minimise basis risk. We arrange them in an order that reflects increasing soil-plant-atmosphere interactions and provide more technical details in Section 1 of the online supplement.

2.1.1. *Cumulative precipitation index (CPI).* The cumulative precipitation index is the absolute sum of precipitation within a certain time period and can therefore indicate an inadequate water supply. It is the most frequently applied underlying index in weather index insurance publications (e.g. Martin, Barnett and Coble, 2001; Berg, Quirion and Sultan, 2009; Pelka, Musshoff and Finger, 2014; Conradt, Finger and Spörri, 2015b; Dalhaus, Musshoff and Finger, 2018), probably due to its simplicity, the general availability of precipitation data and verified risk-reducing potential.

2.1.2. *Standardised precipitation index (SPI).* The standardised precipitation index shows standardised anomalies in the cumulative precipitation index with respect to the site-specific, long-term average so that negative values indicate below-average precipitation amounts (McKee, Doesken and Kleist, 1993; Vicente-Serrano, Cuadrat-Prats and Romo, 2006). Standardised values reflect location-specific climates, which improves comparisons in drought severity across space and time versus the use of absolute precipitation amounts.

2.1.3. *Standardised precipitation evapotranspiration index (SPEI).* The standardised precipitation evapotranspiration index represents standardised anomalies in the climatic water balance (precipitation minus potential evapotranspiration) with respect to the site-specific, long-term average (Vicente-Serrano, Beguería and López-Moreno, 2010). Negative values indicate comparatively dry conditions because the atmospheric water demand, represented by potential evapotranspiration, exceeds the atmospheric water supply represented by precipitation. Temperature is the main driver of potential evapotranspiration, which is the sum of potential water evaporation and potential plant transpiration from a well-watered reference surface (Beguería et al., 2014).[5] The advantage of the SPEI is its ability to reflect the joint effect of insufficient precipitation amounts and high temperatures on drought occurrence without the need of comprehensive weather data.

2.1.4. *Soil moisture index (SMI).* The soil moisture index is the average plant available soil moisture during the index measurement period (Kellner and Musshoff, 2011). Soil moisture depends on site-specific characteristics (e.g. water retention capacity, topography), management decisions (e.g. tillage, cover) and weather conditions (Friesland and Löpmeier, 2007; Zhang et al., 2009; Mozny et al., 2012). Changes in the stock of soil moisture result mainly

5 Simple estimation models of potential evapotranspiration only require temperature data (e.g. Hargreaves method), whereas more complex models also consider solar radiation, air humidity and wind speed (Penman-Monteith model). See Beguería et al. (2014) for details.

from an imbalance between precipitation and temperature-driven evapotranspiration. The advantage of soil moisture is its direct indication of inadequate water supply within the root zone and memory of weather conditions prior to the start of index measurement period.

2.1.5. *Evaporative stress index (ESI).* The evaporative stress index (ESI) shows the standardised anomaly in the ratio of actual to potential evapotranspiration[6] with respect to the site-specific, long-term average (Anderson et al., 2016; Enenkel et al., 2019). Negative values indicate dry conditions resulting from a below-average satisfaction of the atmospheric water demand (i.e. potential evapotranspiration) with actual evapotranspiration.[7] As the actual evapotranspiration depends on water supply in the soil-plant system, the ESI is closely interrelated to the soil moisture index but focuses on water fluxes instead of water stocks.

2.1.6. *Period of index measurement.* The indices presented above measure drought over a certain period of time. A suitable weather index insurance specification should ensure that the index measurement period covers the critical growth phases in which crops are especially vulnerable to drought stress. Temperature is the main driver of crop growth in temperate regions, but other weather variables and management decisions (e.g. sowing date) can also have an influence (Porter and Gawith, 1999; Rezaei, Siebert and Ewert, 2015). Since the timing of growth phases varies across space and time, an index measurement period based on fixed calendar dates is unlikely to coincide with the actual timing of certain growth phases. Therefore, we follow Dalhaus, Musshoff and Finger (2018) and use phenology observations to define farm-specific index measurement periods covering the growth phases from stem elongation to the beginning of milk ripeness. Drought occurrence during these growth phases of winter wheat causes the greatest losses in absolute yield potentials (Barnabás, Jäger and Fehér, 2008; Farooq, Hussain and Siddique, 2014; Varga et al., 2015).

2.2. Definition of contract specifics

Low values of the above-mentioned indices represent drought occurrence. The payout determination of weather index insurance thus follows the design of a European put option as illustrated in Equation (2) (Martin, Barnett and Coble,

6 This ratio shows the amount of actual evapotranspiration relative to the maximum possible amount of evapotranspiration.

7 Lysimeter, remote-sensing technology or agrometeorological models can derive actual evapotranspiration and soil moisture (e.g. Friesland and Löpmeier, 2007; Enenkel et al., 2019). Note that the potential evapotranspiration is the evaporative (i.e. the water) demand of the atmosphere, independent of current soil moisture supply and only under well-watered conditions equal to actual evapotranspiration.

2001; Turvey, 2001).[8] More specifically, farmer i has a weather index insurance with underlying index k and receives a payout π_{it}^{k} in year t whenever the realised value of the underlying index I_{it}^{k} falls below a strike level S_{i}^{k} at the end of the index measurement period. The strike level S_{i}^{k} is a predefined threshold value of the underlying index and is farm-specific to reflect different drought vulnerabilities. The tick size T_{i}^{k} represents the expected yield loss per missing unit of the underlying index and is monetarised with a predefined price P, whilst the tick size represents the payout per index unit.

$$\pi_{it}^{k} = P^{*}T_{i}^{k\,*}\text{argmax}\left\{\left(S_{i}^{k} - I_{it}^{k}\right), 0\right\} \tag{2}$$

We tailor farm- and index-specific tick sizes and strike levels based on empirical index-yield[9] relationships to reflect individual drought vulnerability.[10] We therefore transform Equations (1)–(3) where the slope coefficient β_{i}^{k} shows the expected yield loss per missing unit of the underlying index k, i.e. the slope coefficient in Equation (3) is the tick size in Equation (2). As we estimate Equation (3) for each farm individually, we account for differences in yield potentials and time invariant farm characteristics (e.g. soil conditions).

$$y_{it} = c_{i}^{k} + \beta_{i}^{k\,*}I_{it}^{k} + \tilde{\varepsilon}_{it}^{k} \tag{3}$$

We use the quantile regression estimator illustrated in Equation (4) to estimate Equation (3) because it results in lower basis risk than the mean-based ordinary least square estimator (Conradt, Finger and Bokusheva, 2015a).[11] The quantile regression estimator focuses on a quantile of interest τ by asymmetrically weighting positive and negative residuals. Moreover, it is robust to outlier values because it minimises the absolute rather than the squared residual (Koenker and Bassett Jr., 1978). This allows the slope coefficient (tick size) to be conditioned on lower yield observations, i.e. the estimated slope coefficients are quantile specific and tailor the insurance design on a quantile of interest, whilst the ordinary least square estimator focuses on mean responses rather than downside risks. We set $\tau = 0.3$ to derive tick sizes that best capture the marginal impact of the underlying index on the lowest 30 per cent of yield

8 In practice, insurance provider and farmer would agree on a maximum yearly payout to plan the farmer's coverage, the insurer's geographical spread of potential claims and need for reinsurance. In Equation (2), farmers have full coverage after the strike level.

9 We use detrended yields to account for technological progress. Earlier yield observations without detrending can be comparatively low even under good weather conditions and thus bias empirical index-yield relationships and our risk analysis. See Section 2 of the online supplement for details of detrending yield data.

10 Farm-individual contract calibration is available in practice (e.g. USDA-RMA, 2020; Vroege et al., 2019).

11 As a sensitivity analysis, we also calculate contract specifics (tick size and strike level) with the ordinary least square (OLS) estimator.

observations.

$$\hat{\beta}_i^k(\tau) = \mathrm{argmin}_{\beta_i^k \in \mathbb{R}} \left[\tau^* \sum_{y_{it} \geq \beta_i^k * I_{it}^k} \left| y_{it} - \beta_i^{k*} I_{it}^k \right| + (1-\tau)^* \sum_{y_{it} < \beta_i^k * I_{it}^k} \left| y_{it} - \beta_i^k * I_{it}^k \right| \right] \tag{4}$$

We derive the farm-specific strike level S_i^k from the estimated Equation (3) by inserting the 30 per cent quantile of yield observations of farm i for y_i and solve for the realised value of the underlying index I_i^k that is then equal to the strike level S_i^k. Importantly, we use farm-individual yield data to tailor the parameters tick size and strike level to farm-individual drought risks, but the yearly payout is independent of crop yields as shown in Equation (2).[12] As a robustness check, we design insurances protecting against more extreme droughts by setting $\tau = 0.2$ and insert the 20 per cent quantile of yield of farm i to derive the strike level.

3. Empirical risk analysis

We assume that farmers secure forward contracts to guarantee a commercial buyer for their produce and to eliminate price risks. Moreover, we assume that production costs and other revenues (e.g. governmental support) are constant and uncorrelated with drought occurrence during our period of index measurement.[13] Thus, the differences in wealth depend solely on revenues from wheat production, comprising price P times yield y_{it}, as well as the net revenues from the weather index insurance, comprising the payout π_{it}^k and the insurance premium Γ_i^k so that the realised wealth W_{it}^k is

$$W_{it}^k = P^* y_{it} + \pi_{it}^k - \Gamma_i^k \tag{5}$$

We assume the price P to be fixed at EUR 15.80 per deci-ton in both the forward contracts and weather index insurance. This was the price farmers received in 2015 (KTBL, 2019; FAO, 2019a), which is the last year of our yield panel and from which we detrend yields. We use farm-individual actuarially fair insurance premiums, which equal the yield-independent expected payout of farm i and underlying index k ($\Gamma_i^k = E\left(\pi_{it}^k\right)$) to reflect farm-specific drought exposure. Whilst this is a simplistic pricing method, it allows the risk-reducing potential of the drought indices to be identified without being inhibited by any

12 In a cross-validation, we calibrate contract specifics (tick size and strike level) with pooled quantile regression to avoid overfitting. See Section 10 of the online supplement.

13 The consideration of input use and input prices, which we are unable to observe in this study, might influence risk-reducing potentials. Especially if farmers use irrigation, the here-considered relationship between crop yields and droughts as a proxy for shocks in farmers' realised wealth may be biased. However, irrigation is not common in our case study (Siebert et al., 2015). Moreover, we assume that biases due to adjustments in other input-applications such as nitrogen or pesticides are limited.

mis-specified insurance premiums. As a robustness check, we add loadings on the actuarially fair premium.

3.1. Measuring risk with the expected utility model

We use an expected utility maximisation framework in our analysis (e.g. Di Falco and Chavas, 2009),[14] where a risk-averse farmer prefers the underlying index with the lowest basis risk, equivalent to resulting in the highest expected utility $EU\left(W_{it}^{k}\right)$. Following Equation (6), this is equivalent to preferring the underlying drought index with the lowest risk premium R_i^k, which reflects the implicit costs of the risk burden (Di Falco and Chavas, 2006). The risk premium is calculated by solving Equation (6) for R_i^k yielding in Equation (7).

$$EU\left(W_{it}^{k}\right) = U\left[E\left(W_{it}^{k}\right) - R_i^k\right] \tag{6}$$

$$R_i^k = E\left(W_{it}^{k}\right) - (U)^{-1}\left(EU\left(W_{it}^{k}\right)\right) \tag{7}$$

In Equation (8) we present a power utility function used to map farmers' risk preferences and which is especially suitable to reflect aversion against downside risks (Menezes, Geiss and Tressler, 1980). This is of particular importance for our analysis, because weather index insurance should aim at reducing lowest possible wealth realisations.

$$U\left(W_{it}^{k}\right) = (1-\alpha)^{-1}\left(W_{it}^{k}\right)^{1-\alpha} \tag{8}$$

More specifically, we assume moderately risk-averse farmers represented by a coefficient of constant relative risk-aversion α equal to 2 (Chavas, 2004). Other coefficients of constant relative risk-aversion are considered as robustness checks to reflect existing evidence that German farmers are risk-averse but that the heterogeneity of risk preferences is large (Maart-Noelck and Musshoff, 2014; Iyer et al., 2019; Meraner and Finger, 2019).

Finally, we test whether different underlying indices result in significant variations in the risk premium. More specifically, we first test the different underlying indices against the 'uninsured' status to identify their suitability for weather index insurance design. Secondly, we test the risk-reducing potentials of the underlying indices against each other. This allows us to test whether one

14 The risk premium is the amount of money an expected utility maximiser is willing to pay on top of the actuarially fair premium for an insurance that completely eliminates risks. We use the risk premium as a monetarised risk measure to indicate improvements in the ability to reduce financial losses. In addition, a positive risk premium indicates preferences for insurance uptake of risk-averse decision-makers. However, it is known that farmers' insurance uptake does not always conform to EU maximising behaviour and therefore we do not claim to be able to estimate final insurance demand. We refer to Babcock (2015), Du, Feng and Hennesy (2016), Luckstead and Devadoss (2019) and Cao, Weersink, and Ferner (2019), who find that under specific framing, cumulative prospect theory could deliver better insights on how to predict crop insurance demand.

index has a lower average basis risk (i.e. larger risk reduction) than another, resulting in it being preferentially applied in a uniform drought insurance product in which each farm receives the same underlying index.[15] Thirdly, we design weather index insurance contracts where each farm receives its 'superior' underlying drought index (i.e. the underlying index with lowest risk premium) and test this non-uniform set against the uninsured status and against the five uniform insurance products. We use non-parametric one-sided paired Wilcoxon signed rank tests to investigate significant differences in the risk premium and apply Bonferroni corrections to account for the multiple hypotheses tested with the same data.[16] In addition, we conduct robustness checks using lower partial moments as another coherent risk measure. Lower partial moments show removals of downside risks and therefore complement the risk premium that monetarises overall gains of insurance use. See Section 9 of the online supplement for an explanation of lower partial moments.

4. Case study and data

Figure 1 illustrates our case study consisting of 85 winter wheat producers. These are large-scale crop farms with more than 1,000 hectares of arable land each so that insurance premiums can cover the costs for farm-individual insurance calibration. The spatial heterogeneity of farm locations accounts for the heterogeneity of site conditions throughout Eastern Germany, a major European granary facing a high and growing drought risk due to increasing temperatures and changing precipitation patterns (Gornott and Wechsung, 2016; Lüttger and Feike, 2018). One of the severest drought events took place in 2003 when the combination of abnormally high temperatures and a lack of precipitation during the reproductive growth phases caused substantial financial losses in crop production (Ciais et al., 2005; Odening, Mußhoff and Xu, 2007; Rebetez et al., 2006). In Eastern Germany, irrigation in wheat production is uncommon (Siebert et al., 2015; FAO, 2019b) and drought insurance is not widespread, but some new solutions have been launched onto the market recently (Topagrar, 2018).[17] German farmers often use forward contracts to mitigate price risks (Anastassiadis et al., 2014), which amplifies drought risks because farmers have to buy additional winter wheat if their harvest does not meet the contractually agreed quantity. Table 1 shows summary statistics of

15 The weather index insurance contracts still specify farm-specific tick sizes and strike levels to reflect the farm-specific index-yield relationship.

16 Note that relative changes in the risk premium are constant across different price levels as long as prices in forward contracts and weather index insurance are the same. Therefore, a change in price levels does not change the results of the Wilcoxon signed rank test.

17 Some insurers offer weather index insurance based on precipitation or soil moisture, but these insurance products have so far only marginal market penetration. We are not aware of any insurer that offers several drought indices and identifies the one with the largest risk-reducing potential for each farm individually, or of any insurer that offers indemnity-based drought insurance.

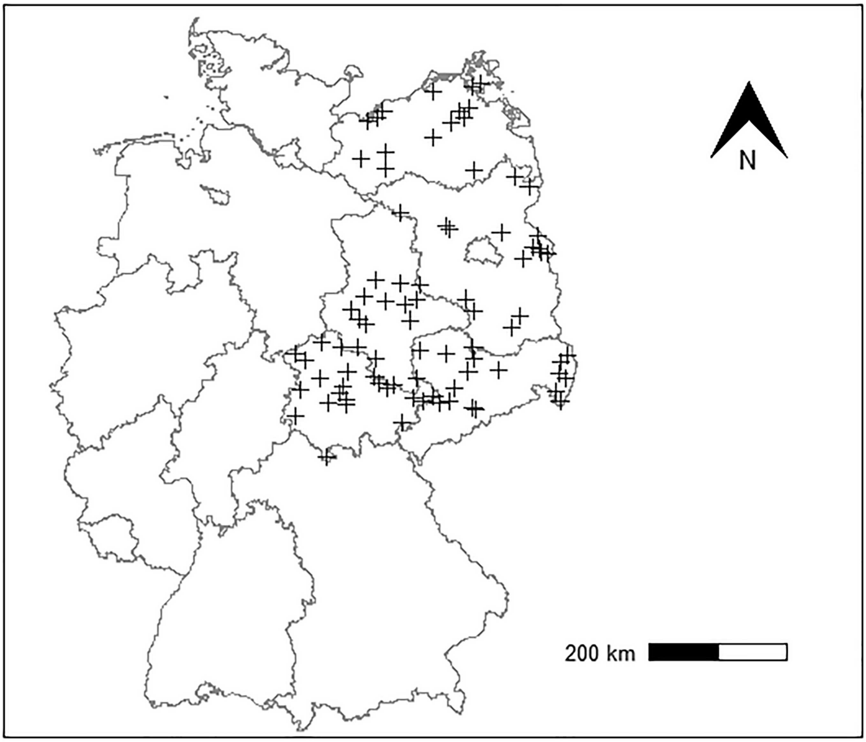

Fig. 1. Location of farms in our case study.

Table 1. Descriptive statistics of detrended yields, index measurement period and drought indices

	Min	Median	Mean	Max	SD
Yield [dt/ha]	19.92	73.92	73.39	116.53	14.43
Index measurement period [days]	20	67	67	113	14
CPI [mm]	8.50	126.30	131.30	400.80	56.17
SPI [SD]	−3.90	0.06	0.00	3.31	1.00
SPEI [SD]	−2.35	0.00	0.00	2.64	0.97
SMI [%]	47.66	68.24	68.84	96.48	8.82
ESI [SD]	−2.78	0.16	0.00	1.98	0.98

Notes. Square brackets show units. dt is deci-ton, ha hectare, mm millimeter and sd standard deviations. CPI is the cumulative precipitation index, SPI the standardised precipitation index, SPEI the standardised precipitation evapotranspiration index, SMI the soil moisture index and ESI the evaporative stress index.

detrended yields, the length of the index measurement period and the values of the five drought indices for our panel.

4.1. Yield data

We use an unbalanced yield panel of 85 farms with yield records ranging from 1995 to 2015 and involving a total of 1,277 yield observations[18] that were provided by the German insurance broker 'gvf VersicherungsMakler AG'. The median number of yield records per farm is 16. We account for technological progress and use the outlier robust M-estimator to linearly detrend historical yields (Finger, 2013). See Section 2 of the online supplement for more information regarding the detrending procedure and results.

4.2. Phenology data

The German meteorological service (Deutscher Wetterdienst, DWD) provides public access to a dataset with observed occurrence dates of winter wheat growth phases reported by a network of approximately 1,200 reporters all over Germany (Kaspar, Zimmermann and Polte-Rudolf, 2015; DWD, 2018a). The index measurement period is defined by using phenology data captured as close as possible to the insured farm by a phenology reporter located in the same natural region. The average distance between the insured farm and the phenology reporter is 17.68 km with a standard deviation of 13.88 km. On average, the index measurement period begins on the 117th day of year (27 April) with the start of the stem elongation growth phase and ends on the 184th day of year (3 July) before the start of the milk ripeness growth phase. The timing of stem elongation depends mainly on the completion of vernalisation[19] (Gerstmann et al., 2016) and, in our panel, occurs on average 194 days after the sowing date on 15 October. See Section 1 of the online supplement for further information on phenology and the index measurement period.

4.3. Meteorological data

We use daily records of precipitation (DWD, 2018b), plant available soil moisture (DWD, 2018c), potential evapotranspiration (DWD, 2018d) and actual evapotranspiration (DWD, 2018e). These gridded datasets are publicly accessible via the German meteorological service (Deutscher Wetterdienst, DWD). They have a spatial resolution of 1 × 1 km and consist of interpolated weather station data. Rauthe et al. (2013) give an overview of the precipitation dataset based on approximately 5,000 ground weather stations. In addition, Löpmeier (1994) and Friesland and Löpmeier (2007) describe how the potential evapotranspiration, actual evapotranspiration and plant available field capacity data are interpolated from a network of 280 weather stations.

18 Yearly yields were reported as the average yield per hectare. Focusing on farm-level data prevents biased results from spatial aggregation (e.g. to average county or country yields per hectare) that smoothens yield volatility and thereby underestimates risk exposure, i.e. farm-level data reflects idiosyncratic shocks better than more aggregated yield levels (Leblois et al., 2014a, 2014b; Marra and Schurle, 1994).

19 Vernalisation is the accumulation of winter and spring temperatures of winter crops before the start of reproductive growth phases.

These 280 stations are set up on sandy loam soil covered with grass and a simulation model (AMBAV—agrometeorological model for calculating actual evapotranspiration) estimates the variables based on various assumptions on site characteristics.[20]

Note that by basing our analysis on publicly available meteorological and phenology datasets, we ensure its transparency and reproducibility so that it can be translated directly into practice. We use the statistical software environment R (R Core Team, 2018) for data handling, computations and creating illustrations. The package 'SPEI' (Beguería and Vicente-Serrano, 2017) calculates the standardised indices and the package 'quantreg' (Koenker, 2018) contains the quantile regression estimator. All codes are available in a supplementary R file.

5. Results

This section presents the results of the expected utility model assuming moderately risk-averse farmers ($\alpha = 2$ in Equation (8)). A lower risk premium reflects a higher effectiveness of the underlying drought index to reduce the financial exposure to drought risks, i.e. reflects lower basis risk. In addition, we summarise various robustness checks at the end of this section. We define uniform insurance as the product in which each farm receives the same underlying index. The non-uniform insurance product, i.e. where each farm receives the underlying index with the lowest risk premium, is defined as BEST. This non-uniform insurance with a tailored underlying index has an average actuarially fair premium of EUR 32.35 per hectare. On average, this reflects 2.94 per cent of expected revenues per hectare. See Section 3 of the online supplement for further details on premiums, contract specifics (e.g. tick size, strike level) and historical payouts of all indices.

5.1. Changes in the risk premium

Table 2 illustrates the average absolute ($RP_m - RP_n$) and relative ($(RP_m - RP_n)/RP_n$) changes in the risk premium, where RP_m denotes the risk premiums for the index in row m and RP_n the risk premiums for the index in column n. For example, the evaporative stress index (ESI) has, on average, a significantly lower risk premium of EUR −2.40 per hectare (−6.55 per cent) compared to a uniform insurance where each farm has the cumulative precipitation index as the underlying drought index. The significance levels of differences evaluated with Wilcoxon signed rank tests stand for the null hypotheses that the risk premiums RP_m are equal to, or larger than, the risk premiums RP_n. See Section 5 of the online supplement for the p-values of the Wilcoxon signed rank tests.

The first five rows of Table 2 show the results for uniform insurance products, i.e. when each farm receives the same underlying index. The last

20 Interpolated data for winter wheat over various soil types is not available from the German meteorological service's climate data centre (https://cdc.dwd.de/portal).

Table 2. Absolute (in €/ha) and in parentheses relative (in %) average differences in the risk premium (RP) and their significance for moderately risk-averse farmers ($\alpha = 2$)

	m/n	CPI	RP_n				
			SPI	SPEI	SMI	ESI	Uninsured
RP_m	CPI	—					**−2.56***** **(−7.30)**
	SPI	−0.15 (−0.38)	—				**−2.72***** **(−8.10)**
	SPEI	0.22 (2.16)	0.37 (2.63)	—			**−2.35***** **(−6.25)**
	SMI	−0.53 (1.08)	−0.38 (1.48)	−0.76 (1.00)	—		**−3.10***** **(−7.92)**
	ESI	**−2.40***** **(−6.55)**	**−2.25***** **(−6.09)**	**−2.61***** **(−7.65)**	**−1.87***** **(−6.43)**	—	**−4.96***** **(−13.41)**
	BEST	**−3.40***** **(−10.55)**	**−3.24***** **(−10.13)**	**−3.61***** **(−11.41)**	**−2.87***** **(−10.36)**	**−1.00***** **(−3.87)**	**−5.96***** **(−16.88)**

Notes. Numbers without brackets display the absolute average reduction in the risk premium ($RP_m - RP_n$) in Euros per hectare (€/ha) of winter wheat. Numbers in brackets display the relative average reduction in the risk premium in percentage ($(RP_m - RP_n)/RP_n$). Numbers are rounded to two decimal places. Asterisks show the Bonferroni-adjusted significance level derived from one-sided paired Wilcoxon signed rank tests: *at the 1 per cent level, **at the 0.2 per cent level and ***at the 0.02 per cent level. Null hypotheses tested are $RP_m \geq RP_n$. Significant differences are highlighted in bold. α is the coefficient of relative risk aversion used in Equation (8), CPI the cumulative precipitation index, SPI the standardised precipitation index, SPEI the standardised precipitation evapotranspiration index, SMI the soil moisture index and ESI the evaporative stress index.

column shows that, on average, farmers with an insurance based on the cumulative precipitation index (CPI), the standardised precipitation index (SPI), the standardised precipitation evapotranspiration index (SPEI), the soil moisture index (SMI) or the evaporative stress index (ESI) have a significantly lower risk premium (lower risk exposure) compared to being uninsured. Consequently, in general all drought indices have a significant risk-reducing potential, i.e. they reduce the financial exposure to drought risks on average. An insurance based on the evaporative stress index has with an average risk reduction of EUR -4.96 per hectare (-13.41 per cent) the largest risk-reducing potential compared to being uninsured. Moreover, the evaporative stress index is generally superior to the other drought indices in terms of basis risk reduction. No further significant differences between uniform insurance products have been identified.

The last row of Table 2 shows the results for the non-uniform insurance product (BEST), i.e. when each farm receives the underlying index resulting in the lowest risk premium (largest risk reduction). This BEST option is: the evaporative stress index for 30 farms (out of 85 farms), the soil moisture index for 13 farms, the standardised precipitation index for 11 farms, the standardised precipitation evapotranspiration index for 8 farms and the cumulative precipitation index for 6 farms. 16 farms do not reveal a substantial drought risk for any of the five drought indices, i.e. they do not benefit from a lower risk premium with any underlying drought index and, in terms of expected utility, are no better off by holding a weather index insurance. However, an insurance is attractive for the majority of the farms analyzed here. Hence, for individual farmers each of the five drought indices can provide the lowest risk premium (lowest basis risk). The average risk premium reduction of BEST compared to being uninsured is EUR -5.96 per hectare (-16.88 per cent) and significantly lower. Moreover, designing a non-uniform insurance product has a significantly lower risk premium than offering uniform insurance products based on one of the five drought indices. In comparison to a uniform insurance product based on the evaporative stress index (i.e. the underlying drought index with, on average, the largest risk reduction), BEST further reduces the risk premium, on average, by EUR -1.00 per hectare (-3.87 per cent). See Section 4 of the online supplement for the spatial distribution, risk-reducing potentials and actuarially fair premiums of BEST across natural regions in Eastern Germany. There is no spatial clustering of the most risk-reducing drought index, but there is a tendency to an increased risk-reducing potential (and increased actuarially fair premium that reflects farm-specific drought risks) towards the eastern parts of Eastern Germany. See Section 5 of the online supplement for further descriptive statistics on changes in the risk premiums for each index.

5.2. Summary of robustness checks

Firstly, we change the coefficient of constant relative risk-aversion, denoted as α in Equation (8), to investigate differences in the risk premium for slightly risk-averse farmers ($\alpha = 0.5$) and extremely risk-averse farmers ($\alpha = 4$) (Chavas, 2004; Iyer et al., 2019). The results provided in Section 5 of the online supplement reveal that our key-findings in Table 2 are robust across different levels of risk-aversion.

Secondly, we add a loading of 10 and 20 per cent, respectively, on the actuarially fair premium to account for internal expenses, taxes and profit margins of insurance providers. Loading the actuarially fair premium reduces the risk-reducing potential so that less farmers are better off if they take out insurance. However, the BEST still outperforms both the uninsured alternative and uniform insurance products. See Section 6 of the online supplement for the results.

Thirdly, we tailor tick sizes and strike levels to more extreme droughts by using the 20 per cent quantile of interest in the quantile regression estimator shown in Equation (4) and for strike level derivation. Our key-findings are robust to this change. Section 7 of the online supplement shows descriptive statistics and the results.

Fourthly, we find that the risk-reducing potential decreases when we derive tick sizes and strike levels with the ordinary least square estimator. This finding is in line with Conradt, Finger and Bokusheva (2015a) who show that using quantile regression to derive tick sizes and strike levels is superior in terms of risk reduction. Other key-findings are robust to a change in the estimator. Results are shown in Section 8 of the online supplement.

As a fifth robustness check, we evaluate downside risk reductions with the lower partial moments of first (expected shortfall) and second order (downside variance). The results of expected shortfall and downside variance confirm the findings in Table 2. The only exception is that the evaporative stress index (ESI) does not have a significantly lower expected shortfall than the soil moisture index (SMI), but it still has a significantly lower downside variance. See Section 9 of the online supplement for the results.

In the sixth robustness check, we run a cross-validation to avoid the risk of overfitting. In this cross-validation, we run pooled quantile regression leaving-out data from farm i and subsequently we test these contracts on the left-out farm i. The results of this cross-validation confirm the findings in Table 2.[21] See Section 10 of the online supplement for more information and results.

To summarise, the robustness checks confirm our key-findings that (i) all of the here-applied drought indices have, on average, risk-reducing potential, (ii) the evaporative stress index (ESI) has, on average, the largest risk-reducing potential in a uniform insurance product and (iii) a non-uniform insurance that tailors the underlying index (BEST) results in the largest risk-reducing potential. Moreover, the composition of the set of BEST indices only changes marginally across robustness checks. Finally, the reduction of lower partial moments of revenue margins due to the use of weather index insurance show

21 Results indicate that some farms experience an increased risk-reducing potential when their insurance contracts are calibrated with data from similar farms.

that the removal of downside risks is indeed the main reason for risk reductions in the expected utility model.

6. Discussion

This paper shows the risk-reducing potential of weather index insurance based on different drought indices, i.e. the cumulative precipitation index, the standardised precipitation index, the standardised precipitation evapotranspiration index, the soil moisture index and the evaporative stress index. Whilst these results confirm and add to previous studies on the risk-reducing potential of single weather indices (e.g. Martin, Barnett and Coble, 2001; Kellner and Musshoff, 2011; Leblois, Quirion and Sultan, 2014b; Dalhaus and Finger, 2016), our findings show that indices perform differently when compared to each other and that tailoring the underlying index to each farm can result in large economic benefits. Therefore, we reject the practice of using one single uniform index for all farms (e.g. Conradt, Finger and Spörri, 2015b) and find that when dealing with a whole agricultural system, a maximum in risk reduction can be achieved by providing each farm with a tailored insurance using the particular index that offers the greatest reduction of the individual farm's risk. Thus, weather index insurance must essentially be tailored to the individual farm by choosing the drought index based on which the insurance delivers the highest risk reduction. This finding is in line with previous studies in drought impact literature that suggest a crop and location specific application of drought indices (Tian, Yuan and Quiring, 2018).

There are several explanations for the absence of a single superior drought index. Firstly, drought-farm interactions are unique and dependent on both site-specific characteristics and farm management (Reidsma et al., 2010; Lesk, Rowhani and Ramankutty, 2016). As drought indices differ in their measurement of drought occurrence, they also differ in their ability to capture different drought-farm interactions. Secondly, data quality differs across indices due to different methods of data collection and interpolation as well as the varying density of weather stations (Auffhammer et al., 2013). In our study, we use interpolated measurements of precipitation from a dense station network, whilst values for soil moisture and evapotranspiration were modelled from a station network of lower density and using a model calibration for grass over sandy loam instead of winter wheat over different soil types. Thirdly, accelerated crop growth resulting in a shortened period of index measurement means fewer daily observations to calculate drought indices and can lead to potentially biased drought indications. In particular, this can occur when the drought index is a (standardised) sum or difference of weather variables.

Our case study taking place in Eastern Germany shows that weather index insurance can reduce farmers' drought risk exposure by particularly removing downside risks. At the actuarially fair premium, the average risk reduction of a tailored contract is approximately 16 per cent for moderately risk-averse farmers ($\alpha = 2$), but risk-reductions vary considerably across farms. Yet, the risk-reducing potential of weather index insurance is likely to increase with climate change in Eastern Germany (Gornott and Wechsung, 2016; Lüttger and Feike, 2018).

There is only little room to load the actuarially fair premium and farm-specific tailoring of insurance contracts might raise concerns about additional transaction costs for data collection, risk assessment and maintenance and even lead to market failure (Barnett, Barrett and Skees, 2008). However, digital underwriting tools[22] allow cost-efficient tailoring of insurance contracts, also for smaller farms that generate a lower premium volume than large-scale producers. Moreover, free access to open data and tools to assess drought risks for each individual farm and index should be declared a public good and provided by independent state institutions (see also Thomson et al., 2011). For our study, we publish a programming code together with the paper. This not only permits the replication of the results but also the reduction of transaction costs of insurance design in practice.

Using historical yield data of the insured farm for contract calibration accounts for farm-individual drought vulnerability (Reidsma et al., 2010), but requires rich yield data.[23] New data sources (e.g. due to the digitalisation of agriculture, Finger et al., 2019; Woodard et al., 2018) and combinations of data sources from different aggregation levels (e.g. Dalhaus, 2018) will help to reduce problems of data scarcity. Moreover, our cross-validation suggests that data from similar farms can improve insurance calibration under data scarcity. When to calibrate insurance contracts with data from the insured farm only (e.g. Conradt, Finger and Bokusheva, 2015a) and when to include data from similar farms (e.g. Leblois, Quirion and Sultan, 2014b) is a promising field for future research but beyond the scope of this paper. Continuous recalibration of tick size, strike level, optimal drought index and the insurance premium will account for changing index-yield relationships due to technological progress and ongoing climate change (Fuchs and Wolff, 2011; Tack, Coble and Barnett, 2018).

The risk-reducing potential of weather index insurance and its demand do not only depend on the farm's drought vulnerability, but also on the farmer's level of risk-aversion. The heterogeneity of farmers' risk preferences is large (Maart-Noelck and Musshoff, 2014; Iyer et al., 2019; Meraner and Finger, 2019) and usually not observable at low costs so that insurance calibration based on risk preferences might be limited in practice. Yet, our results show that the most risk-reducing underlying index is relatively stable across levels of risk-aversion and between the expected utility model and lower partial moments, which are independent of risk preferences.

In summary, tailored weather index insurance can be a viable risk management tool to cover systemic drought risks in the here-analyzed case study

22 For instance, the gvf Versicherungsmakler AG developed the tool 'Crop Yield Analysis' and Swiss Re the tool 'opti-crop' to calculate premiums of tailored contracts. See https://www.youtube.com/watch?v=BHfBOlMey9M (gvf) and https://www.youtube.com/watch?v=K7TQn6bPsMI (Swiss Re) for short descriptions. Last accessed: 18 February 2020.

23 World Bank (2011) suggests 30 years of daily weather records.

of wheat production in Eastern Germany, particularly because weather index insurance avoids asymmetric information problems, can be provided at low costs and triggers immediate payouts after risk exposure.

Our set of applicable drought indices is extendable and could for instance include the rainfall deficit index (Musshoff, Odening and Xu, 2011) or mixed indices based on precipitation and temperature (Vedenov and Barnett, 2004). Offering a wider spectrum of drought indices is likely to contribute to a higher resilience in the insured agricultural system as the overall financial exposure to drought risks can be reduced (see also Meuwissen et al., 2019). Yet, lack of data and access to digital underwriting tools currently limit the provision of highly tailored weather index insurance to smallholders in developing countries and requires further research.

7. Conclusion

In this paper, we examined the risk-reducing potential of the cumulative precipitation index, standardised precipitation index, standardised precipitation evapotranspiration index, soil moisture index and evaporative stress index as underlying index in weather index insurance. We find a statistically and economically significant risk-reducing potential of weather index insurance based on each of these drought indices for a case study of winter wheat production in Eastern Germany. On average, the evaporative stress index has the significantly greatest risk-reducing potential. Most importantly, this study provides evidence that each farm has an individual 'best' underlying drought index to minimise basis risk, i.e. there is no single universally best underlying drought index for weather index insurance.

Insurers should offer tailored weather index insurance because it can cover systemic drought risks at low administrative costs and keeps basis risk low. Tailoring insurance contracts should not only include the definition of farm-specific tick size and strike level, but also the identification of the most risk-reducing underlying drought index. Such tailoring of insurance contracts requires rich farm-specific yield records. Recalibration of insurance contracts at every renewal will progressively reduce potential biases of currently short-time series and account for ongoing climate change. New data sources (e.g. due to the digitalisation of agriculture) and inclusion of data from similar farms can help to improve insurance calibration.

Our results underline that policy-makers should support the public provision of better drought, weather and phenology data because it improves the viability of insurance systems, without providing premium subsidies. Moreover, tailored weather index insurance should be considered as a viable market-based risk management tool that complements other insurance products and increases the insurability of drought risks. If this part of the risk management toolbox is strengthened, more farms would be able to take out insurance against drought risks, thereby improving farmers' financial well-being, making farming systems more resilient and enhancing the ability to adapt to climate change.

Future research should investigate the potential of using different data sources for farm-individual insurance calibration and tailoring of weather index insurance for other climate conditions and production systems. Moreover, research should develop measures to facilitate the provision of tailored weather index insurance to smallholders in developing countries.

7. Supplementary data

Supplementary data are available at *ERAE* online.

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