Comparing the Hedging Effectiveness of Weather Derivatives Based on Remotely Sensed Vegetation Health Indices and Meteorological Indices

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ABSTRACT

Weather derivatives are considered a promising agricultural risk management tool. Station-based meteorological indices typically provide the data underlying these instruments. However, the main shortcoming of these weather derivatives is an imperfect correlation between the weather index and the yield of the insured crop, called basis risk. This paper considers three available remotely sensed vegetation health (VH) indices, namely, the vegetation condition index (VCI), the temperature condition index (TCI), and the vegetation health index (VHI), as indices for weather derivatives in a German case study. We investigated the correlation and period of highest correlation with winter wheat yield. Moreover, we analyzed whether the use of remotely sensed VH indices for weather derivatives can reduce basis risk and thus improve the performance of weather derivatives. The two commonly used meteorological indices, precipitation and temperature sums, were employed as benchmarks. Quantile regression and index value simulation were used for the design and pricing of the weather derivatives. The analysis for the selected farms and corresponding counties in northeastern Germany revealed that, on average, the VHI resulted in the highest correlation with winter wheat yield, and VHI-based weather derivatives were also superior in terms of the hedging effectiveness. The total periods of the highest correlations ranged from the beginning of April to the end of July. VHI- and VCI-based weather derivatives led to statistically significant reductions of basis risk, compared to the benchmarks. Our results indicate that the VHI-based weather derivatives can be useful alternatives to meteorological indices, especially in regions with sparser weather station networks.

1. Introduction

Weather is a main determinant of agricultural production, yet it cannot be controlled. To reduce weather-related production risks, farmers can utilize different insurance products. Indemnity-based crop insurance, such as multiperil crop insurance (MPCI), is commonly used to insure farmers against damages caused by drought, hail, or frost, for example. To do so, the indemnity payments depend on the extent of the actual damage. However, indemnity-based insurance faces various challenges like high administrative costs due to a costly loss assessment to check farmers' claims, as well as adverse selection and moral hazard problems (Turvey 2001; Leblois and Quirion 2013). To overcome these issues, weather index–based insurance, formally known as weather derivatives, has been identified as a promising risk management tool in agriculture (e.g., Turvey 2001; Vedenov and Barnett 2004; Woodard and Garcia 2008b; Glauber 2013; Leblois and Quirion 2013). In contrast to traditional crop insurance, the indemnity payments of weather derivatives depend on the level of an objectively measurable weather index. If the realized value of the index falls below or exceeds a certain threshold value, an indemnity is paid.

Common underlying indices for weather derivatives are based on in situ weather measurements. The literature mainly refers to precipitation or temperature sums over certain accumulation periods (e.g., Leblois and Quirion 2013; Turvey 2001; Vedenov and Barnett 2004). Other meteorological indices refer to water stress indices that are based on measurements of evapotranspiration and drought indices that determine air and soil dryness based on temperature and precipitation data. For an extensive review of these different indices, see Leblois and Quirion (2013). So far, most applications under practical conditions have used precipitation sum indices (World Bank 2011). However, insurances based on in situ weather measurements are especially limited in developing countries due to the scarcity of weather

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station networks and the unavailability of long-term continuous time series of weather data (Meroni et al. 2013). In particular, the performance of precipitation index–based weather derivatives is affected by the distance to the next weather station due to the spatial variability of precipitation. With an increasing distance to the next weather station, the performance of precipitation index–based weather derivatives usually decreases (cf. e.g., Heimfarth and Musshoff 2011; Norton et al. 2012; Gommes and Göbel 2013).

The most important criterion for choosing a reasonable underlying index is a high correlation with the returns of the insured crop, which is often approximated by the crop yield. However, a basis risk remains, which is defined as an imperfect correlation between the chosen weather index and the actual crop yield on the farm. Thus, the payoffs from the weather derivative do not perfectly match the yield shortfall experienced by the insured farmer (Barnett 2004; Jensen et al. 2016; Woodard and Garcia 2008a). The basis risk can be broken down into two components. First, there is usually a difference between the weather events at the farm site and the reference weather station, which is known as geographical basis risk (Leblois et al. 2014; Norton et al. 2012; Woodard and Garcia 2008a). Second, crop yield is not only determined by the weather index, but also by other weather and biological variables, collectively referred to as design basis risk (Leblois et al. 2014).

Besides in situ measured weather data, remotely sensed data can be used to derive underlying indices for weather derivatives. A major advantage of remotely sensed data is that the accuracy does not depend on the density and distribution of weather stations. The data are provided nearly in real time and are globally available (Quiring and Ganesh 2010). The use of remotely sensed data for insurance purposes mainly focuses on the use of the normalized difference vegetation index (NDVI) with mixed results. The NDVI determines the density and vigor of green biomass and is thus an indicator for the health of the vegetation. Leblois and Quirion (2013) state that the NDVI is highly adapted to biomass assessment, while showing an inconsistent relationship to crop yield. Thus, the NDVI is primarily used as an index for forage insurance (Miranda and Farrin 2012; Leblois and Quirion 2013; Lang 2013). On the contrary, in a case study in Zimbabwe, Makaudze and Miranda (2010) designed a weather derivative based on an NDVI time series as well as maize and cotton yields aggregated at the county level. They found that an NDVI-based weather derivative exhibits less basis risk for farmers than the commonly used precipitation-based weather derivatives. Turvey and McLaurin (2012) tested the applicability of the NDVI as an underlying of weather derivatives. Their findings revealed that the NDVI is not a suitable index without site-specific calibrations.

To account for site-specific differences, Kogan (1990) defined the so-called vegetation health (VH) indices, including the vegetation condition index (VCI), the temperature condition index (TCI), and the vegetation health index (VHI). In recent years, VH indices have been used in the agricultural context for yield prediction and drought monitoring. The results of various case studies have proven that the VCI and TCI exhibit high correlations with crop yield for different climatic conditions in countries like Kazakhstan (Bokusheva et al. 2016), Poland (Dabrowska-Zielinska et al. 2002), the midwestern United States (Kogan et al. 2012; Salazar et al. 2007), Russia (Kogan et al. 2016), Argentina (Seiler et al. 1998), and South Africa (Unganai and Kogan 1998). Since the VHI is a composite index combining the VCI and the TCI, the correlation between the VHI and crop yield has been found to be even higher (Kogan et al. 2016). In a Russian case study, Kogan et al. (2016) found that compared to the other VH indices, the correlation between the VHI and cereal yields was the strongest, with correlation coefficients as high as 0.80 explaining 64% of the cereal yield variance. The use of VH indices for weather derivatives potentially addresses both components of basis risk because the VH indices are provided in a gridded format and directly describe the health of the vegetation, unlike meteorological indices (Quiring and Ganesh 2010).

Thus far, surprisingly little effort has been made to examine the applicability of the VCI, the TCI, and particularly the VHI as indices for weather derivatives. To the best of the authors' knowledge, the only study considering the VCI and the TCI in this context is a recent study by Bokusheva et al. (2016). They calculated the VCI and TCI for five counties in Kazakhstan using data with a spatial resolution of 16 km $\times$ 16 km. Based on these county-level indices, they designed weather derivatives for each county and the individual farms located in these counties.

However, there have been no studies considering the VHI for weather derivatives or comparing VH index–based weather derivatives with weather derivatives based on the commonly used precipitation and temperature indices. Additionally, the potential of VH indices for explaining winter wheat yield variations in a study area with farm parcels surrounded by adjacent forests and lakes, diversified crop rotations, and temperate climate conditions such as prevalent in northeastern Germany has not been investigated to date. Moreover, differences between the farm level and the county level with regard to the correlations between VH indices and winter wheat yield, as well as the hedging effectiveness of weather derivatives based on VH indices, have not yet been analyzed. To fill these gaps, the objective of this paper is twofold. First, we investigate the correlation of the VH indices with winter wheat yield and determine the period of highest correlation in northeastern Germany. Second, we compare VH index–based with meteorological index–based weather derivatives as benchmarks in terms of hedging effectiveness and basis risk. To do so, weather derivatives based on all three VH indices as well as the temperature and precipitation indices were designed both at the farm and county levels using farm-level and county-level yield data, respectively.

We used NDVI and brightness temperature (BT) data with a spatial resolution of 4 km × 4 km to calculate the VCI, TCI, and VHI. To determine the relationship between crop yield and the respective index, we applied quantile regression (QR). It has been proven that QR outperforms ordinary least squares in terms of the representation of the relationship between yield and index, especially in the lower tails of the distribution (Conradt et al. 2015). Northeastern Germany is well suited for this study. On account of the prevailing weather conditions, drought- and heat-related weather events occur frequently, jeopardizing the yields of crops mainly grown on sandy soils (Zebisch et al. 2005). Consequently, revenues from arable farming as the major source of farm income in northeastern Germany fluctuate substantially. Moreover, a dense weather station network enables us to design suitable meteorological benchmarks.

The paper is structured as follows. In section 2, we provide a description of the study area, the data used, and the applied methodology. Section 3 presents and discusses the results. The conclusions can be found in section 4.

2. Materials and methods

a. Study area and data

The study area was located in the northeastern German federal states of Brandenburg, Mecklenburg-Western Pomerania, Saxony, and Saxony-Anhalt (Fig. 1). In the study region, winter wheat is planted around the calendar weeks 40–44 (October) and harvested around the calendar weeks 33–35 (August). The northeastern part of Germany is characterized by low precipitation and poor soil quality, in comparison to other parts of central Europe. The prevalent soil types are sandy soils, but clayey soils are also present. The mean annual precipitation measured by the weather stations assigned to the sample farms ranged from 499 to 638 mm within the study period 1995–2015. Across all stations in the study

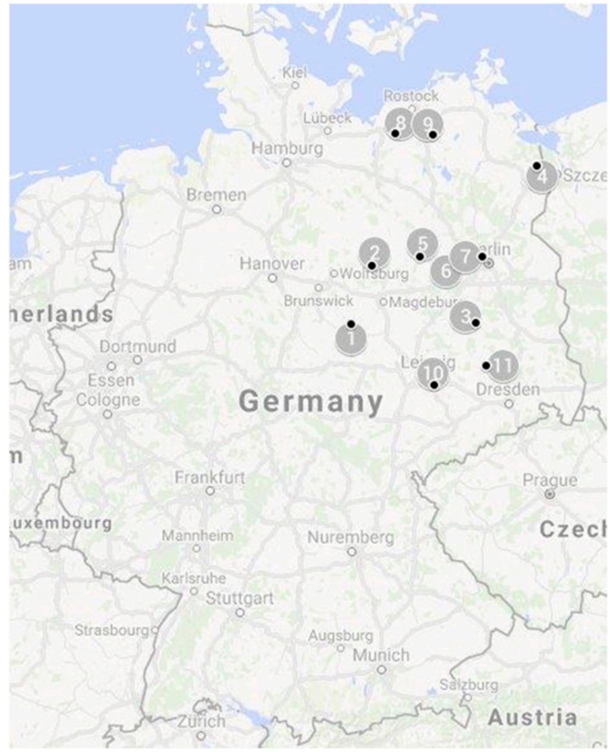

FIG. 1. Location of study farms and corresponding weather stations. Farms are indicated as numbered points and weather stations as black points (source: https://maps.google.com/).

area, the mean annual precipitation was 563 mm, which is considerably less than the average annual precipitation of 789 mm in Germany (German National Meteorological Service 2015a). The annual average temperature in northeastern Germany is between 8° and 9°C (German National Meteorological Service 2015a). In general, northeastern Germany is suited for winter wheat cultivation. However, the low soil water-holding capacity of the sandy soils and the continental climate cause interannual winter wheat yield variations due to heat and drought events (Lüttger and Feike 2018). Additionally, eastern Germany exhibits a high future vulnerability to a further decrease in summer precipitation, an increase in temperatures, and, consequently, increased evaporation due to climate change (Zebisch et al. 2005; Lüttger and Feike 2018). Despite these conditions, farmers in Germany have rarely used weather derivatives. The low demand for weather derivatives is mainly due to the prevailing problem of basis risk (Smith and Watts 2012).

Our analysis was based on a yield dataset from 11 farms and eight corresponding counties. The average farm size in this sample was around 1000 ha. We used a winter wheat yield time series from 1995 to 2015. Farm-level yield data were provided by an insurance office.

TABLE 1. Summary statistics of winter wheat yields of study farms and counties from 1995 to 2015 in $dt\ (\mathrm{ha})^{-1}$.

County	Mean	Min	Max	Std dev	Farm[a]	Mean	Min	Max	Std dev
a	79.31	65.60	92.50	6.72	1	66.13	50.33	83.04	9.75
b	62.33	39.30	80.90	8.19	2	68.07	42.70	86.94	11.53
c	60.57	39.10	77.60	10.01	3	64.79	40.24	87.46	12.75
d	72.07	43.40	92.20	11.52	4	63.91	37.00	88.00	13.21
e	57.99	40.80	73.00	8.76	5	35.11	20.50	56.91	9.27
					6	65.09	38.00	79.00	11.72
					7	58.83	40.00	73.00	10.55
f	75.86	61.20	90.00	7.65	8	73.22	60.00	87.82	8.91
					9	77.38	61.00	100.00	9.58
g	69.84	50.80	87.50	7.94	10	72.70	48.40	93.50	9.65
h	56.31	35.10	78.40	10.60	11	52.61	29.44	76.37	12.33

[a] The farm number equals the number in Fig. 1.

Moreover, winter wheat yields for each county were provided by the statistical offices of the specific county. The winter wheat yield data are summarized in Table 1. According to Gallagher (1986), we corrected the yield data for technological progress using linear regressions.

Daily precipitation and temperature data from 1995 to 2015 were provided by the German National Meteorological Service (2015b). We selected nearby stations with complete precipitation and temperature time series for each farm (Fig. 1). Because of the dense network of weather stations in Germany, the average distance between the farms and the weather stations was around 12 km, ranging from only 4 to 29 km. Averages of the data from three weather stations per county were used to calculate precipitation indices for the corresponding counties. The data from two weather stations per county were averaged to calculate the county-level temperature indices. In contrast to precipitation, which can be spatially heterogeneous, temperature varies less across geographic areas (Norton et al. 2012).

For this study, we used the Advanced Very High Resolution Radiometer (AVHRR) satellite dataset provided by the National Oceanic and Atmospheric Administration (NOAA/STAR 1981). Statistically smoothed NDVI and BT 7-day composites with a resolution of 4 km × 4 km for the period of 1995–2015 were taken from this dataset. By means of pre- and postlaunch calibration coefficients, the data were converted to reflectance. Since the NDVI and BT data for the year 2004 are incomplete, we skipped this year in our analysis of VH, yield, and meteorological data.

The NDVI is a widely used vegetation index for yield assessment, drought, and vegetation monitoring (Kogan 1990; Mkhabela et al. 2005; Ren et al. 2008; Wan et al. 2004). The NDVI is calculated from the visible (VIS) and near-infrared (NIR) spectral bands observed by the AVHRR sensors according to the formula $\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{VIS})/(\mathrm{VIS} + \mathrm{NIR})$. Healthy vegetation is characterized by little reflection of VIS and strong reflection of NIR. The green leaf pigment chlorophyll absorbs VIS for use in photosynthesis, while other leaf structures reflect NIR. If vegetation is under stress (e.g., water stress), the NDVI becomes smaller due to a higher reflectance of VIS and a lower reflectance of NIR. Thus, higher NDVI values correspond to healthier vegetation. The BT is a measurement of the land and vegetation surface temperature. Because of reduced transpiration, the temperature of the vegetation surface under water stress is higher than for unstressed, healthy vegetation (Kogan 1995; Kogan et al. 2016).

For the design of the weather derivatives, we employed three so-called VH indices: 1) VCI, 2) TCI, and 3) VHI. The VCI is derived from the normalization of NDVI values based on the maximum and minimum NDVI values for a specific region and is expressed as (Kogan et al. 2016; Unganai and Kogan 1998; Kogan 1990)

$$\mathrm{VCI}_w = 100 \times \frac{\mathrm{NDVI}_w - \mathrm{NDVI}_{\min}}{\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min}}, \tag{1}$$

where NDVI_w is the smoothed 7-day NDVI for week w, and $\mathrm{NDVI}_{\max}$ and $\mathrm{NDVI}_{\min}$ are the absolute maximum and minimum values calculated for each pixel over the entire observation period 1995–2015. The VCI was proposed as a means to separate the spatial variability of the NDVI into the effect of weather and the effect of geographical resources like soil type, vegetation type, geographic region, and climate zone (Kogan 1990). The principle of the VCI is based on the assumption that the vegetation reaches a maximum biomass with optimal weather conditions because such weather leads to an efficient use of geographic resources. In contrast, if the weather conditions are unfavorable due to water stress, the plant's ability to benefit from the geographic resources is reduced. The calculation of the VCI includes the minimum and maximum values over the whole observation period in order to relate weekly measurements to the worst and the best possible weather conditions. In doing so, it is possible to quantify the potential of the specific region given by its geographic resources. The VCI has been found to better capture the precipitation dynamics than the NDVI and still provides a description of land cover as well as spatial and temporal vegetation change. Producing values between 0 and 100, the VCI indicates how far vegetation development is from the minimum and maximum of the geographical potential in the region of interest (Kogan 1995; Unganai and Kogan 1998).

The formula for the TCI is similar to the VCI, except for a change to address the fact that a high BT reflects unfavorable conditions due to high vegetation surface temperatures, while a low BT indicates more favorable conditions. Consequently, the TCI is calculated as follows (Kogan et al. 2016; Unganai and Kogan 1998):

$$\mathrm{TCI}_w = 100 \times \frac{\mathrm{BT}_{\max} - \mathrm{BT}_w}{\mathrm{BT}_{\max} - \mathrm{BT}_{\min}}, \tag{2}$$

where BT_w is the smoothed 7-day BT for week w, and $\mathrm{BT}_{\max}$ and $\mathrm{BT}_{\min}$ are the absolute maximum and minimum values calculated for each pixel over the entire observation period. The values of the TCI also range from 0 to 100. Corresponding to the VCI, values close to 0 indicate thermal vegetation stress, and values close to 100 indicate that the maximum benefit has been derived from the given geographical resources of the specific region (Kogan et al. 2016).

Combining both indices results in the weighted additive composite called VHI, which is expressed as (Kogan et al. 2016; Unganai and Kogan 1998)

$$\mathrm{VHI}_w = a \times \mathrm{VCI}_w + (1 - a) \times \mathrm{TCI}_w, \tag{3}$$

where a is the weighting coefficient quantifying the contribution of VCI and TCI to the VHI. According to Kogan et al. (2016), equal weights of VCI and TCI can be assumed ($a = 0.5$) because the relative contribution of moisture and temperature to vegetation health is currently not known. The weekly values of the VH indices for each farm were derived by calculating the average values for each index over all relevant pixels. For the calculation of the farm-level indices, the values of four pixels covering the cultivated areas were averaged. County-level indices were obtained by averaging the values of all pixels within the county borders. To only consider pixels covering arable land, we used the GLC2000 land-cover map with a spatial resolution of 1 km × 1 km (Bartholomé and Belward 2005) and Google Earth imagery to mask out bare soil, lakes, and forest. However, this procedure was limited because of the lower resolution (4 km × 4 km) of the remotely sensed data.

b. Design and pricing of weather derivatives

We designed weather derivatives that were hypothetically offered to farmers over the counter. The meteorological weather derivatives were based on accumulation indices, to which the literature often refers (Dalhaus and Finger 2016; Turvey 2001; Vedenov and Barnett 2004). The daily precipitation and temperature data were converted to weekly data to get the same temporal resolution as for the VH data. For the purpose of creating benchmarks, we designed the precipitation and temperature indices so that the index $R_{t,i}$ corresponds to the precipitation sum, and the index $T_{t,i}$ corresponds to the temperature sum for year t and farm or county i (Jewson and Brix 2005):

$$R_{t,i} = \sum_{w=1}^{x} R_w^{t,i}, \tag{4}$$

$$T_{t,i} = \sum_{w=1}^{x} T_w^{t,i}, \tag{5}$$

where $R_w^{t,i}$ indicates the precipitation sum and $T_w^{t,i}$ the temperature sum for week w, in year t and for farm or county i, while x indicates the length of the accumulation period in weeks.

This approach is suitable for accumulated meteorological indices. Since the VH indices were derived by a normalization technique resulting in values between 0 and 100, we used a slightly different approach by applying averages instead of sums. Thus, the indices $\mathrm{VCI}_{t,i}$, $\mathrm{TCI}_{t,i}$, and $\mathrm{VHI}_{t,i}$ correspond to average values of VCI, TCI, and VHI (Jewson and Brix 2005):

$$\mathrm{VCI}_{t,i} = \frac{1}{x} \sum_{w=1}^{x} \mathrm{VCI}_w^{t,i}, \tag{6}$$

$$\mathrm{TCI}_{t,i} = \frac{1}{x} \sum_{w=1}^{x} \mathrm{TCI}_w^{t,i}, \tag{7}$$

$$\mathrm{VHI}_{t,i} = \frac{1}{x} \sum_{w=1}^{x} \mathrm{VHI}_w^{t,i}, \tag{8}$$

where $\mathrm{VCI}_w^{t,i}$, $\mathrm{TCI}_w^{t,i}$, and $\mathrm{VHI}_w^{t,i}$ indicate the respective VH index for week w, in year t, and for farm or county i, while x indicates the length of the accumulation period in weeks. The accumulation periods were determined for each farm and county individually by identifying the period with the highest Spearman correlation coefficient between the respective index and winter wheat yield. Summary statistics of the indices can be found in Table A1 of the appendix.

The concept of weather derivatives builds on the assumption that the relationship between crop yield and an index is represented by a function $g(\cdot)$, which can be described by the following model:

$$y_i = g(I_{t,i}) + \varepsilon_i, \qquad (9)$$

where y_i is the detrended winter wheat yield of farm or county i, and $I_{t,i}$ is one of the indices described in Eqs. (4)–(8). The hedging effectiveness of weather derivatives depends on how accurate the index $I_{t,i}$ correlates with the winter wheat yield. Since there are other factors not captured by meteorological and VH indices, there is a portion of the variance remaining that cannot be explained by the underlying index. These factors are captured by the error term ε_i. The error term ε_i, thus, refers to the two dimensions of basis risk: the design and the geographical basis risk.

The weather derivatives were designed as European[1] put options in the case of the precipitation and the VH index–based weather derivatives and as European call options in the case of the temperature indices. The payout of the put (call) option was triggered if the index fell below (exceeded) the strike-level S_i threshold. Therefore, the payout of the put option was defined as $\mathrm{PO}_{t,i}^{\mathrm{put}} = \max(S_i - I_{t,i}, 0) \times V_i$, and the payout of the call option was defined as $\mathrm{PO}_{t,i}^{\mathrm{call}} = \max(I_{t,i} - S_i, 0) \times V_i$. The term V_i denotes the tick size, which is the payment per unit change in the difference between $I_{t,i}$ and S_i. Following Dalhaus and Finger (2016), S_i and V_i were calculated by rearranging Eq. (9) to

$$y_i = c_i + \beta_i I_i + \varepsilon_i, \qquad (10)$$

where y_i is the yield, c_i is a constant, $\beta_i I_i$ is the product of a slope coefficient and the index, and ε_i is an error term. The tick size V_i was determined by the estimation of the slope coefficient β_i, such that one unit change in the index I_i triggered β_i units change in the yield. In contrast to the widespread method of defining the strike level as the average of the historical index distribution, we defined the strike level using the average winter wheat yield, following Conradt et al. (2015). The advantage of this approach is that the calculation of the strike level is based on the insured variable. The strike level was calculated by inserting the average yield $\overline{y}_i$ and the estimates of β_i and c_i into Eq. (10) and solving for I_i: $I_i = (\overline{y}_i - c_i)/\beta_i$ (Dalhaus and Finger 2016).

For the estimation of β_i and c_i in Eq. (10), we applied QR (Conradt et al. 2015; Dalhaus and Finger 2016). QR was developed by Koenker and Bassett (1978) and allows estimation of the independent variable's effect on a specified quantile of the dependent variable. For insurance purposes, this enables the indemnification of low yield events and, thus, leads to better downside risk-reduction properties of the insurance contract. That is why the application of QR was more suitable in this context than standard ordinary least squares. Another advantage of QR is that it is robust to outliers and is not affected by nonnormally distributed data. The application of QR leads to the following estimation problem:

$$\hat{\beta}(\tau) = \underset{\beta \in \mathbb{R}}{\arg\min}\left[\tau \times \sum_{y_i \geq I_i \beta_i} |y_i - I_i \times \beta_i| + (1-\tau) \times \sum_{y_i < I_i \beta_i} |y_i - I_i \times \beta_i|\right]. \qquad (11)$$

QR minimizes the sum of weighted absolute deviations, where the weights are denoted by $\tau \in (0, 1)$. As we were focused on the lower tail of the yield distribution, we chose $\tau = 0.3$ according to Conradt et al. (2015).

In our analysis, we considered the farmer-paid premium Υ_i to be actuarially fair.[2] For the calculation of the fair premium, we applied the index value simulation. Therefore, we approximated theoretical distributions for the index variables and winter wheat yields. The best fitting distributions were determined by chi-square, Kolmogorov–Smirnov, and Anderson–Darling tests. We only tested for distributions that do not allow negative values. We derived 10 000 values for the indices by randomly drawing values from the estimated distributions. In each simulation run, the payouts $\mathrm{PO}_{t,i}^{\mathrm{put}}$ and $\mathrm{PO}_{t,i}^{\mathrm{call}}$ were calculated. The fair premium was equal to the average payout of the weather derivative[3] (Musshoff et al. 2011).

[1] European options differ from their American counterparts by the fact that European options can only be exercised on the expiration date. American options can be exercised at any time between purchase and expiration date (Little et al. 2015). In the context of weather derivatives, European options are used (cf. Vedenov and Barnett 2004; Woodard and Garcia 2008b; Leblois and Quirion 2013; Dalhaus and Finger 2016).

[2] By offering insurance policies to farmers, costs incur that are related to delivery and management of the insurance contracts. These so-called administration and operating costs amount to about 35% of the fair premium for traditional yield crop insurance (Wang et al. 1998). Because of the absence of damage assessment and asymmetric information problems, weather derivatives are assumed to be less costly. Hence, administration and operating costs of 10%–20% of the fair premium are commonly added to the price of weather derivatives (e.g., Buchholz and Musshoff 2014). Since our analysis solely focuses on the risk-reduction properties of weather derivatives based on VH indices in comparison to a benchmark, we do not consider administration and operating costs. In contrast to a demand analysis, the results of our study do not depend on these costs.

[3] The discount rate was assumed to be 0%.

c. Risk measures and statistical test procedure

The revenue $\pi_{t,i}$ per hectare winter wheat for each farm and county i and year t was given by the following equation:

$$\pi_{t,i} = p \times y_{t,i} + z_i \times \mathrm{PO}_{t,i} - z_i \times \Upsilon_i\,, \tag{12}$$

where $z_i \geq 0$ is the optimal number of insurance contracts chosen by the farmer to maximize the hedging effectiveness of the insurance contract, and p is the winter wheat price (Breustedt et al. 2008; Miranda 1991). The winter wheat price was assumed to be EUR 160 per ton. To evaluate the hedging effectiveness of each contract, we compared winter wheat revenues with and without insurance contracts. The latter were based on the indices presented in Eqs. (4)–(8). More specifically, we applied the expected shortfall (ES), a downside risk measure (e.g., Bokusheva et al. 2016; Conradt et al. 2015). The ES is the average of the losses below a certain quantile of the loss distribution and satisfies the five properties of a coherent risk measure (Artzner et al. 1999). The ES was calculated as follows:

$$\mathrm{ES}_\alpha = \frac{1}{1-\alpha}\int_\alpha^1 q_k\,dk\,, \tag{13}$$

where α denotes the confidence interval, and q_k is the k loss quantile. In accordance with the choice of τ, we set $k = 0.3$. We assigned the same weights of $1/(1-\alpha)$ to all loss quantiles, and all nontail quantiles exhibited a weight of zero (Acerbi 2002; Dowd et al. 2008). The hedging effectiveness was, thus, defined as the change of the expected shortfall of the winter wheat revenue by the use of an insurance contract. A higher hedging effectiveness corresponded to a lower basis risk due to a reduction in the part of the winter wheat yield variability that could not be explained by the considered index.

To test for significant differences between the hedging effectiveness of the calculated indices presented in Eqs. (4)–(8), we applied nonparametric Wilcoxon rank sum tests. The Wilcoxon rank sum test examines the null hypothesis that ranks of two groups are not significantly different. In contrast to the t test, data are not required to be normally distributed.

3. Results and discussion

To investigate in which period the VH indices revealed the highest correlations with winter wheat yield, we first studied the dynamics of the correlation coefficients for each calendar week's VCI, TCI, and VHI starting from 1995 until 2015. Figure 2 shows the results for two example farms and the corresponding counties. Winter wheat yield correlated strongly with the VH indices around the months May and June, in which the growing phases of stem elongation, ear emergence, and ripeness occur. This period can be seen as the most critical in winter wheat production in the region under investigation (Farooq et al. 2012).

The average start and end weeks of the periods with the highest correlations between the considered indices and winter wheat yield for all farms and counties are shown in Fig. 3. Summary statistics for these periods can be found in Table A2. The estimated periods ranged from calendar week 14 (beginning of April) to calendar week 30 (end of July). On average, the length of the periods ranged from 7 to 10 weeks at the farm level and from 6 to 11 weeks at the county level.

With respect to the average correlation coefficients, we found the highest correlation between the VHI and winter wheat yield, compared to the other indices[4] (Fig. 4). This is in line with the findings of Kogan et al. (2016), who also found the VHI to show the highest correlation with the yield of cereals in a Russian case study. On average, the correlation coefficient at the farm level was 0.56, whereas at the county level, the correlation coefficient was even higher (0.62 on average). Except for one farm, all correlation coefficients between the VHI and winter wheat yield were at least significant at the 5% level. On average, the second highest correlation coefficient at the farm level (0.49) was achieved for the relationship between the VCI and winter wheat yield. At the county level, the second highest correlation coefficient (0.59 on average) was found for the relationship between the temperature index and winter wheat yield. The lowest average correlation coefficients were estimated between the TCI and winter wheat yield, as well as the precipitation index (PCPN) and winter wheat yield (Fig. 4). Except for the VHI and the temperature index (TEMP), our estimates show only marginal differences between the average correlation coefficients at the farm and the county level (Fig. 4).

Figure 5 reports the hedging effectiveness of the weather derivatives based on the VH indices and the benchmark indices precipitation and temperature. The farm-level results showed an average hedging effectiveness of 16% for VHI-based, 12% for VCI-based, and 9% for TCI-based weather derivatives. Among the

[4] Because of the high correlations with winter wheat yield, the VHI can be used as a predictor for crop yield (Kogan et al. 2016). To assess the median winter wheat yield, the QR approach could be utilized to estimate the slope β_i and intercept c_i of Eq. (10). Therefore, τ needs to be set to 0.5. In doing so, the VHI could also be used for winter wheat yield assessment in the study region.

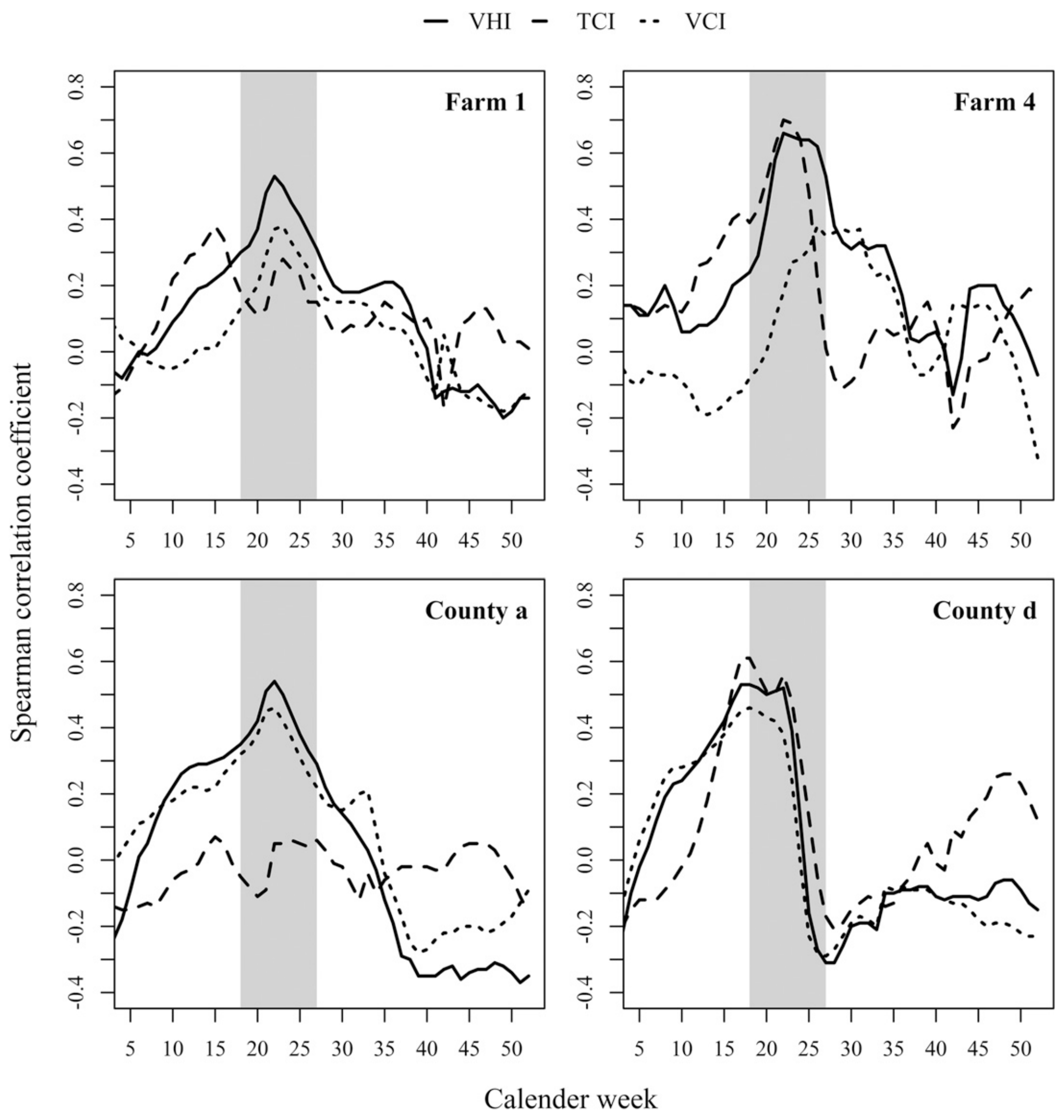

FIG. 2. Dynamics of the Spearman correlation coefficient between winter wheat yield and the VHI, TCI, and VCI for farms 1 and 4 and the corresponding counties a and d.

VH index–based weather derivatives, the VHI resulted in the highest average hedging effectiveness, which was, according to the Wilcoxon rank sum test, significantly higher, compared to the TCI-based weather derivatives (Table 2). At the county level, the average hedging effectiveness of the VHI-, VCI-, and TCI-based weather derivatives amounted to 19%, 14%, and 10%, respectively (Fig. 5). Among the VH index–based weather derivatives, the VHI resulted in the highest average hedging effectiveness, which was significantly higher, compared to both VCI- and TCI-based weather derivatives at the county level (Table 2).

By calculating the absolute difference in the average hedging effectiveness between the weather derivatives, the reduction of basis risk can be quantified. According to the Wilcoxon rank sum test, VHI- and VCI-based weather derivatives achieved a significant average basis risk reduction, compared to the precipitation benchmark at the farm and the county level. Using the VHI as an index, the basis risk could be reduced by 7% at the farm level and 12% at the county level. The use of VCI-based weather derivatives resulted in a basis risk reduction of 3% at the farm level and 5% at the county level. Compared to the temperature benchmark, a significant basis risk reduction could only be observed for VHI-based weather derivatives at the farm level. This reduction amounted to 6% (Table 2, Fig. 5).

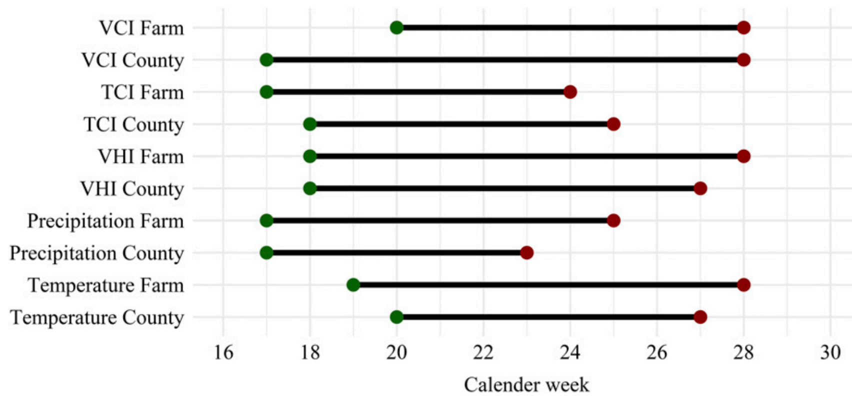

FIG. 3. Timelines showing the average start and end weeks of the periods with the highest correlation between the considered indices and winter wheat yields.

The absolute differences in the hedging effectiveness between the farm and county level are marginal, except for the temperature index–based weather derivatives (Fig. 5). The results reveal a significantly ($p \leq 0.05$) higher average hedging effectiveness of temperature-based weather derivatives at the county level. This is in line with the findings of Woodard and Garcia (2008b), who also found a higher performance of temperature index–based weather derivatives at higher levels of spatial aggregation. Because of the increase in the average hedging effectiveness of the temperature benchmark, the basis risk reduction of the VHI-based weather derivatives that we observed at the farm level is no longer significant at the county level (Table 2).

We found considerable variation in the correlation coefficients and correspondingly in the hedging effectiveness among individual farms and counties, as indicated in the boxplot diagrams (Figs. 4, 5). Correlation coefficients and the hedging effectiveness for each farm and county are documented in Tables A3–A6. To analyze these variations in more detail, we utilized scatterplots (Fig. 6). We focused on the comparison of weather derivatives with a significantly different average hedging effectiveness (Table 2). With regard to the benchmarks, the VHI-based weather derivatives outperformed the precipitation index–based weather derivatives for 82% of the study farms and the temperature index–based weather derivatives for 73% of the study farms. The VCI-based weather derivatives outperformed the precipitation index–based weather derivatives for 63% of the study farms. At the county level, the VHI- and the VCI-based weather derivatives outperformed the precipitation index–based weather derivatives for 88% and 76% of the study counties, respectively (Fig. 6).

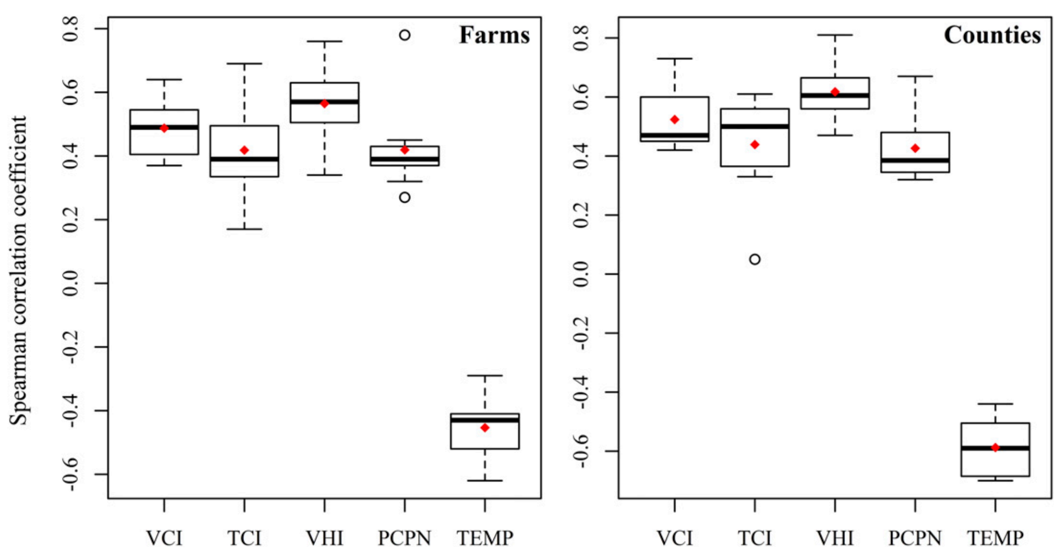

FIG. 4. Boxplots showing the Spearman correlation coefficients for the considered indices with winter wheat yield at the (left) farm level and (right) county level; red diamonds report the means.

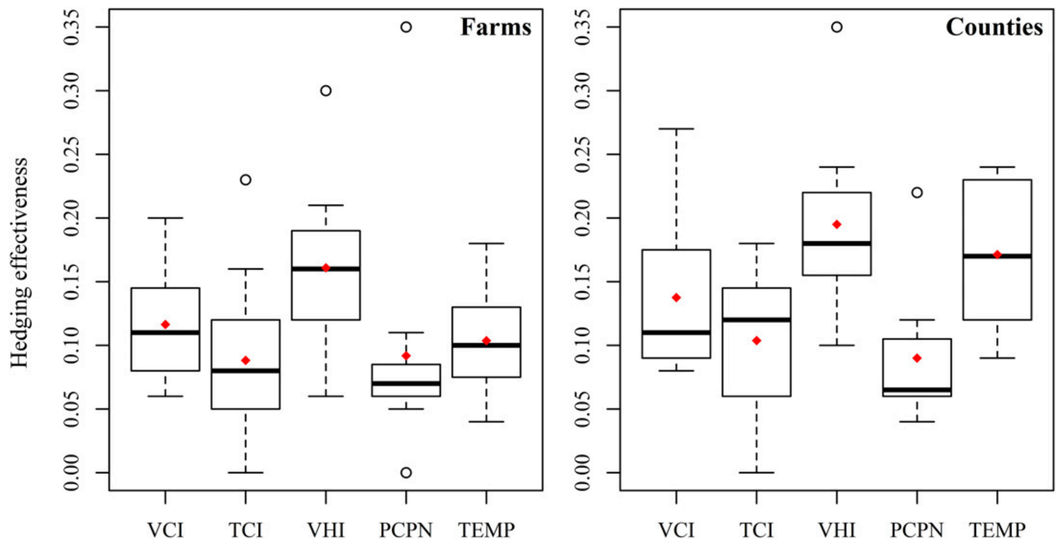

FIG. 5. Boxplots showing the hedging effectiveness in percent estimated by means of the ES at the (left) farm level and (right) county level; red diamonds report the means.

We even observed considerable variation in the hedging effectiveness within a single county. For example, farms 5, 6, and 7 are located in county e. While farm 5 is located in the northwest, farms 6 and 7 are located in the south of county e (Fig. 1). We estimated a higher hedging effectiveness of VCI- and VHI-based weather derivatives for farms 6 and 7, compared to farm 5, and a higher hedging effectiveness for TCI-based weather derivatives for farm 5, compared to farms 6 and 7. The differences in the hedging effectiveness among the farms in county f were considerably lower. This might be related to the locations of the farms within county f that were more concentrated, compared to those in county e.

The differences between farms within a single county and those between farms of different counties suggest that the representation of vegetation conditions seems to be related to location-specific factors like differing soil types or topographies. While the differing soil types might influence the crops' response to the different VH indices, the differing topographies cause issues in allocating the pixels to the cultivated area of each farm. Northeastern Germany is characterized by farm parcels with adjacent forests and small lakes. Hence, because of the spatial resolution of the remotely sensed data, it is not always possible to completely isolate the area of each farm that is cultivated with winter wheat. The NDVI and BT values for some farms might therefore be influenced by the adjacent forests and lakes as well as other cultivated crops. This could also explain the relatively low hedging effectiveness of the VH index–based weather derivatives for some farms, compared to others.

A possible explanation for the variations in the performance of the benchmarks relative to the VHI-based weather derivatives might be related to the distance between the weather station and the farm. For example, the distance between farm 3 and its assigned weather

TABLE 2. *P* values of the Wilcoxon rank sum test for the hedging effectiveness of weather derivatives based on different indices.

	VCI	TCI	VHI	Precipitation	Temperature
Farms					
VCI	1.0000	0.1580	0.1396	0.0527	0.5327
TCI		1.0000	0.0278	0.8696	0.3410
VHI			1.0000	0.0115	0.0386
Precipitation				1.0000	0.1228
Temperature					1.0000
Counties					
VCI	1.0000	0.5995	0.0157	0.0587	0.1722
TCI		1.0000	0.0157	0.2936	0.1152
VHI			1.0000	0.0087	0.5995
Precipitation				1.0000	0.0117
Temperature					1.0000

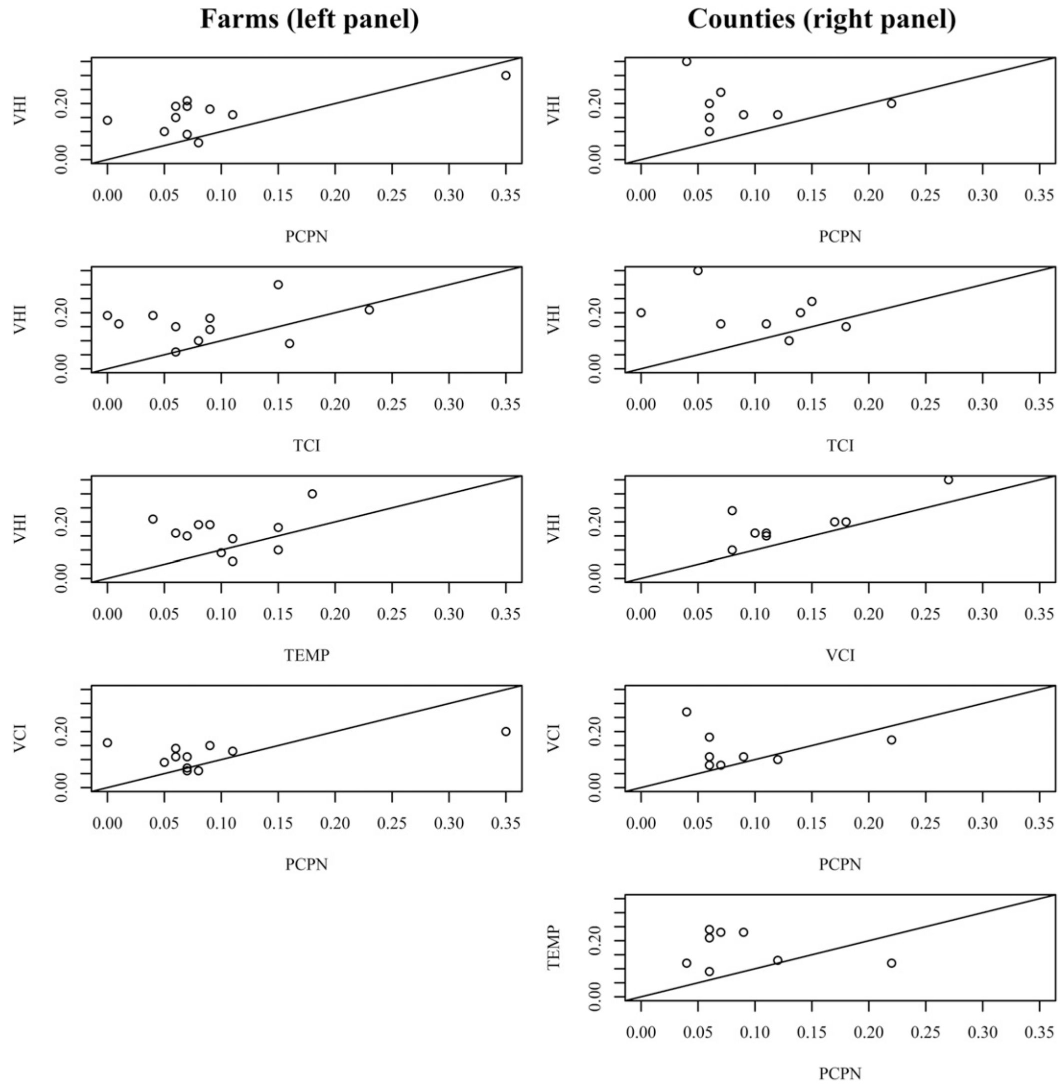

FIG. 6. Scatterplots showing the relationship between the hedging effectiveness of weather derivatives based on the VH indices and the meteorological benchmarks at the (left) farm level and (right) county level.

station was 4 km, considerably less than the average distance of 12 km. Hence, for farm 3, the precipitation index–based weather derivative resulted in a smaller basis risk (higher hedging effectiveness), compared to the VHI- and VCI-based weather derivatives (Fig. 6). This corresponds with the findings in the literature that the performance of precipitation index–based weather derivatives strongly depends on the distance to the next weather station (Heimfarth and Musshoff 2011; Norton et al. 2012; Gommes and Göbel 2013).

4. Conclusions

Weather derivatives are a possible risk management tool to hedge against drought-related risks in agriculture. Nevertheless, the uptake of these insurance products is still low mainly due to basis risk, which is often seen as the major shortcoming of traditional weather derivatives (Smith and Watts 2012; Woodard and Garcia 2008a). In this regard, remotely sensed VH indices could contribute to reducing two dimensions of basis risk commonly referred to as geographical and design basis risk.

In our German case study, we investigated the use of remotely sensed VH indices and their ability to enhance the performance of weather derivatives. We compared weather derivatives based on the VCI, the TCI, and their weighted composite, the VHI, with weather derivatives based on two benchmark indices: the commonly used precipitation sum and temperature sum indices.

TABLE A1. Summary statistics of the considered VH indices in percent and the two benchmark indices: the precipitation sum index in mm and the temperature sum index in °C.

County	Mean	Min	Max	Std dev	Farm	Mean	Min	Max	Std dev
					VCI				
a	77.62	65.85	86.53	5.13	1	78.69	68.41	91.25	6.43
b	70.54	60.84	78.44	4.11	2	70.49	58.37	80.63	6.46
c	70.19	63.17	75.16	3.27	3	72.71	63.56	82.01	5.09
d	53.29	43.53	61.55	5.35	4	78.99	65.67	87.13	5.23
e	78.55	66.56	83.77	4.43	5	72.17	45.81	82.87	7.55
					6	77.07	70.35	86.72	4.18
					7	84.72	77.97	90.02	3.64
f	80.74	74.93	87.51	3.64	8	82.75	67.29	90.30	6.29
					9	76.38	68.11	82.14	3.62
g	69.97	57.22	77.72	5.12	10	76.11	58.55	84.35	7.48
h	57.85	45.85	66.15	4.99	11	81.12	65.89	91.90	6.04
					TCI				
a	26.88	18.31	37.92	4.97	1	18.00	12.82	28.50	3.47
b	20.05	15.50	26.11	2.74	2	28.04	18.70	39.79	5.86
c	19.12	12.91	23.23	3.19	3	20.85	14.75	25.33	3.44
d	23.15	20.09	26.52	1.61	4	11.60	7.40	15.41	2.63
e	18.84	15.06	21.81	2.05	5	16.33	11.39	22.37	2.59
					6	19.33	15.00	24.07	2.42
					7	26.24	18.68	32.78	4.02
f	25.84	20.35	33.23	3.76	8	25.82	18.93	33.41	4.10
					9	25.81	17.76	34.69	4.22
g	20.81	15.60	24.84	2.67	10	10.90	4.65	25.06	4.55
h	20.24	16.25	23.54	2.12	11	18.88	11.55	22.66	2.92
					VHI				
a	47.39	42.16	50.90	2.28	1	47.98	40.73	53.27	3.00
b	44.59	41.04	47.06	1.69	2	41.98	36.22	46.27	2.98
c	45.20	39.52	48.70	2.34	3	46.61	40.32	52.61	3.10
d	39.59	30.05	50.63	5.69	4	45.92	40.97	48.81	2.23
e	48.99	44.19	51.85	1.92	5	46.78	39.97	50.06	2.36
					6	47.59	42.46	51.54	2.24
					7	51.69	47.69	53.99	1.79
f	47.43	42.94	50.50	2.11	8	46.94	31.61	51.85	4.86
					9	50.86	45.97	56.23	2.68
g	43.59	38.14	47.08	1.98	10	40.84	31.09	47.18	3.14
h	41.24	35.56	45.79	2.32	11	47.66	40.44	52.57	2.80
					Precipitation				
a	29.03	6.63	55.43	15.54	1	26.69	2.60	63.00	17.51
b	65.44	32.43	148.07	32.04	2	130.79	53.30	239.20	39.90
c	135.38	55.93	209.03	39.62	3	141.55	82.20	216.10	41.46
d	73.29	38.17	120.00	22.50	4	60.69	0.00	124.90	29.92
e	67.82	28.33	147.33	30.69	5	62.76	26.00	167.40	33.35
					6	34.13	1.40	74.50	21.73
					7	149.48	86.30	336.80	58.30
f	30.55	1.30	65.73	17.69	8	124.52	63.10	271.20	43.85
					9	74.79	29.70	116.20	24.65
g	115.23	55.47	249.20	42.49	10	124.79	79.30	269.00	41.00
h	112.87	60.13	226.87	40.50	11	138.87	83.80	246.60	39.19
					Temperature				
a	15.96	13.99	17.24	0.86	1	15.51	13.56	16.86	0.90
b	14.88	13.25	16.18	0.78	2	15.13	11.47	16.70	1.20
c	16.44	14.18	17.63	0.91	3	16.29	13.86	17.55	0.95
d	14.67	12.90	15.87	0.77	4	14.93	13.26	16.07	0.76
e	17.24	15.12	19.52	1.24	5	15.45	13.86	16.92	0.78
					6	17.43	15.30	18.99	0.91
					7	17.21	15.26	18.32	0.87
f	15.46	14.03	17.45	0.97	8	15.62	14.21	17.58	0.88
					9	15.62	14.21	17.58	0.88
g	16.00	14.15	17.55	0.87	10	16.93	15.11	18.85	0.83
h	15.48	13.59	18.02	1.16	11	13.57	12.11	15.47	0.95

TABLE A2. Summary statistics of the periods (calendar weeks) with the highest correlation between the considered indices and winter wheat yields.

	Farms/counties	VCI		TCI		VHI		Precipitation		Temperature	
		Start	End	Start	End	Start	End	Start	End	Start	End
Mean	Farms	20	28	17	24	18	28	17	25	19	28
	Counties	17	28	18	25	18	27	17	23	20	27
Min	Farms	14	26	14	17	14	21	14	17	14	26
	Counties	14	26	14	17	17	21	14	17	18	26
Max	Farms	27	30	27	30	22	30	22	30	22	29
	Counties	19	30	21	30	19	30	22	26	22	29
Std dev	Farms	4	2	4	6	3	3	3	5	2	1
	Counties	2	2	3	5	1	4	4	4	2	1

A correlation analysis between the considered indices and winter wheat yield revealed the highest average correlation for the relationship between the VHI and winter wheat yield. We found the periods of the highest correlation between the VH indices and winter wheat yield ranging from the beginning of April to the end of July. On average, the VHI-based weather derivatives significantly outperformed both benchmarks at the farm level and the precipitation benchmark at the county level in terms of hedging effectiveness. The VCI-based weather derivatives significantly outperformed the precipitation benchmarks at the farm and at the county levels, on average. Since a higher hedging effectiveness corresponds to a reduced basis risk, we can conclude that VHI- and VCI-based weather derivatives can reduce basis risk, compared to the commonly used meteorological index–based weather derivatives. However, unlike traditional weather derivatives based on meteorological indices, our results show that weather derivatives based on VH indices suffer from an additional source of basis risk, which is directly related to the spatial resolution of the available remotely sensed data and could be considered the *basis risk of spatial resolution*.

Our analysis revealed that the VHI- and VCI-based weather derivatives did not outperform the benchmark indices for every farm and county. We found a high variation in the hedging effectiveness among farms and counties and even within a single county. These variations might be related to the following factors that influence the performance of the meteorological indices relative to the VH indices. First, a decreasing distance to the next weather station increases the performance of precipitation index–based weather derivatives (cf. e.g., Norton et al. 2012) relative to the VHI-based weather derivatives. Second, location-specific factors like topography, soil type, and neighboring farm parcels not cultivated with winter wheat could influence the representation of the vegetation conditions of winter wheat by the VH indices. Remotely sensed data with a higher spatial resolution could particularly improve the performance of VH indices for countries with diversified crop rotations, like those in the European Union. According to a regulation within the framework of the Common Agriculture Policy of the European Union, farmers are required to diversify crops (European Parliament 2013).

TABLE A3. Spearman correlation coefficients between the considered indices and winter wheat yield at the farm level. Table uses Wilcoxon rank sum test with the H_0 that correlation equals zero: * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Farm	VCI	TCI	VHI	Precipitation	Temperature
1	0.42	0.39	0.48*	0.32	−0.43
2	0.37	0.34	0.34	0.44*	−0.56*
3	0.64**	0.55*	0.76***	0.78***	−0.62***
4	0.37	0.69***	0.65***	0.39	−0.29
5	0.39	0.59**	0.46*	0.41	−0.48*
6	0.55*	0.43	0.61***	0.42	−0.56**
7	0.50*	0.32	0.63***	0.38	−0.42
8	0.49*	0.35	0.55*	0.39	−0.40
9	0.49*	0.33	0.57**	0.45*	−0.33
10	0.60**	0.44*	0.53*	0.27	−0.48*
11	0.54	0.17	0.63***	0.36	−0.42
Mean	0.49	0.42	0.56	0.42	−0.45

TABLE A4. Spearman correlation coefficients between the considered indices and winter wheat yield at the county level. Table uses Wilcoxon rank sum test with the H_0 that correlation equals zero: * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

County	VCI	TCI	VHI	Precipitation	Temperature
a	0.61***	0.05	0.63***	0.33	−0.44*
b	0.42	0.52*	0.47*	0.36	−0.69**
c	0.59**	0.55**	0.63***	0.67***	−0.51*
d	0.47*	0.48*	0.58**	0.52*	−0.52*
e	0.47	0.61***	0.54**	0.36	−0.66***
f	0.73***	0.33	0.81***	0.32	−0.50*
g	0.46*	0.40	0.58**	0.44*	−0.68***
h	0.44*	0.57**	0.70***	0.41	−0.70***
Mean	0.52	0.44	0.62	0.43	−0.59

TABLE A5. Relative hedging effectiveness for farms estimated by means of the ES.

Farm	VCI	TCI	VHI	Precipitation	Temperature
1	0.09	0.08	0.10	0.05	0.15
2	0.06	0.06	0.06	0.08	0.11
3	0.20	0.15	0.30	0.35	0.18
4	0.07	0.23	0.21	0.07	0.04
5	0.06	0.16	0.09	0.07	0.10
6	0.15	0.09	0.18	0.09	0.15
7	0.11	0.04	0.19	0.07	0.08
8	0.11	0.06	0.15	0.06	0.07
9	0.13	0.01	0.16	0.11	0.06
10	0.16	0.09	0.14	0.00	0.11
11	0.14	0.00	0.19	0.06	0.09
Mean	0.12	0.09	0.16	0.09	0.10

TABLE A6. Relative hedging effectiveness for counties estimated by means of the ES.

County	VCI	TCI	VHI	Precipitation	Temperature
a	0.18	0.00	0.20	0.06	0.09
b	0.08	0.13	0.10	0.06	0.24
c	0.17	0.14	0.20	0.22	0.12
d	0.10	0.11	0.16	0.12	0.13
e	0.11	0.18	0.15	0.06	0.21
f	0.27	0.05	0.35	0.04	0.12
g	0.11	0.07	0.16	0.09	0.23
h	0.08	0.15	0.24	0.07	0.23
Mean	0.14	0.10	0.19	0.09	0.17

A major benefit of remotely sensed VH indices is that the NDVI and BT data from 1981 to the present are globally available. In developing countries in particular, weather station data are often scarce, and the lack of long-term datasets of specific index variables is often considered a handicap preventing the provision of weather derivatives to farmers (Meroni et al. 2013). Hence, the performance of VH index weather derivatives might be even higher for countries with sparse networks of weather stations.

This study confirms the potential of weather derivatives based on remotely sensed VH indices, especially the VHI, to outperform the commonly used precipitation and temperature sum indices. Along these lines, additional research is needed to quantify the extent to which the design basis risk and the geographical basis risk can be reduced by the use of VH index–based weather derivatives. Moreover, the performance of remotely sensed index–based weather derivatives could be further improved. First, the critical periods for winter wheat yield could be determined using NDVI or BT data to account for annual variations in the beginning and end of vegetation periods (cf. Rojas et al. 2011). Second, the availability of remotely sensed data of higher spatial resolution would be desirable. Third, the applicability of alternative indices like the fraction of photosynthetically active radiation (FAPAR) for weather derivatives, as suggested by Meroni et al. (2013), could be investigated in future studies. Finally, the use of mixed indices could be considered (cf. Pelka and Mußhoff 2013). For example, Kogan et al. (2016) used the VH indices from several weeks to explain crop yield variations. However, one should keep in mind that increasing the complexity of the weather derivative reduces market acceptance (Odening and Shen 2014).

APPENDIX

Details on Indices, Periods, Correlations, and Hedging Effectiveness

The appendix contains Tables A1–A6.

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