Can Remotely-Sensed Vegetation Health Indices Increase the Hedging-Effectiveness of Index Insurance? – Insights from Germany

Abstract

Satellite-retrieved vegetation health (VH) indices are under active consideration to be integrated into weather index insurance to reduce the basis risk and increase the attractiveness to farmers. The objective of this study is to obtain a deeper understanding of the hedging effectiveness (HE) of the satellite-retrieved VH indices. By using winter wheat yield records from 79 farms in Northern and Eastern Germany over 20 years, we designed index insurance based on three satellite indices to explore their HE: The Vegetation Condition Index (VCI), the Temperature Condition Index (TCI) and the Vegetation Health Index (VHI) with a spatial resolution of 1x1 km. As the benchmark, a meteorological index related to precipitation is employed. The results indicate that, on average, the TCI and VHI outperform the benchmark index in a statistically significant way. However, considerable differences across regions are observed. In particular, the highest HE, and therefore basis risk reduction, was found for regions with sandy soils in Eastern Germany. Insurers can be advised to accelerate the research and development of satellite-based index insurance in Eastern Germany. By considering our insurance design, products with low transaction costs and therefore comparatively low loading factors can be offered to farmers.

Keywords: Hedging effectiveness, Index insurance, Risk management, Satellite data

1. Introduction

Climate change puts pressure on the risk management of farms worldwide to secure agricultural incomes (Finger and El Benni, 2021). In Western Europe, catastrophic droughts and heat waves are occurring more frequently and affecting crop yields (Harkness *et al.*, 2020; Wreford and Topp, 2020). Drought has already been the most economically relevant production risk for crops in Germany, causing an average annual damage in winter wheat production of EUR 23 million (Schmitt *et al.*, 2022). To cope with the increasing risk of drought, weather index insurance is widely discussed as a means to mitigate economic losses for farmers. Index insurance overcomes the problem of information asymmetry and enables payouts to be determined quickly, making it cost-efficient. Furthermore, adverse selection and the risk of moral hazard can be tackled (Barnett and Mahul, 2007).

Since its introduction in 2015, the availability and variety of index insurance for agricultural purposes has grown in Germany (e.g. Allianz Agrar, 2024; Vereinigte Hagel, 2024). The underlying index mainly refers to weather station data such as precipitation or temperature (Leblois and Quirion, 2013). Nevertheless, farmers' uptake and intention to use drought insurance remains low (Nordmeyer and Mußhoff, 2023). Basis risk is known to be one of the main inhibiting factors of demand. Basis risk has several dimensions. For example, the correlation between the underlying index of an index insurance and the yield on a specific field is imperfect and therefore cannot reflect the yield loss perfectly, causing a basis risk of design (Heimfarth and Musshoff, 2011). In addition, a rainfall event occurs at the referring weather station, but not at the respective field, creating a geographical basis risk. Despite a dense network of weather stations in Germany, this kind of idiosyncratic event might be missed. Addressing this problem is crucial for the future adoption of index insurance products by farmers (Clarke, 2016).

The digitalization of the agricultural sector increases the availability of long-term and site-specific data which can be used to design better index insurance (Walter *et al.*, 2017). Researchers have turned their attention to satellite data to explore their potential to reduce the basis risk and thereby increase the hedging effectiveness (HE) of index insurance. Nowadays, satellites provide data globally, regardless of the density of weather stations (Quiring and Ganesh, 2010). This reduces transaction costs for multinational insurance providers because the information is not restricted to national borders (Vroege *et al.*, 2021). In addition, farmers are interested in the integration of satellite data in index insurance in general (Nordmeyer and Musshoff, 2023).

Satellites can provide information regarding soil moisture or the crop's health status based on biomass data. For example, the normalized difference vegetation index (NDVI) describes the density and vigor of green biomass and is thus an indicator of the health of the vegetation (Leblois and Quirion, 2013). While the NDVI is highly correlated to biomass assessment, an inconsistent relationship to crop yield was identified in Germany (Panek and Gozdowski, 2020). As a result, the NDVI is primarily investigated for use in forage index insurance (Turvey and Mclaurin, 2012; Vrieling *et al.*, 2014). To overcome this, the relationship between crops and satellite-retrieved vegetation health (VH) indices defined by Kogan (1990) are under active discussion (Bokusheva *et al.*, 2016; Kern *et al.*, 2018; Pei *et al.*, 2018). Three VH indices are of major interest: The Vegetation Condition Index (VCI), the Temperature Condition Index (TCI), and the Vegetation Health Index (VHI). The VCI is a relative indicator that shows how a specific crop develops between the minimum and maximum potential of a particular region, the TCI is a relative indicator of favorable or unfavorable thermal conditions at a specific location, while the VHI is a combination of both indices (Kogan *et al.*, 2016).

While the HE of index insurance based on satellite-retrieved soil moisture has received considerable research attention (Vroege *et al.*, 2021), only limited knowledge regarding the HE of satellite-retrieved VH indices exists. At present, the HE of VH indices in the German context has been previously investigated by Möllmann *et al.* (2019) and Kölle *et al.* (2022). Möllmann *et al.* (2019) considered eleven arable farms in Northeastern Germany in their pioneer study, while Kölle *et al.* (2022) investigated the basis risk reduction of satellite-retrieved VH indices for three farms in Northeastern Germany, distinguishing between the farm and field level. Although the authors provide initial insights suggesting that satellite-based VH indices can enhance HE and reduce basis risk, their results are limited in terms of sample size and regional focus. It remains to be investigated how the consideration of the critical phenological growth stages as well as a higher spatial resolution of the VCI, TCI, and VHI affects the HE as this has not received attention so far. In addition, the HE across different soil types is still unknown. Investigating the HE on a larger scale by considering different soil and climate conditions throughout a country is crucial to providing sufficient guidance to insurers in designing index insurance and to policymakers in designing agricultural policy. Therefore, this study explores the HE of satellite-retrieved VH indices in different regions with heterogeneous climate and soil conditions compared to a benchmark index. The coverage period is defined by phenological growth stages.

For our purpose, we use a large data set of winter wheat yield records from 79 farms over 20 years. To design index insurance, we use publicly available MODerate-resolution Imaging Spectroradiometer (MODIS) satellite data. In particular, we designed index insurance based on the three satellite-retrieved VH indices: The VCI, the TCI, and VHI with a spatial resolution of 1x1 km. As the benchmark, a precipitation index based on meteorological observations provided by the German Meteorological Service is employed (Deutscher Wetterdienst, 2020).

To the best of our knowledge, this is the first study that explicitly investigates the HE of index insurance based on satellite-retrieved VH on a large scale and across different regions for winter wheat. This is of particular interest as the share of German farmers who have index insurance remains very low with only 1-2% (Nordmeyer and Mußhoff, 2023). This is unique for such a developed country even though the discussion of index insurance has become more prevalent after the catastrophic drought in 2018 as it led to substantial disaster payments to farmers (Bundesministerium für Ernährung und Landwirtschaft, 2018). Yet, the debate is relevant since recent research has shown that German farmers prefer satellite-based index insurance over precipitation-based (Nordmeyer *et al.*, 2023). Furthermore, winter wheat is the most important crop in Germany (Destatis, 2021). Thus, our results are of interest to insurers who are designing index insurance and to policymakers considering policy intervention. Researchers focusing on the performance of index insurance can also benefit from this study. The structure of this article is as follows: In section 2, we describe the study area of our case study as well as the satellite and meteorological data used. Section 3 provides a detailed description of the applied methodology. In Section 4, we present and discuss the results, before we draw our main conclusions in Section 5.

2. Study area and data

To investigate the HE of the satellite-retrieved VH indices, we use balanced winter wheat yield records from 79 farms in Northern and Eastern Germany between 2000 and 2019, which highly exceeds datasets used in previous literature (Kölle *et al.*, 2022; Möllmann *et al.*, 2019). The data were provided by an insurance broker. More specifically, the study area includes the federal states of Brandenburg, Lower Saxony, Saxony, Saxony-Anhalt, and Thuringia as well as single farms from Mecklenburg-Western Pomerania and Schleswig-Holstein. Around all these federal states, winter wheat is the most important winter crop. According to differences in latitude and altitude, the harvest period of winter wheat takes place between mid-July and mid-August. Across the whole study region, the long-term annual precipitation ranges from 557 mm to 788 mm which is lower than the long-term average annual precipitation for Germany (791 mm) (Deutscher Wetterdienst, 2022). Therefore, we cover a wide range of different regions and arable farming conditions in Germany. The locations of the 79 farms under investigation are shown in Figure I.

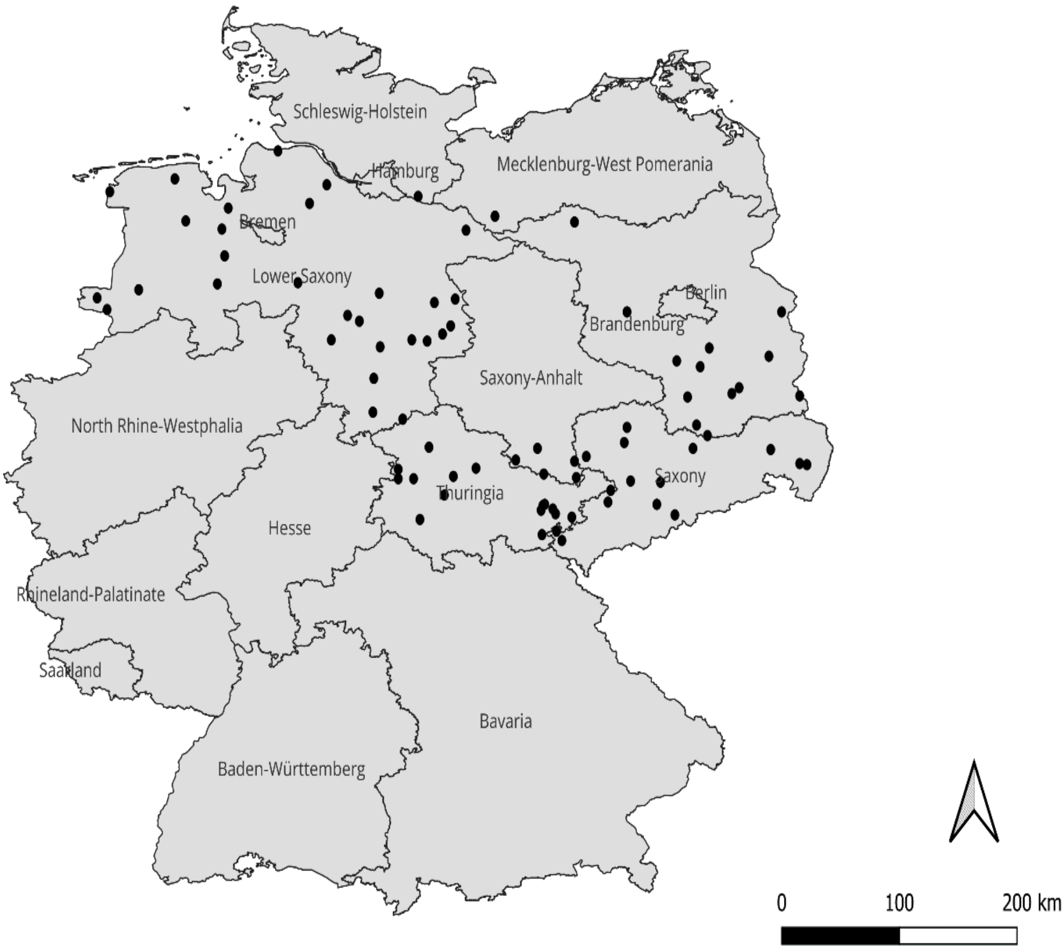

Figure I Locations of the farms under investigation. Farms are indicated as black points.
Source: Own illustration

Since the farms are located in different regions of Germany, the climate and soil conditions vary considerably. For a better comparison of the farming conditions, we consider the agricultural area segmentation suggested by Roßberg *et al.* (2007). Based on area segmentation, the authors defined soil-climate regions across Germany. The soil-climate regions allow to assign farms to smaller areas as they are similar in terms of soil conditions and water holding capacity as well as climate conditions. Given that the soil-climate regions are relatively small, there are some soil-climate regions with only one or only a few farms. As this would lead to biased results, we build on findings by Dachbrodt-Saaydeh *et al.* (2019) who clustered the soil-climate regions into broader regions for a regional evaluation and analysis of pesticide use intensity. Within these clusters, arable farming deals with similar conditions. A major advantage of this segmentation is that it does not depend on federal-state borders. The clusters defined by Dachbrodt-Saaydeh *et al.* (2019) are presented in Figure II.

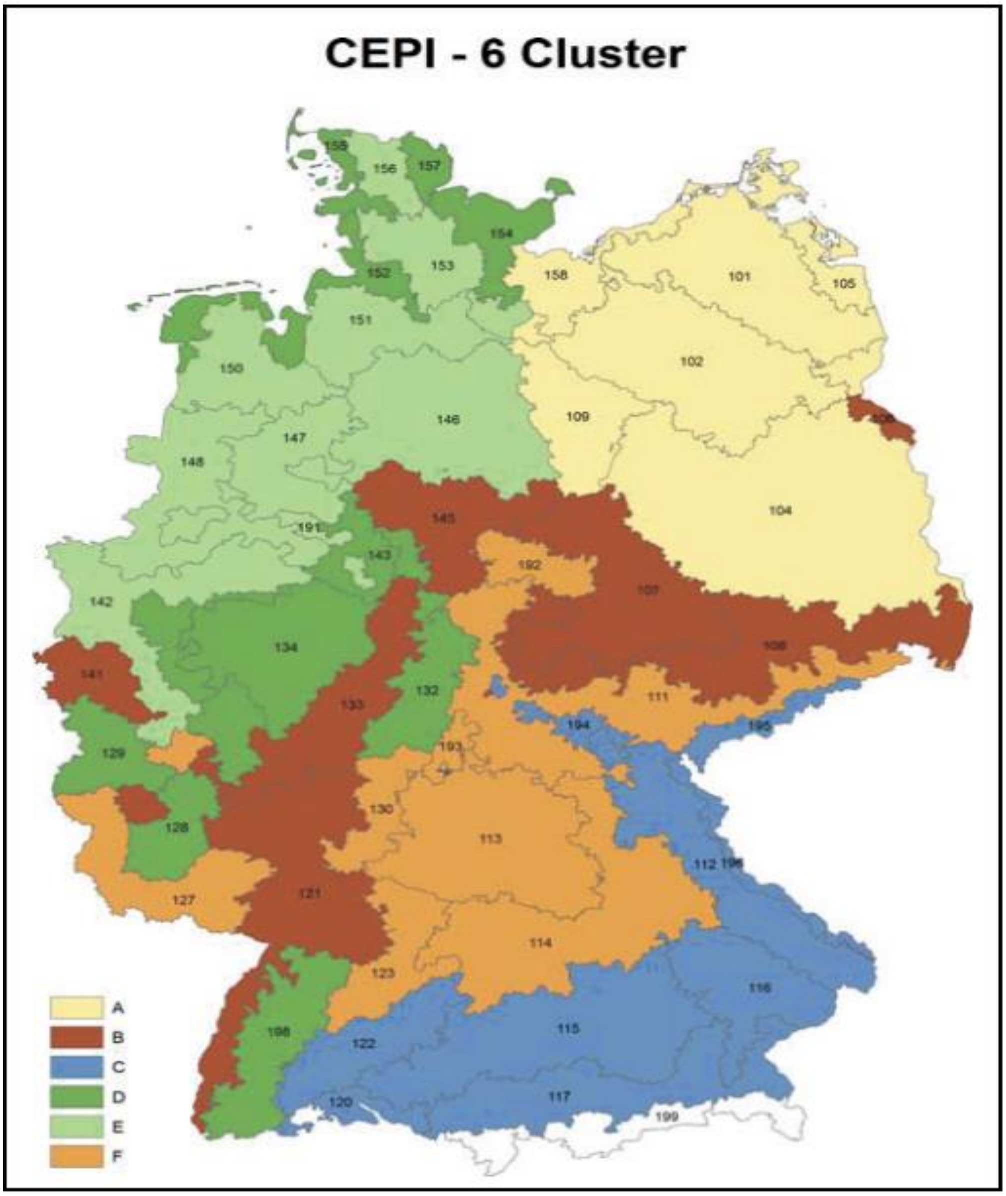

Figure II Clusters for the regional evaluation and analysis of pesticide use intensity (CEPI) in arable crops
Source: (Dachbrodt-Saaydeh *et al.*, 2019)

The 79 farms in our case study are located in cluster A (16), cluster B (27), cluster E (18) and cluster F (18). Hence, we cover four out of six clusters. Cluster A covers the area of Brandenburg, Mecklenburg-Western Pomerania, and parts of Saxony and Saxony-Anhalt. Cluster A is characterized by the lowest soil quality and lowest precipitation but the highest mean daily temperatures during the vegetation period. Particularly, the low water-holding capacity of the sandy soils increases the high variability in winter wheat yield due to heat and drought events. In addition, a further decrease in precipitation during the vegetation period and an increase in temperatures leading to increased evaporation due to climate change is expected in this region (Lüttger and Feike, 2018).

Cluster B is characterized by the highest soil quality compared to the other clusters, but the annual precipitation is lower than in clusters E and F. In addition, comparatively high daily mean temperatures are observed. Cluster B covers the southern part of Lower Saxony and parts of Saxony, Saxony-Anhalt, and Thuringia. The other farms in Lower Saxony belong to cluster E. The soil quality in this area is low (similar to cluster A), however, the amount of precipitation during the vegetation period is higher compared to other clusters. The fourth cluster of relevance in our case study is Cluster F. Cluster F is characterized by lower soil quality compared to Cluster B, but higher compared to Cluster A and E. Furthermore, this cluster is characterized by higher precipitation compared to other clusters and lower daily mean temperatures. due to higher altitude on average given that this area includes low mountain ranges.

Table I shows the winter wheat yield statistics for all farms and the different clusters. The average winter wheat yield is 72.12 dt/ha with a standard deviation of 12.67 dt/ha. The highest yields were observed for clusters E (76.47) and B (75.85), and the lowest for farms in cluster A (60.87). The highest standard deviation was also observed for cluster A (14.73).

Table I Summary statistics of winter wheat yields across different clusters from 2000-2019 in dt/ha

	N	Mean	Min	Max	SD	CV
Full sample	79	72.12	25.70	100.60	12.67	17.6%
Cluster A	16	60.87	25.70	99.00	14.73	24.2%
Cluster B	27	75.85	35.98	100.60	10.93	14.4%
Cluster E	18	76.47	41.10	97.60	9.07	11.9%
Cluster F	18	72.19	40.30	97.60	9.79	13.6%

Notes: SD indicates standard deviation. CV indicates the coefficient of variation.
Source: Own illustration

With respect to the VH indices, we compute three satellite indices: VCI, TCI, and VHI. The calculation of the VCI involves the use of the Enhanced Vegetation Index (EVI). Similar to the NDVI, the EVI serves as a satellite index that reflects changes in green plant biomass throughout the vegetation period (Salem *et al.*, 1995). The EVI measures the overall quantity of green biomass within each pixel of a satellite image over a specified period. In comparison to the NDVI, the EVI exhibits greater sensitivity to areas with elevated biomass (Didan *et al.*, 2015; Kölle *et al.*, 2021).

The VCI is computed through the normalization of EVI values using the absolute minimum and maximum values persisting throughout the entire observation period 2000-2019. This normalization process mitigates the influences of natural site conditions such as soil and topography, which can affect EVI values differently. As a result, identical EVI values require distinct interpretations based on the ecological potential of the region. The absolute maximum and minimum EVI values for each pixel encompass extreme weather conditions, serving as reference points that delineate the minimum or maximum limitations of yield capacity specified as the ecosystem. In addition, the VCI signifies the extent to which prevailing weather conditions exploit the ecological potential of the region (Kogan, 1995). The VCI is determined by the minimum (EVI_{min}) and maximum (EVI_{max}) EVI values for each 1x1 km pixel throughout the study period and for each satellite image on day d as follows:

$$VCI_d = 100 \times \frac{EVI_d - EVI_{min}}{EVI_{max} - EVI_{min}} \tag{1}$$

The VCI is represented on a scale from 0 to 100 (Kogan 1995). Consequently, higher VCI values indicate vital vegetation that is not characterized by moisture stress. In contrast, dry years are characterized by lower green biomass and correspondingly lower VCI values, which are caused by thermal vegetation stress due to drought. However, other factors, such as plant diseases or insects, can also influence the amount of green biomass. We calculated VCI values with a spatial resolution of 1x1 km and a temporal resolution of 16 days.

The TCI is calculated by considering Land Surface Temperature (LST) values within the defined study period in every year with the index-specific temporal resolution of *d* as follows:

$$TCI_d = 100 \times \frac{LST_{max} - LST_d}{LST_{max} - LST_{min}} \tag{2}$$

where the LST_{min} and LST_{max} correspond to the minimum and maximum LST values during the defined coverage period in each year between 2000-2019 (Unganai and Kogan, 1998). Corresponding to the VCI, values close to 0 reflect thermal vegetation stress, and values close to 100 reflect that the maximum benefit has been derived from the given geographical resources of the area of the respective farm. We calculated TCI values with a spatial resolution of 1x1 km and a temporal resolution of 8 days.

To calculate the VHI in year, the average value of all satellite images of both indices during a defined coverage period as suggested by Kogan *et al.* (2016) is used as follows:

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \tag{3}$$

where α depicts the weighting coefficient. Similar to Möllmann *et al.* (2019), we assume equal weights of the VCI and the TCI (α=0.5) as suggested by Kogan *et al.* (2016). This can be assumed given that the relative contribution of temperature and moisture is not exactly known. Given the different temporal resolutions of the satellite indices, the values of the VCI and TCI for each farm were derived by considering the average values of all observations for both indices in the relevant coverage period in every year. To derive the three indices on the farm level, we include five or even more 1x1 km pixels to address the lack of information on the exact geographic position of the respective fields. Since we are only interested in pixels covering arable land, we use Google Earth to detect lakes, forests, and villages and mask them out by purely focusing on pixels covering arable land.

3. Methodology

To investigate the HE, we designed realistic, but not yet offered index insurance products for each of the 79 farms. Particularly, we designed index insurance based on the three satellite indices. As the benchmark, an index insurance related to precipitation is employed (R). In contrast to the VH indices, the precipitation-based index insurance refers to the sum instead auf of the average to be in line with currently available products (e.g. Vereinigte Hagel, 2024). Particularly, the precipitation-based index insurance was defined as the farm-individual average sum of daily precipitation of the nearest three weather stations during the coverage period of the insurance in every year. Accordingly, the precipitation index $R_{t,i}$ is defined as follows:

$$R_{t,i} = \sum_{d=1}^{n} R_d^{t,i} \tag{4}$$

where $R_d^{t,i}$ depicts the sum of precipitation on day d of year t reported for the area of farm i. Given that the satellite indices are calculated as values between 0 and 100, we use the average instead of the sum. Hence, the $VCI_{t,i}$ and $TCI_{t,i}$ were calculated by considering:

$$VCI_{t,i} = \frac{1}{n} \sum_{d=1}^{n} VCI_d^{t,i} \tag{5}$$

$$TCI_{t,i} = \frac{1}{n} \sum_{d=1}^{n} TCI_d^{t,i} \tag{6}$$

where $VCI_d^{t,i}$ and $TCI_d^{t,i}$ indicate the value of the vegetation indices for farm i at observation d in year *t*. Considering the different temporal resolutions of the VCI and TCI, the $VHI_{t,i}$ is calculated as the weighted average of all observations of the TCI and the VCI on farm i in year t:

$$VHI_{t,i} = \alpha \times VCI_{t,i} + (1 - \alpha) \times TCI_{t,i} \quad (7)$$

Following Dalhaus *et al.* (2018), we focus on the critical phenological phases of winter wheat as the coverage period of the index insurance for each farm individually. With respect to winter wheat, the most vulnerable time frame for damage by water deficit is between stem elongation and the beginning of milk ripeness (Acevedo *et al.*, 2002; Conradt *et al.*, 2015). The database is provided by the German Meteorological Service and is based on real phenology reports of voluntary observers from over 1200 active stations throughout the country. Based on that, the "day of the year" of the crop-specific growth phases can be determined to define the farm-specific coverage period in every year. Descriptive statistics of the indices for all farms and clusters using phenological time frames can be found in Table A1 of the appendix.

We designed the index insurance products as European put-options. Hence, the farmer receives a payout if the respective index ($I_{t,i}$) falls below a pre-defined threshold called strike-level (S_i). Thus, the payout (PO) is calculated as $PO_{t,i}^{put} = \max\ (S_i - I_{t,i}) \times\ T_i$. The term T_i represents the tick size representing the payment per unit change in the difference between $I_{t,i}$ and S_i.

As suggested by Dalhaus and Finger (2016), we apply a farm-specific regression framework for estimations:

$$y_{i,t} = \beta_{0_{i,t,v}} + \ \beta_{1_{i,t,v}} \times I_{i,t,v} + \varepsilon_{i,t,v} \quad (8)$$

where $y_{i,t}$ indicates the winter wheat yield reported by farm *i* in year *t*. The regression coefficients $\beta_{0_{i,v}}$ and $\beta_{1_{i,v}}$ represent the farm individual intercept and slope for the different indices v and $I_{i,v}$ depicts the index value at farm i in year t for the index v. The error term $\varepsilon_{i,t,v}$ includes the farm, year and index-specific basis risk which can lead to a mismatch between the crop yield and the index value. Given that our research purpose is related to heavy drought-related yield losses, we follow Conradt *et al.* (2015) and apply quantile regressions similarly to Möllmann *et al.* (2019) and Vroege *et al.* (2021). In doing so, we determine the relationship between VH indices and lower yields individually.

For insurance purposes, quantile regression enables the indemnification of low-yield events and leads to a more appropriate downside risk reduction properties of the insurance contract (Conradt *et al.*, 2015). In particular, quantile regression allows to estimate ${\beta_0}_{i,v}$ and ${\beta_1}_{i,v}$ on $I_{i,v}$ on the lower bound of yield observations to calculate farm-individual strike levels and tick sizes. Furthermore, quantile regression is not affected by normally distributed data and is more robust to outliers compared to ordinary least squares regression. Thus, quantile regression is highly suitable for our research aim. Quantile regression minimizes the sum of absolute distances between fitted values $I_{i,v} \times {\beta_1}_{i,v}$ and observed values $y_{i,t}$ with a specific emphasis on weighting downside yield events by $(1-\tau)$ and upward residuals by τ as follows:

$$\beta(\tau) = \underset{\beta \epsilon \mathbb{R}}{\arg\min} \left[\tau \times \sum_{y_i < I_{i,}\beta_i} \left| y_{i,t} - I_{i,v} \times {\beta_1}_{i,v} \right| + (1-\tau) \times \sum_{y_i < I_{i,}\beta_i} \left| y_{i,t} - I_{i,v} \times {\beta_1}_{i,v} \right| \right] \tag{9}$$

In line with relevant literature, the quantile of interest is the lowest 30 per cent of the yield distribution ($\tau = 0.3$). Similar to Vroege *et al.* (2021), we apply a quantile approach to calculate the strike level $S_{i,v}$ in contrast to Conradt *et al.* (2015) who used the average winter wheat yield. Particularly, we use the quantile regression coefficients ${\beta_0}_{i,v}$ and ${\beta_1}_{i,v}$ to define the strike level by:

$$S_{i,v} = \frac{q_{0.3}(y_i) - \beta_{0_{i,v}}}{\beta_{1_{i,v}}} \tag{10}$$

where $q_{0.3}$ reflects the focus on the 30 per cent percentile value of the winter wheat yield distribution of a farmer *i*. The tick size T_i was equal to the slope of the quantile regression ($\beta_{1_{i,v}}$) multiplied by a constant price (*P*). Following Vroege *et al.* (2021), a strike level and tick size were only calculated in cases where a positive relation between the index and yields indicated by a positive value of $\beta_{1_{i,v}}$ was identified for the lower tail of the yield distribution. In the case of a negative value of $\beta_{1_{i,v}}$, corresponding to a negative relation, drought cannot be seen as a major production risk for the farm and a premium calculation under actuarially fair conditions would not be possible.

However, our study aims to investigate the HE under a fair premium scenario. Consequently, we applied the burn analysis to identify the actuarially fair premium (Heimfarth and Musshoff, 2011; Heimfarth *et al.*, 2012; Taib and Benth, 2012). We calculated the payouts considering strike level and tick size for all indices based on the historical farm-specific data. Finally, the fair premium (PR_i) was set as the average payout observed (Musshoff *et al.*, 2011). We use the farmers' winter wheat revenue distribution to examine the HE. In particular, the revenue per hectare ($\pi_{t,i}$) was defined as follows:

$$\pi_{t,i} = P \times y_{t,i} + c_i \times PO_{t,i} - c_i \times PR_i \tag{11}$$

where c_i describes the optimal number of insurance contracts bought by the farmers to reach the highest HE. We used a constant level of winter wheat price at a level of EUR 200 per ton. Following Bucheli *et al.* (2021) and Möllmann *et al.* (2019), we detrended the winter wheat yield $y_{t,i}$ by assuming a linear regression as the methodological approach. The HE was obtained by comparing the farmers' revenue without index insurance and with the index insurance product designed by us. In accordance with Conradt *et al.* (2015), we use the expected shortfall as a risk reduction indicator. The expected shortfall indicates the average of losses below a defined value at risk (k), which is represented by the 0.3 quantile of the yield distribution. The expected shortfall ES is calculated by:

$$ES_{\alpha} = \frac{1}{1-\alpha}\int_{\alpha}^{1} q_k dk, \tag{12}$$

where α depicts the confidence interval. With respect to the quantile of interest ($\tau = 0.3$), we set k=0.3. We allocated equal weights of $1/(1-\alpha)$ to all loss quantiles, with all non-tail quantiles showing a weight of zero (Dowd *et al.*, 2008). Hence, the HE was calculated by the change in the expected shortfall for every farm with and without index insurance. Finally, the non-parametric Wilcoxon rank sum test was used to test whether statistically significant differences in HE between the VH indices and the benchmark could be identified. A major advantage of this test is that it does not require normally distributed data.

4. Results and discussion

Following Conradt *et al.* (2015), we focus on the lower bound of the winter wheat revenue distribution. As mentioned, a positive relationship between the respective index and the winter wheat yield in the 0.3 quantile was the precondition to be incorporated in our analysis to calculate fair premiums. A drought risk can be identified at between 65% (51 farms) for the VCI and 96% (76 farms) for the TCI. For the VHI, a drought risk was identified for 66 farms and concerning the benchmark index for 62 farms. Across the different indices, the highest correlation coefficient was estimated between the TCI and winter wheat, followed by the VHI. Particularly, the correlation coefficient was 0.42 on average for the TCI and 0.39 for the VHI. The lowest average correlation coefficients were found between the VCI and the winter yield (0.24) and between precipitation and winter wheat (0.27). This is in line with the findings of Möllmann *et al.* (2019). Most notably, our estimates show considerable differences across the farms and clusters. The highest correlation for all indices was found in cluster A. For perspective, the correlation coefficient between the TCI and winter wheat was 0.60, between the VHI and winter wheat 0.55, between precipitation and winter wheat 0.41, and for the VCI and winter wheat 0.33. On the contrary, the lowest correlation coefficients for all indices were estimated in cluster E. More precisely, the correlation coefficients were 0.16 for the VCI, 0.33 for the TCI, 0.31 for the VHI, and 0.21 for precipitation.

With respect to the insurance contracts, the average coverage period of the index insurance was 63 days on average across all farms. Statistics regarding the insurance premiums for the different indices and across the four clusters can be found in Table II. Based on the burn-rate analysis, the HE was calculated under a fair premium scenario. Consequently, overall revenues are equal for the uninsured and the insured scenarios.

Table II Insurance premiums statistics in EUR

	Mean	**SD**	**Max**	**Min**	**Insured farm**	**Share insured farm**
Full sample						
VCI	34.30	27.40	114.68	0.33	51	0.65
TCI	34.91	24.53	133.75	1.45	76	0.96
VHI	32.97	26.48	130.36	0.38	66	0.84
R	31.11	24.67	107.09	0.66	65	0.82
Cluster A						
VCI	46.86	30.09	114.68	6.83	15	0.94
TCI	52.49	31.63	133.75	7.90	16	1.00
VHI	54.54	31.10	130.36	7.94	16	1.00
R	50.73	25.85	92.13	9.32	15	0.94
Cluster B						
VCI	26.19	23.14	85.71	2.65	14	0.52
TCI	33.46	20.27	81.77	1.91	27	1.00
VHI	28.14	22.91	89.81	2.56	21	0.78
R	23.50	19.79	79.54	0.66	22	0.81
Cluster E						
VCI	29.02	27.47	80.76	0.33	14	0.78
TCI	26.74	23.68	82.09	1.45	18	1.00
VHI	22.96	21.74	90.45	0.38	16	0.89
R	22.31	12.80	46.26	7.74	12	0.67
Cluster F						
VCI	34.76	23.12	81.58	10.01	8	0.44
TCI	28.57	14.89	45.90	3.66	15	0.83
VHI	26.56	16.83	62.72	2.09	13	0.72
R	29.80	27.77	107.09	1.35	16	0.89

Note: SD indicates standard deviation.
Source: Own illustration

The fair index insurance premiums were, depending on the index, varying between 2.2% to 2.4 % of the mean revenues from winter wheat per hectare on average. On average, the highest insurance premiums were found in cluster A. The average insurance premiums in cluster A were EUR 46.86 for the VCI, EUR 52.49 for the TCI, EUR 54.54 for the VHI, and EUR 50.73 for the benchmark per hectare, corresponding to 3.8% to 4.4% of the mean annual revenue of winter wheat per hectare of farms in this cluster. Further information regarding the contract parameters can be found in the appendix including intercept and coefficient statistics of the quantile regression (Table A2) and strike level and tick size statistics (Table A3).

The results of the HE in terms of relative increase in the expected shortfall are presented in Table III. By assessing the individual insurance premium all of the satellite-based VH indices and the benchmark index show a positive effect on the HE compared to no insurance on average. Considering the full sample, a HE of 2.11% was found for the TCI-based index insurance. The average HE for the VHI-based and the VCI-based were 1.96% and 1.35% respectively. All indices outperformed the benchmark precipitation index given an average HE of 1.28%. Therefore, the TCI-based index insurance showed the highest HE. The Wilcoxon rank sum test results in Table IV confirm that the HE of the TCI-based and the VHI-based were statistically significantly higher compared to the benchmark. In addition, the HE of the TCI-based and the VHI-based were statistically significantly higher compared to the VCI-based index insurance considering the full sample. No statistically significant higher HE was identified for the VCI-based compared to the precipitation-based index insurance. The TCI-based and VHI-based outperformed the benchmark index in 73% and 63% of the farms in the case that a drought risk was identified for both.

Table III Results of the hedging effectiveness of index insurance based on different indices

	Mean HE	SD HE	Insured farms	Share insured farm
Full sample				
VCI	1.35%	1.85%	51	0.65
TCI	2.11%	2.10%	76	0.96
VHI	1.96%	2.20%	66	0.84
R	1.28%	1.85%	65	0.82
Cluster A				
VCI	2.34%	2.48%	15	0.94
TCI	4.76%	2.34%	16	1.00
VHI	4.46%	2.27%	16	1.00
R	3.27%	2.84%	15	0.94
Cluster B				
VCI	0.99%	1.33%	14	0.52
TCI	1.70%	1.38%	27	1.00
VHI	1.43%	1.80%	21	0.78
R	0.65%	0.73%	22	0.81
Cluster E				
VCI	0.85%	1.65%	14	0.78
TCI	0.99%	0.88%	18	1.00
VHI	0.93%	1.48%	16	0.89
R	0.53%	0.60%	12	0.67
Cluster F				
VCI	0.87%	0.86%	8	0.44
TCI	1.37%	0.95%	15	0.83
VHI	0.92%	0.74%	13	0.72
R	0.74%	0.93%	16	0.89

Note: SD indicates standard deviation.
Source: Own illustration

To quantify the reduction in basis risk by the VH indices, the absolute difference in the average HE between the different index insurance can be calculated. Thus, the TCI-based index insurance reduces the basis risk by 0.83% index and the VHI-based by 0.68% compared to the benchmark on average. According to the Wilcoxon rank sum test, the reduction in basis risk is statistically significant, however, the effect is smaller compared to the results of Möllmann *et al.* (2019).

A huge heterogeneity in the HE across the farms and correspondingly the four clusters was observed. Most notably, cluster A shows the highest HE for all indices. The average HE for the TCI-based was 4.76%, for the VHI-based 4.46%, for the VCI-based 2.34% and the precipitation-based 3.27%. Based on Wilcoxon rank sum test results, the HE of the TCI-based outperforms the precipitation-based in a statistically significant way. Consequently, the TCI-based can reduce the basis risk by 1.49% compared to the precipitation-based index insurance. In this cluster, the TCI outperformed the benchmark index in 67% of the farms and the VHI outperformed the benchmark index in 73% of the farms.

Table IV Results of the Wilcoxon rank sum test for the HE of index insurance expressed as p-values

	VCI	TCI	VHI	R
Full sample				
VCI	1.0000	0.0097	0.0474	0.4338
TCI		1.0000	0.2390	0.0015
VHI			1.0000	0.0237
R				1.0000
Cluster A				
VCI	1.0000	0.0060	0.0084	0.1700
TCI		1.0000	0.3188	0.0465
VHI			1.0000	0.0745
R				1.0000
Cluster B				
VCI	1.0000	0.1387	0.2667	0.2878
TCI		1.0000	0.2945	0.0212
VHI			1.0000	0.1640
R				1.0000
Cluster E				
VCI	1.0000	0.0772	0.3163	0.6052
TCI		1.0000	0.2087	0.0966
VHI			1.0000	0.3547
R				1.0000
Cluster F				
VCI	1.0000	0.2324	0.9135	0.4979
TCI		1.0000	0.2136	0.0745
VHI			1.0000	0.3569
R				1.0000

Source: Own illustration

On the contrary, the HE observed in the other clusters is considerably lower. Across all clusters, the TCI-based index insurance shows the highest HE. A HE of 1.70% in cluster B, 1.37% in cluster F, and 0.99% in cluster E was found for the TCI-based insurance. Although the HE is low, the TCI-based index insurance statistically significantly outperforms the precipitation-based in clusters B and F according to the result of the Wilcoxon rank sum test, corresponding to a basis risk reduction by 1.05% in cluster B and 0.63% in clusters F. Furthermore, the VHI-based index insurance performed second best with a HE of 1.43% in cluster B, of 0.93% cluster E and of 0.92% in cluster F. However, no statistically significant reduction in basis risk compared to the benchmark can be identified. This also applies to the VCI-based index insurance, for which a HE of 0.99% (cluster B), 0.85% (cluster E), and 0.87% (cluster F) was determined. We elicited considerable variation in the HE across the clusters, but also within the clusters. More information regarding this can be found in Figure III.

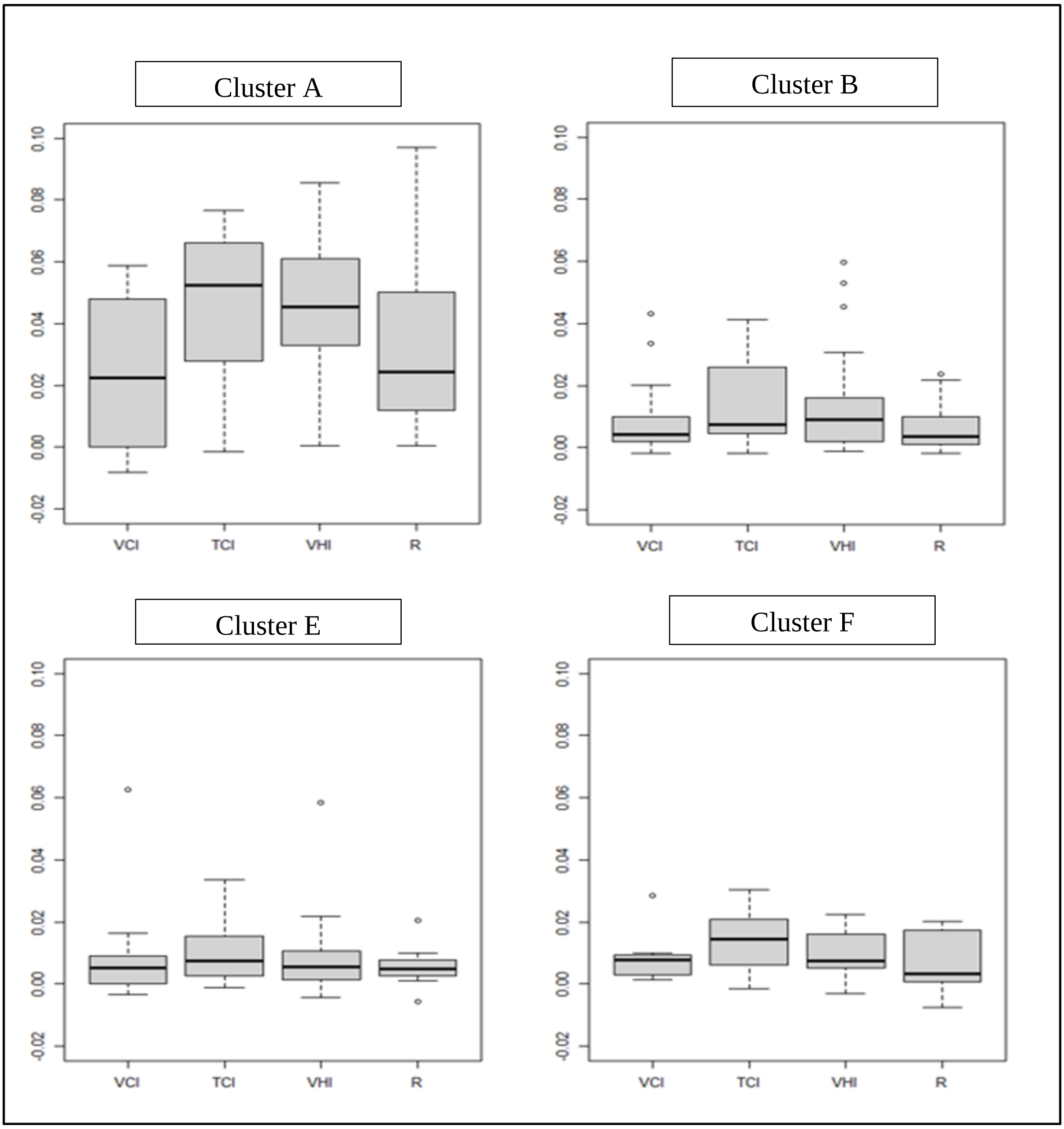

Figure III Boxplots showing the hedging effectiveness in percent estimated by means of the expected shortfall across the different clusters
Source: Own illustration

Our results show that index insurance based on the TCI and VHI outperformed the benchmark index on average and in every cluster. However, they did not outperform the benchmark index for every farm. More specifically, we identified a high variation in the HE across farms and counties and even within clusters. Correspondingly, the basis risk reduction varies between the different clusters. Our results are robust when considering the satellite image before and after the coverage period. Therefore, the location-specific conditions including climate and soil types might affect the performance of the VH indices. As mentioned, cluster A is characterized by low-quality sandy soils and a low amount of precipitation. Thus, this area is more prone to drought-related yield losses. Indeed, the highest HE observed shows that this cluster is well suited for index insurance based on VH indices. Thus, our results are in line with Möllmann *et al.* (2019) who purely focused on farms in this region in their analysis.

However, the HE is lower compared to their findings which may be caused by using objectively measured phenological growth stages instead of the best correlated period as the coverage period. This can be claimed considering that also Vroege *et al.* (2021) achieved a larger on-average risk reduction when using the best individually tailored coverage period. Nevertheless, insurers can be advised to incorporate VH-indices with a spatial resolution of 1x1 km in general and the TCI in particular to design standardized new insurance products for farmers in Northeastern Germany which come up with low transaction costs for insurers. In doing so, the basis risk for farmers in this region can be reduced statistically significantly.

Conversely, the HE in clusters with better soil conditions and higher annual precipitation was lower. Although the TCI and VHI outperformed the benchmark in all clusters, the effect sizes of basis risk reduction are small. Hence, the VH indices used in this study may not be the key to designing index insurance on better soils. This finding is of importance considering that higher relative drought-related yield losses were observed in regions with better soils during the past decade (Schmitt *et al.*, 2022; Trnka *et al.*, 2014). Since we already excluded forests, lakes, and villages, a distortion of the results through these factors may not be a problem. Therefore, insurers and researchers should further investigate the performance of other types of satellite data on better soils with high yield potentials. For example, the findings of Vroege *et al.* (2021) who investigated the risk reduction potential satellite-retrieved soil moisture data for farms in Eastern Germany should be checked in regions with better soils. The recently published work by Duden *et al.* (2024) offers a starting point for a broader analysis of the HE for different crops throughout Germany. Identifying a high-performing index in regions with better soils is crucial to increasing farmers' adoption rate of index insurance and enhancing the resilience of these farms.

One possible explanation for a better performance of the TCI compared to the VCI and VHI might be the difference in temporal resolution since the TCI has a temporal resolution of 8 days and the VCI of 16 days, which leads to a different number of observations per year. However, when we extended the coverage period by using the satellite image before and after the phenological growth stages, we did not find a statistically significant difference in the results. Moreover, Möllmann *et al.* (2019) also found the lowest HE for the VCI-based index insurance even though their data had a similar temporal resolution compared to the TCI. Thus, a higher temporal resolution may not automatically increase the performance of the VCI- and VHI-based index insurance. However, according to Vroege *et al.* (2021), fewer observations in general may decrease the performance of the insurance, highlighting the importance of long historical records. Thus, possible effects need to be investigated when the data is available. In addition, our approach to determining the strike level might influence the results as this was highlighted by Vroege *et al.* (2021). As mentioned we used the quantile value of the yield distribution instead of the average winter wheat yield.

Besides the performance of the VH indices, there are remaining challenges regarding their practical implementation (see Nordmeyer *et al.* (2023) for a broader discussion). For one, a low

VH index is not automatically linked to drought. In particular, it cannot accurately be identified if a drought or late frosts, for example, cause damage to growing winter crops in spring (Frederiks *et al.*, 2015). However, frosts may play a minor role in winter wheat in Germany (Schmitt *et al.*, 2022). Furthermore, considering our high granularity, the risk of moral hazard occurs given that diseases and farming practices might affect the health of the crops (Webber *et al.*, 2020). Avoiding the risk of moral hazard would increase the transaction costs for insurers, leading to higher loadings for index insurance products (Clement *et al.*, 2018). Therefore, overcoming this should also be prioritized by insurers.

5. Conclusion

Even though index insurance is a promising tool to mitigate drought-related income losses in agriculture, farmers' demand in Europe and Germany in particular remains low given basis risk concerns as a major reason. To reduce the basis risk of index insurance and therefore increase its attractiveness of index insurance to farmers, researchers turned their attention to satellite-retrieved data. Given limited knowledge regarding the performance index insurance based on satellite-retrieved VH indices, this paper contributes to the existing literature by investigating the HE of VH indices in Northern and Eastern Germany by using winter wheat yield records from 79 farms over 20 years. In doing so, we designed index insurance based on the VCI, TCI, and VHI with a spatial resolution of 1x1 km. As a benchmark, an index based on precipitation sum was designed.

Our results indicate that the TCI and VHI reached the highest HE on average and outperformed the benchmark index in every cluster. In particular, a statistically significant reduction in basis risk was found on average. More specifically, the basis risk reduction is statistically significantly higher in regions in Eastern Germany that are characterized by sandy soils like Brandenburg and Saxony Anhalt which are therefore more prone to droughts. The HE and basis risk reduction were considerably higher than in regions with better soil and climate conditions. A statistically significant higher HE and basis risk reduction, on average, for the TCI-based compared to the benchmark was also found for farms in Saxony, southern parts of Lower Saxony, and Thuringia, but at a lower level. However, a basis risk reduction was not found for every farm.

The observed heterogeneity in the HE highlights the relevance of this study and leads to several implications. For one, insurers can be advised to accelerate research and development of index insurance based on the VH indices in regions of Eastern Germany and with respect to the TCI-based in particular. By considering our design, index insurance with low transaction costs and comparatively low loading factors can be offered to farmers. In contrast, farmers in regions like Lower Saxony still lack sufficient insurance schemes as no statistically significant increase in the HE compared to the benchmark was found on average even though they also experienced high drought-related yield losses. Thus, ongoing research is needed to identify drought indicators on better soils.

Policymakers can be advised that index insurance products using satellite data can improve the risk management of many farmers in eastern Germany. However, it's important to note that, in relative terms, the HE of the VH observed in our case study and also on the sandy soils is lower compared to studies focusing on individually tailored coverage periods. In addition to regional characteristics, the effect of satellite-based weather index insurance contracts depends strongly on the quality of satellite and yield data (Kölle *et al.*, 2021). Therefore, policymakers should be aware that our results indicate that the resilience of the agricultural sector could be magnified by higher data availability and accessibility for insurers.

In addition, our results highlight the trade-off between individually tailored index insurance and index insurance with low transaction costs. Furthermore, it can be argued that the focus on the county level instead of the farm level could improve the HE as this was shown by Möllmann *et al.* (2019). However, previous literature has shown that market acceptance decreases as the complexity of index insurance products increases (Odening and Shen, 2014).

As the data preparation of meteorological and satellite data, as well as the calculation of the index insurance products with our approach, are very challenging, our study can contribute to reducing the effort and transaction costs for insurers and researchers. Given our large sample, we can recommend focusing on the TCI and VHI when designing index insurance products. In addition, digitalization could further reduce transaction costs, as data preparation is the most labor-intensive part. Thus, the direct availability of VHI and TCI could reduce transaction costs, as the calculation of index insurance for an additional farm is only associated with comparatively low marginal costs.

Nonetheless, our study is limited with respect to the low temporal resolution of the VCI compared to the TCI, which also affects the VHI. Although no statistically significant difference was found when extending the number of satellite images considered, future research should investigate the performance of the VCI if data with higher temporal resolution is available. Furthermore, crop rotation might influence our results. Since crop rotation is mandatory in the European Union, our satellite images do not cover winter wheat every year. Consequently, the specific crop rotation might influence the performance of the VCI and VHI. However, this paper should be seen as part of a larger set of studies that investigate the potential of satellite-retrieved data that offer starting points for ongoing research. Future research could also transfer our approach to the global south which is strongly affected by climate change. Especially in countries with a lower density of weather stations, satellite-retrieved VH could reduce the basis risk considerably.

Appendix

Table A1 Descriptive statistics of the satellite-retrieved VH indices and the benchmark index between 2000 to 2019 (N=79)

	Mean	**SD**	**Max**	**Min**
Full sample				
VCI	79.46	5.98	95.76	56.56
TCI	24.81	5.06	37.03	8.79
VHI	52.13	4.19	63.97	35.78
R	113.85	48.97	342.10	15.63
Cluster A				
VCI	80.19	5.87	95.76	62.06
TCI	24.03	5.34	37.03	9.49
VHI	52.11	4.50	63.97	37.02
R	90.74	42.10	290.17	13.20
Cluster B				
VCI	79.36	5.63	95.79	63.31
TCI	26.57	4.30	37.01	14.04
VHI	52.96	3.68	61.46	42.45
R	112.44	46.12	318.45	12.83
Cluster E				
VCI	76.82	9.12	91.98	56.56
TCI	26.10	14.31	35.62	8.79
VHI	49.14	7.29	60.94	35.78
R	128.90	48.68	290.23	15.63
Cluster F				
VCI	79.86	6.46	92.10	66.74
TCI	24.66	5.04	36.69	9.46
VHI	52.36	3.90	61.43	39.95
R	121.45	51.45	342.10	30.30

Note: SD indicates standard deviation.
Source: Own illustration

Table A2 Intercept and coefficients of the quantile regression

	Intercept		Coefficient			
	Mean	SD	Mean	SD	Insured farm	Share insured farm
Full sample						
VCI	3.73	53.00	0.83	0.62	51	0.65
TCI	38.07	24.96	1.23	0.76	76	0.96
VHI	3.16	48.52	1.27	0.84	66	0.84
R	60.23	15.33	0.09	0.08	65	0.82
Cluster A						
VCI	-34.07	55.60	1.19	0.61	15	0.94
TCI	16.21	15.42	1.82	1.11	16	1.00
VHI	-46.33	45.43	2.05	0.83	16	1.00
R	42.70	16.88	0.18	0.11	15	0.94
Cluster B						
VCI	20.61	39.91	0.65	0.48	14	0.52
TCI	42.29	19.12	1.16	0.53	27	1.00
VHI	11.68	44.49	1.13	0.75	21	0.78
R	67.47	12.04	0.06	0.05	22	0.81
Cluster E						
VCI	15.55	52.57	0.77	0.68	14	0.78
TCI	48.91	34.03	0.89	0.61	18	1.00
VHI	24.58	36.47	0.98	0.71	16	0.89
R	67.84	4.74	0.06	0.03	12	0.67
Cluster F						
VCI	24.37	37.29	0.56	0.48	8	0.44
TCI	40.81	16.07	1.13	0.53	15	0.83
VHI	23.94	27.17	0.87	0.51	13	0.72
R	60.99	9.31	0.06	0.06	16	0.89

Note: SD indicates standard deviation.
Source: Own illustration

Table A3 Strike level and tick size (in EUR) statistics of the insurance contracts

	Strike level		**Tick size**			
	Mean	SD	Mean	SD	Insured farm	Share insured farm
Full sample						
VCI	79.64	5.98	15.88	12.54	51	0.65
TCI	25.22	7.51	24.29	15.51	76	0.96
VHI	52.15	3.12	25.01	17.05	66	0.84
R	121.60	38.38	1.72	1.73	65	0.82
Cluster A						
VCI	80.92	5.04	22.31	13.28	15	0.94
TCI	23.57	3.44	36.36	22.23	16	1.00
VHI	52.00	3.16	41.02	16.63	16	1.00
R	93.57	22.02	3.67	2.20	15	0.94
Cluster B						
VCI	79.81	3.29	12.20	10.09	14	0.52
TCI	26.09	2.86	22.35	11.36	27	1.00
VHI	53.20	2.09	21.60	15.73	21	0.78
R	122.47	38.37	1.18	1.10	22	0.81
Cluster E						
VCI	76.77	8.85	15.34	13.68	14	0.78
TCI	25.08	14.78	17.80	12.12	18	1.00
VHI	49.88	3.85	19.69	14.16	16	0.89
R	133.24	41.20	1.12	0.58	12	0.67
Cluster F						
VCI	81.98	3.59	11.18	9.58	8	0.44
TCI	25.60	2.04	22.69	10.54	15	0.83
VHI	53.42	1.96	17.34	10.16	13	0.72
R	137.96	35.80	1.09	1.14	16	0.89

Note: SD indicates standard deviation.
Source: Own illustration

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