Modeling of dynamic weather indexes by coupling spatial phenological and precipitation data – A practical application in the context of weather index-based insurances

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Abstract

A key challenge for the design of weather index insurances (WII) is the presence of basis risk, i.e. the actual loss of the insured farm is not fully covered by the insurance payment. Basis risk can occur dependent on the distance between the point of measurement of a specific weather event and the farm's location (spatial basis risk). The present study aimed to derive spatial data sets and use them for the design of test site- and phenological phase-specific precipitation indexes. We studied for 20 German crop farms the hedging efficiency of WII, i.e. how the variability of farm specific total gross margins would have changed if farmers had purchased the designed WII. The hedging efficiency is different from farm to farm and not always a risk reduction (positive HE) results. Although these might be not the best results, a new methodology to minimize spatial basis risk could be introduced by designing highly dynamic indexes, which are flexible and precise in terms of time and space. The contribution of the present study to the WII research is the analysis of the HE of WII based on these indexes.

Keywords: Performance risk, risk management, weather index insurances, spatial basis risk, raster data

1 Introduction

Due to climate change, the interest on weather index insurances (WII) to reduce income volatility in crop production caused by certain weather events increased. Contrary to classical indemnity insurances WII do not cover crop yield losses due to physical damages like storms or hail. Instead, payments of WII depend on indexes which relate long-term weather conditions (Goodwin and Mahul 2004, Barnett and Mahul 2007). They are totally independent from actual on farm losses, because the index is externally measured. Mostly a weather component is aggregated over a hedging period using different approaches. In case of a put-option, a payment is triggered, if the index falls below a predefined threshold (strike level). If the underlying contract structure is a call-option, a payment results if the index is above the strike level (Jewson and Brix 2005).

A key challenge of designing weather index insurances is the presence of basis risk, i.e. the actual loss may be not fully covered by the insurance payment (Norton et al. 2012). It can be differentiated between spatial basis risk and basis risk of production. Spatial basis risk can occur if there is a difference between the weather measured at the point of measurement and the actual weather that occurred on the farm (Skees 2008). Basis risk of production can be present as crop yields vary also due to other reasons such as quality of seeds and fertilizer (Woodard and Garcia 2008). If one is interested in the hedging efficiency of WII, it is important to minimize basis risk.

Previous studies already tried to improve WII and to minimize basis risk (cf., e.g. Odening et al. 2007). Mostly the focus is on the design of the index, which is a key element of WII (Hellmuth et al. 2009). The hedging efficiency of WII based on several indexes is analyzed. The indexes aggregate either one weather parameter such as temperature or precipitation data or more weather parameter (mixed indexes) over a fixed period of time of major importance for production. Mostly the period of time is based on calender dates (cf., e.g. Turvey 2001, Pelka and Musshoff 2013).

Few studies use phenological information instead of calender dates (e.g. Conradt et al. 2015, Dalhaus and Finger 2016). Conradt et al. (2015), for example, designed an index accumulating the precipitation measured at the weather station next to a farm over the most critical phenological phases of winter wheat (*tillering*, *shooting* and *heading*) and exemplary for Kazakhstan. The underlying assumption is an higher effect of damaging weather events on the plant growth in critical growing phases. By comparing the fixed and flexible index type the authors showed that WII based on phenological phases are more effective in reducing risk. Using the same index design, Dalhaus and Finger (2016) compared the use of raster and weather station data. An index based on raster data can be – contrary to an index based on weather station data – modeled for any geographic point and also for a location of a specific farm. Hence, spatial basis risk can be minimized. As no spatial phenological data are publicly available for Germany, the authors used information of the nearest phenological reporter to a farm provided by the German Weather Service (Kaspar et al. 2014). The focus of both studies is on the cultivation of winter wheat as it is the primarily produced crop by the investigated farms. Further, they assume that the farmers realize only two activities: winter wheat production and purchase of a WII.

However, the effect of specific weather events on winter wheat yields and thus yield-related income volatility is not only relevant for single farms. This is because Germany is the second largest wheat producer in the European Union (FAOSTAT 2015).

This article addresses two objectives. First, we show how Germany-wide spatial phenological data sets can be derived and used to model dynamic and reproducible precipitation indexes, which are specific for both test sites and phenological phases. Second, the resulting dynamic indexes are used for analyzing the farm-specific hedging efficiency of WII. In doing so, we apply a whole farm approach to consider portfolio effects caused by the different production activities which farms usually realize. 20 farms located in North Rhine-Westphalia and Lower Saxony are analyzed. The hedging efficiency of WII is calculated based on the volatility of farm specific historic total gross margins in the period between 1994 and 2014. The natural conditions, which influence crop cultivation to a great extent, can generally be characterized as "moderate" in these regions. We analyze these farms assuming that not only farms located in regions with extreme climatic conditions are interested in hedging weather-related income volatility. Farms which are located in regions with moderate natural conditions might also purchase WII.

We design the WII explicitly for hedging the yield-related volatility of historic total gross margins due to too low or too much precipitation during the phenological phases *shooting (phase 15-18)*, *shooting and heading (phase 15-21)* and *heading (phase 18-21)* of winter wheat. We focus on winter wheat as it is the only crop cultivated continuously by all farms under investigation. Hence, we can ensure a certain degree of comparability of the results. We focus on the phenological phases *shooting*, *shooting and heading* and *heading* since this is the main growth phase of winter wheat including a high water demand (Lütke Entrup and Schäfer 2011). Hence, drought or wet during these phases is assumed to be highly important for the economic success of farming and therefore a high influence on the volatility of total gross margins is assumed. To our knowledge, the present study is the first that develops indexes totally based on spatial data and analyzes the hedging efficiency of WII based on these indexes in context of a whole farm approach.

2 Data

2.1 Phenological and weather data

In Germany, a phenological and meteorological monitoring network is driven by the German Weather Service (in German: *Deutscher Wetterdienst*[1]). The phenological network consists of approximately 1200 volunteer observers of which about 700 observe the beginning of principle growth stages of the most frequently cultivated crops according to standardized criteria (Kaspar et al. 2014). Each plant is observed on a different number of stations, depending on the abundance and agrometeorological relevance of the respective crop type. The positional accuracy of the point data set is about 2×2 km (Fig. 1a).

[1] *http://www.dwd.de*

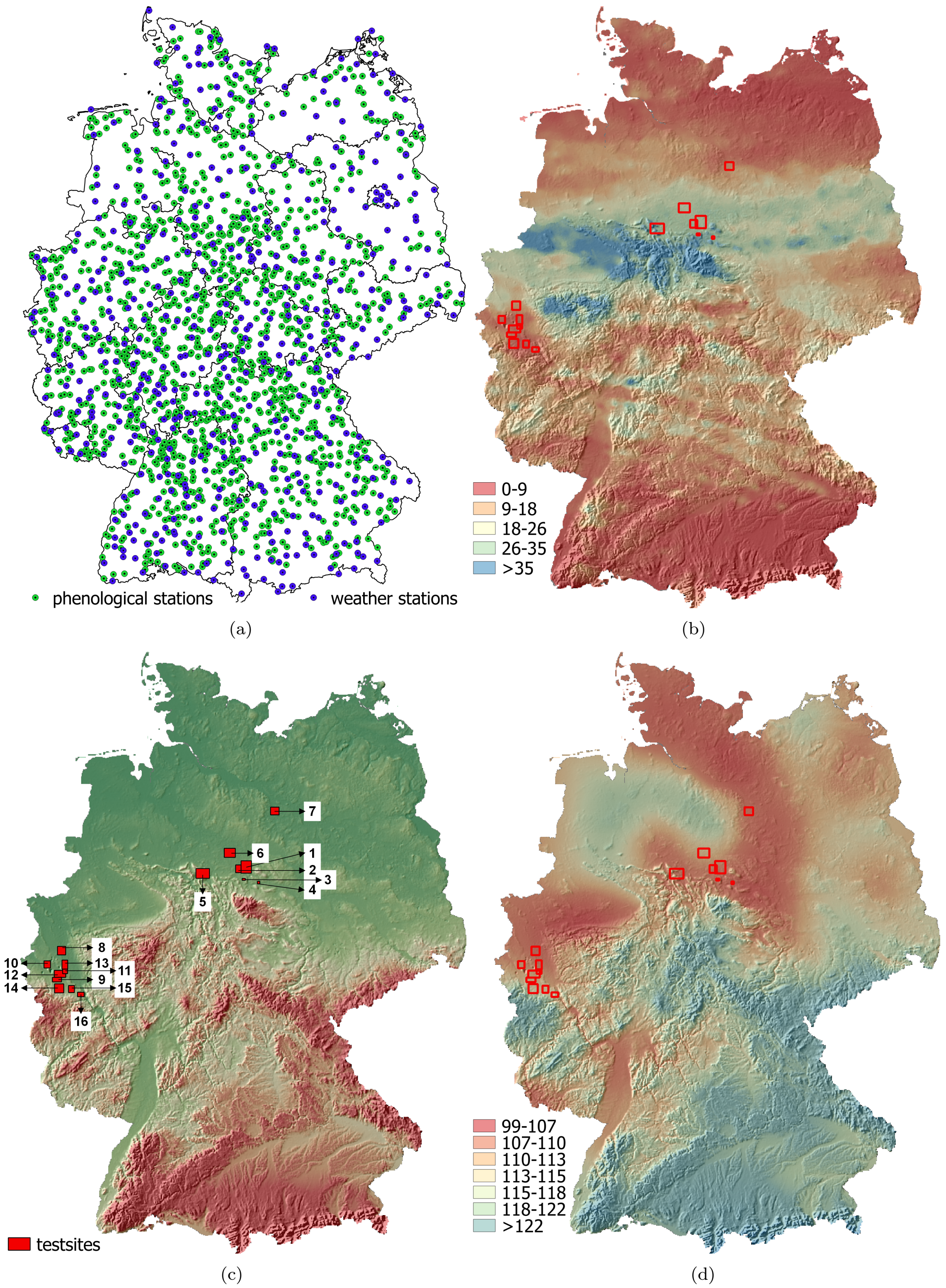


Figure 1: Locations of phenological and meteorological stations stations (a), REGNIE precipitation raster [mm] for May 7th 2007 ($DOY = 127$) (b), a colored SRTM DEM hill shade overlayed by test sites (c) as well as exemplary the interpolated start of the phenological phase *shooting (phase 15)* of winter wheat in 2007 [DOY] (d).

Furthermore, the German Weather Service provides daily precipitation data. The data are calculated using the specific rationalization method REGNIE (Rauthe et al. 2013). In particular, daily precipitation data measured at weather stations irregularly distributed over Germany are interpolated on a grid of 1×1 km (Fig. 1b). REGNIE data can be directly downloaded from the FTP server of the German Weather Service[2].

2.2 SRTM DEM

The Shuttle Radar Topography Mission (SRTM[3]) resulted in a almost world-wide and freely available digital elevation model (DEM) with a geometric resolution of 90×90 m (Fig. 1c). The horizontal and vertical accuracy is about 20 and 16 m (Rabus et al. 2003). Because of its signal noise, the DEM has been filtered (Lee 1980) and then aggregated to 1×1 km pixel size with a total number of 358,320 pixels. The pixel raster size corresponds to the positional inaccuracy of the phenological observations (Sec. 2.1).

2.3 Farm data

The chambers of agriculture of North Rhine-Westphalia and Lower Saxony provided data of 20 farms over a period of 21 years (from 1994 to 2014). In particular, information about the realized main production activities for dominating crops like winter wheat, winter and summer barley, winter rye, oat, sugar beats, corn and peas are considered. The data set contains information about the single gross margins of the production activities including prices, yields and variable costs such as costs for seed and fertilizer as well as variable machinery costs and the area cultivated with each crop in hectares.

The farms are situated in the south of North Rhine-Westphalia (12 farms) and in the south east of Lower Saxony (8 farms) (Fig. 1c). The test sites (TS) are equal to the municipalities where the farms are located as we do not know the exact location of the farm. In case of test site 2 and 12 more than one farm belong to a municipality. Hence, the number of test sites (N=16) is not equal to the number of farms (N=20). The climatic conditions in North Rhine-Westphalia and Lower Saxony can be characterized as moderate compared to regions, where extreme climatic conditions predominate such as in Brandenburg or in some parts of Bavaria (Tab. 1). The soils on the farms are predominately loamy. In 2014 the farm size was 243 hectares on average and the average total gross margin was €312,072. The minimum farm size was 86 ha and the maximum 521 ha. The minimum total gross margin accounted for €74,812 and the maximum €641,166. This shows the heterogeneity of the farms regarding the farm size and their economic success.

Table 1: Climatic conditions of selected regions in Germany (Source: DWD 2015).

Regions	**Average annual precipitation [mm]**	**Average annual temperature [°C]**
North Rhine-Westphalia	875	8.9
Lower Saxony	746	8.6
Brandenburg[1]	557	8.7
Bavaria[2]	940	7.5

[1]Federal state with the lowest average annual precipitation.

[2]Federal state with the second highest average annual precipitation.

[2] *ftp://ftp-cdc.dwd.de/pub/CDC/grids_germany/daily/regnie*

[3] *https://earthexplorer.usgs.gov*

3 Methodological approach

3.1 General insurance design

Various WII are designed for hedging the yield-related volatility of historic total gross margins due to too low or too much precipitation during specific phenological phases of winter wheat. The WII differ in the general contract structure. The design of the insurance is fairly simple as the focus is on modeling of a dynamic test site and phase-specific index in the present study. Due to the moderate temperate and humid conditions the farms are exposed to, we aim to compare the hedging efficiency of a put-option and a call-option. The put-option is intended to compensate drought-related volatility of farms total gross margins because droughts are assumed to gain more importance for farmers. As the farms under investigation are not faced with extreme natural conditions, we assume that not only drought-related volatility of farm specific total gross margins need to be hedged but also performance risk due to (strongly) wet conditions. Hence, we also analyzed the risk reducing capacity of call-options. The general pay-off structure of a put-option per contract in year t is defined according to equation (1).

$$P_t^p = V \cdot max(K - I_t^P; 0) \tag{1}$$

In case of a put-option, a payoff P_t^p is only triggered if a specific weather index I_t^P falls below a certain strike level K. In contrast, call-options hedge deviations of the index only above the strike level. The respective payoff structure per contract in year t is calculated according to equation (2).

$$P_t^c = V \cdot max(I_t^P - K; 0) \tag{2}$$

V is a tick size monetizing the difference between the index and the strike level. The tick size is defined as 1 €per mm throughout the following analysis as already used in previous studies (Musshoff et al. 2008). I_t^P is a cumulative dynamic precipitation index. Here, we assume that precipitation is a crucial factor for plant growth. The technical implementation of the index is described in the following section 3.2. The strike level K equals the long-term average of the chosen index (period 1994-2014) and is the same for the put- and call-option (Jewson and Brix 2005). The strike level is calculated separately for each test site.

The price of the insurance equals the actuarially fair premium. We used this option because we are interested in the risk reducing potential of the insurance and not in the change of income level caused by the insurance purchase or the costs a farmer would accept or not. Following Woodard and Garcia (2008), burn analysis is used for determining the fair premium, i.e. it is calculated as the arithmetic mean of the payoffs of the WII and equals the expected value of the payoffs of the WII. No loading is added. Hence, the WII used in this article is income-neutral. Furthermore, we assume that the farmer is able to buy one contract per hectare.

3.2 Dynamic weather index calculation

Figure 2 summarizes the technical workflow for the dynamic calculation of weather indexes I_t^P on the example of the phenological phase *shooting* of winter wheat. I_t^P is defined according to Eq. (3) where $min(DOY(\mathrm{WW}^{15}))$ equals the beginning of phase *shooting* of winter wheat (WW^{15}) and $min(DOY(\mathrm{WW}^{18}))$ the beginning of phase *heading* of winter wheat. The procedure is implemented within the statistical software environment **R** (R Core Team 2015) and combines (1.) interpolated phenological observations (DOY) as well as (2.) Germany-wide spatial data sets of daily precipitation means ($\overline{x}(P_{DOY})$) to (3.) the precipitation sums ΣP:

$$I_t^P = \Sigma_{min(DOY(\mathrm{WW}^{15}))}^{min(DOY(\mathrm{WW}^{18}))} \overline{x}(P_{DOY}) \tag{3}$$

1. Germany-wide phenological raster data have been derived by using the phenological model PHASE (Gerstmann et al. 2016). The model is based on the growing degree days concept which relates plant phenological development to phase-specific accumulated heat sums. During the modeling procedure, an indicator temperature sum is determined by analyzing the distribution of the temperature sums

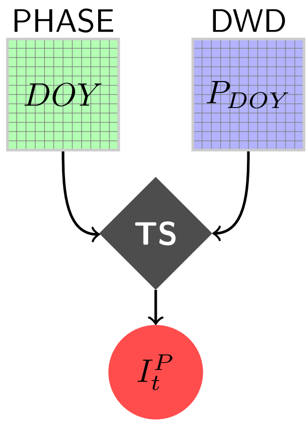


Figure 2: Technical workflow for the derivation of test site- and phase-specific precipitation sums exemplary for the phenological phase *shooting* of winter wheat. DOY **– day of year expressing the beginning of a specific phenological phase |** P_{DOY} **– daily precipitation |** I_t^P **– weather index.**

accumulated between sowing and the date of phase observation. Germany-wide temperatures result from the interpolation of daily mean temperatures which are provided by DWD-weather stations. For each location, the day on which the accumulated temperatures exceed the indicator sum is modeled and spatially interpolated using regression kriging. The model was applied for modeling of the phases *beginning of shooting*, *beginning of heading* and *beginning of yellow ripeness* of winter wheat for all years from 1994 to 2014.

2. REGNIE precipitation values are available in plain text format. Each DOY is stored as single file. The REGNIE data were read by using the **R** function `read_regnie`[4] which is part of the package `esmisc` (Szoecs 2016). The function creates Germany-wide 1×1 km raster data sets and assigns each precipitation value to a specific raster cell.
3. The actual calculation of precipitation sums ΣP, e.g. during the phase *shooting*, requires the definition of its start and end. In this study, *shooting* is considered as the temporal window between the phenological event *beginning of shooting* (WW^{15}) and the following event *beginning of heading* (WW^{18}) (Möller et al. 2017). The same procedure is applied for the other hedging periods *heading* and as well the combined phases *shooting* and *heading*.

3.3 Historical simulation

Based on information about the realized production programs and the single gross margins for each of the farm's activities of the 20 crop farms from 1994 to 2014, we calculated the farm's historic total gross margins (TGM) without WII (status quo) for each year of the observed period following equation (4).

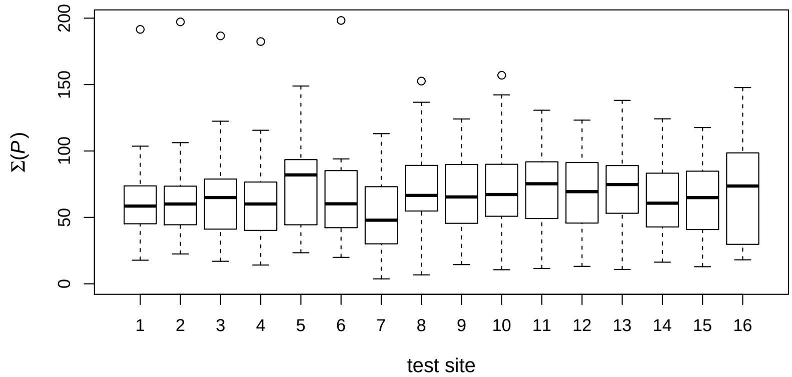
$$TGM_t^{withoutWII} = (\Sigma_{i=1}^{I} GM_t^i \cdot x_t^i) \tag{4}$$

$TGM_t^{withoutWII}$ is the farm specific total gross margin without weather index insurance in year t. The total gross margin is calculated based on the farm's whole production program in year t, which consists of I different crops. GM_t^i relates to the yearly gross margin of each cultivated crops and x_t^i is equal to the area of each cultivated crop i in hectares in a year.

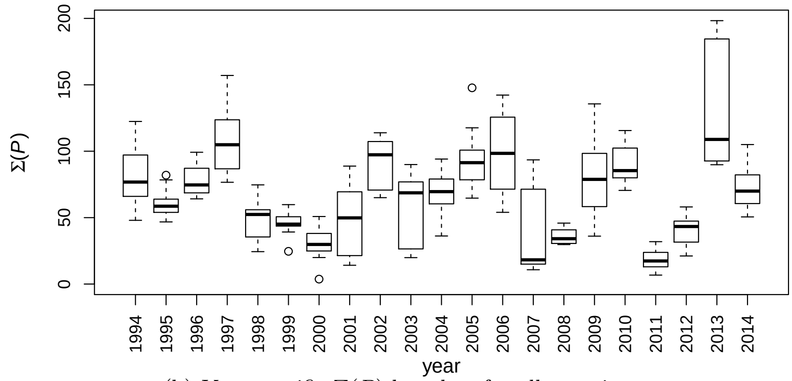
To be independent from farm size, we normalized the total gross margins per hectare by dividing the yearly TGM through the yearly farm acreage in ha. The TGMs per hectare are adjusted for inflation and a linear trend assuming that a farmer may get better or worse on doing their business over time.

Using historic simulation, the hedging efficiency of the designed weather index insurance is analyzed ex-post and defined as the relative change of the standard deviation of normalized potential total gross

[4] *https://github.com/EDiLD/esmisc/blob/master/R/read_regnie.R*



(a) Test site-specific $\Sigma(P)$ boxplots for the period between 1994 and 2014



(b) Year-specific $\Sigma(P)$ boxplots for all test sites

Figure 3: Year- and test site-specific distributions of phase-specific precipitation sums ($\Sigma(P)$) [in mm] illustrated on the example for the phase shooting.

margins with WII compared to the standard deviation of the normalized total gross margins without WII (Golden et al. 2007). The standard deviation is a risk measure used to quantify the volatility of farm's TGM over the whole observation period. The procedure of historic simulation is calculated as follows:

1. For each farm the historic volatility of the normalized TGM without WII from 1994 to 2014 is determined by calculating the standard deviation.
2. It is assumed that the farmer would have purchased the designed WII in every year over the whole observation period. Hence, we also suppose that the farmer would not have changed his risk management strategy over a 21 year period. The hypothetical purchase of this WII is considered as an additional activity, which would have been added to the farm specific production program.
3. The hypothetical time series of gross margins of the WII (yearly payoff subtracted by the actuarially fair premium) is determined from 1994 to 2014.
4. The hypothetical yearly gross margins of the insurance are added to the total gross margin in each single year. The result is a hypothetical time series of farm specific total gross margins with WII per hectare.

On this basis, the standard deviation of total gross margins with WII is calculated. Finally, the hedging efficiency of WII is determined as described above.

4 Results

4.1 Precipitation sums

Figure 1d shows the interpolated start of the phenological phase *shooting* of winter wheat in 2007. The DOY-pattern follows the typical spatial trends in Germany with earlier dates in the favored regions in the eastern and central parts of Germany and delayed plant development in more mountainous and coastal regions. Figure 3 displays the year- and test site-specific distributions of phase-specific precipitation

Table 2: Correlation results of farm specific winter wheat yield and test site and phase specific indices.

Federal state	Testsite ID	Farm ID	ρ^{15-18}	ρ^{15-21}	ρ^{18-21}
North Rhine-Westphalia	**16**	**1**	**0.20**	**0.09**	-0.21
	12	**2**	**0.15**	**0.12**	-0.03
	9	**3**	-0.21	**0.14**	**0.16**
	13	**4**	**0.12**	**0.06**	-0.05
	12	**5**	**0.19**	***0.39**	**0.16**
	12	**6**	**0,29**	**0.02**	0.32
	10	**7**	**0.06**	-0.28	*-0.41
	12	**8**	-0.05	-0.22	-0.30
	15	**9**	**0.03**	**0.27**	**0.15**
	14	**10**	**0.10**	**0.36**	**0.20**
	8	**11**	***0.40**	**0.20**	-0.16
	11	**12**	**0.14**	**0.30**	**0.13**
Lower Saxony	**6**	**13**	-0.07	**0.18**	**0.30**
	2	**14**	0.00	-0.18	-0.13
	7	**15**	-0.11	-0.06	0.00
	3	**16**	-0.04	-0.25	-0.19
	2	**17**	**0.07**	-0.29	-0.37
	1	**18**	-0.09	**0.23**	**0.29**
	5	**19**	-0.01	**0.22**	**0.28**
	4	**20**	**0.16**	**0.15**	**0.01**

Explanatory note: *correlation is statistically significant at the 10% level, **correlation is statistically significant at the 5% level, ***correlation is statistically significant at the 1% level. Due to technical progress, the winter wheat yields are detrended.

sums ($\Sigma(P)$) [in mm] for the phase shooting. Accordingly, no regional differences are visible. However, all test sites show a high variation of precipitation sums over the years (Fig. 3a). The figure indicates that precipitation can be a source of risk for the farms located in these test sites. The year-specific distribution of phase-specific precipitation sums reveal inter-annual changes of precipitation sums (Fig. 3b). Both figures demonstrate that even regions with moderate natural conditions are characterized by a high spatio-temporal precipitation variability.

4.2 Yield-index correlations

Table 2 presents for each farm the correlation between the dynamic test-site and phase specific indexes and the farm-specific winter wheat yield. The correlations show how well the test-site specific indexes fit to the farm specific winter wheat yields. This can be a first indication about the suitability of the designed weather index insurances to hedge weather-related performance risk. But, due to portfolio effects and the influence of other factors than volatile winter wheat yields on the volatility of total gross margins this does nothing tell about the real capacity of the insurance to reduce the volatility of farm specific total gross margins.

The correlations vary highly among the farms and depend on the hedging period. When looking only at the positive correlations (highlighted in bold printing), it can be seen that they are low for most of the farms. As also other factors such as e.g. temperature influence yields, correlations equal to 1 could not be expected. But, although we are aware that the study farms are not located in regions with extreme climatic conditions and cultivate predominately loamy soils, the correlations are lower than expected.

Table 3: **Hedging efficiency of the analyzed put- and call-option for the specific strike level**

Federal state	TS-ID	Farm ID	Phase 15-18			Phase 15-21			Phase 18-21		
			Strike Level	Put	Call	Strike Level	Put	Call	Strike Level	Put	Call
			(mm)	(%)	(%)	(mm)	(%)	(%)	(mm)	(%)	(%)
North Rhine-Westphalia	**16**	**1**	70.98	-4.44	**5.63**	185.98	-2.98	**1.37**	115.50	**1.29**	-3.14
	12	**2**	66.69	-3.09	**2.83**	171.98	-5.09	**2.37**	106.60	-1.81	-0.36
	9	**3**	66.54	-0.92	**0.87**	172.63	-1.62	**1.36**	106.18	-0.79	-0.16
	13	**4**	72.38	-1.37	**3.38**	184.30	-4.20	**1.91**	111.94	-1.35	**0.39**
	12	**5**	66.69	-3.68	**3.39**	171.98	-5.15	**1.35**	106.60	-0.49	-0.52
	12	**6**	66.69	-0.26	-0.18	171.98	-1.67	-0.08	106.60	-1.06	**0.42**
	10	**7**	71.83	**0.44**	-1.32	179.22	-2.08	**0.62**	109.63	-2.61	**0.96**
	12	**8**	66.69	**0.51**	-1.23	171.98	-2.08	-0.80	106.60	-1.61	**1.02**
	15	**9**	64.21	-0.69	**2.51**	169.73	-0.89	**0.06**	105.59	**1.84**	0.00
	14	**10**	64.00	**0.41**	**0.19**	168.65	-1.27	**0.56**	102.42	-1.23	**0.27**
	8	**11**	71.62	-2.38	**0.22**	181.65	-6.44	**0.75**	112.46	-2.56	**2.60**
	11	**12**	70.90	-1.03	**2.85**	183.36	-3.55	**1.69**	114.00	-0.51	**3.69**
Lower Saxony	**6**	**13**	67.05	**0.66**	-4.26	157.75	-0.27	-0.21	92.28	-2.29	**1.88**
	2	**14**	66.31	-0.21	-3.27	161.77	**1.94**	-0.82	98.33	-0.36	-0.81
	7	**15**	53.08	**0.59**	-1.40	151.63	**1.34**	**3.66**	99.33	-0.52	**4.46**
	3	**16**	68.39	-1.23	-5.96	168.66	**4.57**	-0.56	101.75	**0.47**	-0.74
	2	**17**	66.31	-2.91	-4.57	161.77	**0.18**	-1.26	98.33	**0.16**	-1.56
	1	**18**	57.93	-3.03	**0.30**	151.76	**1.57**	-2.25	96.32	**4.66**	-3.37
	5	**19**	74.25	-0.58	-1.18	175.90	**1.22**	-1.94	103.84	**0.43**	-2.14
	4	**20**	64.16	-2.15	-2.48	153.57	**1.39**	-2.46	90.23	**1.77**	-2.71

Explanatory note: A positive sign of the hedging efficiency indicates that the volatility of farm specific TGM is reduced after the implementation of the WII (positive hedging efficiency).

This suggests that precipitation is not a decisive factor for the winter wheat yields of the farms under investigation.

4.3 Hedging efficiency of dynamic weather index insurances

Table 3 shows the resulting hedging efficiencies of the analyzed put- and call- options for the specific strike levels. The values are farm specific and vary considerably among the farms. Further, the hedging efficiency depends highly on the analyzed contract type.

Contrary to this, the purchase of the analyzed WII can also increase the volatility of farm specific total gross margins, which can be clearly seen based on the negative hedging efficiencies. Further, it needs to be highlighted that the hedging efficiency varies also among the farms located in the same test site (see farm 2, 5, 6, 8, test site 12). This indicates that the volatility of farm specific total gross margins depends not only on one specific source of risk such as yield volatility due to too less or too much precipitation, but also on many other risk sources such as volatile input and output prices as well as uncertain amounts of inputs.

5 Discussion

5.1 Modeling dynamic and reproducible precipitation indexes

In this study, we introduced a WII approach which is based on a weather index automatically derived from and publicly available data sets. Following Conradt et al. (2015) and Dalhaus and Finger (2016), the index design is based on the assumption that drought or wet conditions during the phenological phase *shooting*, *shooting and heading* and *heading* of winter wheat may influence yields to a great extent and therefore contributes to the volatility of farm specific total gross margins. Compared to Dalhaus and Finger (2016), our study represents a further development as we were able to fully reduce scale distortions in the index design, which occurred as no spatial phenological data sets were available until now. This means that the introduced index can be designed for each part of Germany and each phenological phase of the main crops cultivated in Germany. Hence, spatial basis risk can be reduced considering interpolation inaccuracies (Gerstmann et al. 2016).

5.2 The importance of precipitation events in the analyzed regions and yield-index dependency

Applying our dynamic precipitation index on single farm level showed that precipitation can be a source of risk for the cultivation of winter wheat of the analyzed farms (see sec. 4.1). The resulting yield-index correlations suggest that precipitation is not the limiting factor for farm specific winter wheat yields, as the designed indexes fit not very well to the farm specific yield time series.

The fact that the yield-index correlation varies highly from farm to farm shows that correlation results never can be generalized. Hence, studies focusing on farm level are of major importance. The poor correlation results can be explained, on the one hand, by the fact that our study farms are not exposed to extreme farming conditions such as drought and sandy soils. On the other hand, we needed to refer to the municipalities the farms belonging to as we do not know the exact locations of them. Hence, the scale does not fully fit in the application of the introduced dynamic precipitation index. Thus, we cannot assume that spatial basis risk is totally reduced. Due to this, further farm specific risk analysis is needed.

Furthermore, due to portfolio effects and the influence of other factors on winter wheat yields such as quality of seed or fertilizer, the results do not give any information about the real capacity of the insurance to reduce the volatility of farm specific total gross margins. This is why we also analyzed the potential of insurances based on our dynamic precipitation indexes to reduce farm specific income volatility.

5.3 Potential of the analyzed weather index insurance to reduce farm specific income volatility

Although we used a simple insurance design, we found that the designed call-option outperforms the put-option. This is especially true for the study farms located in North Rhine-Westphalia. It can be concluded that these study farms battle with conditions that are rather too wet than too dry.

Further, the resulting low positive hedging efficiencies show that yield-index correlations can not be an indication for a potential risk reducing effect. An explanation for this result can be the occurrence of a natural hedge as income not only depends on yields but also on prices. A natural hedge occurs if yields and prices are negatively correlated. Furthermore, a decisive factor in the insurance design is the strike level, which determines when a payoff is triggered and thus highly influences a possible risk reducing effect.

Our results can be not really compared with previous studies also analyzing the hedging efficiency of weather index insurances applying a whole farm approach (e.g. Kellner and Musshoff 2011) as the authors apply different indexes and use different analytical methods such as a whole farm risk programming approach instead of a historical simulation.

6 Conclusions and outlook

In this paper we introduced the modeling of a dynamic test site and phase specific precipitation index as a new approach in the weather index insurance research. In addition, we analyzed the capacity of WII based on these indexes to reduce the volatility of farm specific total gross margins. Using data from 1994 to 2014 of 20 farms in North Rhine-Westphalia and Lower Saxony, which are exposed to moderate climatic conditions, we studied how the volatility of farm specific total gross margins would have changed if the farmers had purchased our designed weather index insurance. As we focused on the index design, we applied a standardized insurance. Hence, the design of the insurance was fairly simple. The resulting hedging efficiency did not always show a clear risk reduction and varies strongly among the farms.

Due to the small sample size and the specific farming conditions in our study regions, our findings can not be generalized. Nevertheless, some general conclusions can be drawn. For reasons of comparability, we decide to apply the same weather index insurance for all study farms. But, there is need for a farm specific risk analysis. This became obvious as the results for our farms with moderate farming conditions varied highly. Farmers should make their risk management decision based on the results of the risk analysis. Further, due to portfolio effects it is necessary to analyze the hedging efficiency of risk management instruments in context of a whole farm approach.

To further improve this research, a comparison of the hedging efficiency between the proposed methodology and the use of the closest weather station to a farm should be done. Based on this comparison it should be analyzed whether spatial basis risk can be really reduced using the proposed methodology and whether the risk reducing effect is much better compared to the use of station based data. Further, we intend to include other weather variables such as temperature grid data in our model. Instead of applying the same index referring to winter wheat for all farms, a farm specific index design should be applied. Furthermore, the risk reducing capacity of the designed insurance should be analyzed for farms in regions with extreme farming conditions such as low precipitation and sandy soils.

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