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German farmers' perceived usefulness of satellite-based index insurance – Insights from a transtheoretical model

Abstract

Index insurance is a promising tool to mitigate drought-related income losses in agriculture. Yet, the basis risk of index insurance based on meteorological observations inhibits farmers' demand. To reduce the basis risk, the integration of satellite data has received research attention. However, farmers' perceptions of satellite-based index insurance remain unknown. To derive initial insights into German farmers' perceived usefulness (PU) of satellite-based index insurance, we surveyed 127 German farmers in a risk management context and applied a modified transtheoretical model of behavioral change (TTMC). This revealed detailed information on German farmers' PU of satellite-based index insurance and its influencing factors. The results indicate that the average farmer perceives satellite-based index insurance as useful. Particularly, a higher educational level in the agricultural context as well as higher trust in index insurance products increases farmers' PU. Moreover, higher relative climate-related income losses increase farmers' PU. The results are of importance to insurers interested in the drivers of farmers' PU of upcoming satellite-based index insurance and offers a starting point for researchers focusing on acceptance of index insurance and satellite data as well as for further applications of the TTMU.

1. Introduction

Climate change puts pressure on risk management of farms worldwide to secure agricultural incomes (Finger and El Benni, 2021). In Central Europe, catastrophic droughts and heat waves occur more frequently and affect crop yields negatively (Grillakis, 2019; Schmitt *et al.*, 2022; Trnka *et al.*, 2014). Index insurance is widely discussed to protect farmers from economic losses. Index insurance is cost efficient, reduces the problem of asymmetric information and allows quick determination of payouts. Moreover, the risk of moral hazard and adverse selection can be addressed (Barnett and Mahul, 2007; Turvey, 2001). The underlying index mainly refers to weather station data such as precipitation or temperature (see Leblois and Quirion, 2013). Even though the availability and variety of index insurance products provided by insurers in Europe has grown in the past decade, farmers' uptake remains low given concerns about basis risk. Since the correlation between meteorological indices and the yield on a specific field is imperfect, they cannot reflect the yield loss perfectly (Heimfarth and Musshoff, 2011). Likewise, a rainfall event occurs at the referring weather station, but not at the respective field. Although a country like Germany has a dense network of weather stations, this kind of idiosyncratic event might be missed. Overcoming this problem is of great importance for the adoption of index insurance by farmers (Clarke, 2016).

Satellite data seem promising to address basis risk given that they are globally available in nearly real time and independent of the density of weather stations (Quiring and Ganesh, 2010). Satellites provide data on crops' health status or evapotranspiration (e.g. Jensen et al., 2019; Leblois and Quirion,

2013) or detect soil moisture at the surface or in deeper layers with different spatial and temporal resolutions (e.g. Enenkel *et al.*, 2018; Vroege *et al.*, 2021). Hence, there is a large research interest regarding their effect on hedging effectiveness and basis risk (e.g. Kölle *et al.*, 2020; Vroege *et al.*, 2021). In general, a potentially higher hedging effectiveness or a reduction in basis risk was found for various satellite-based indices compared to meteorological measurements. Therefore, from a theoretical point of view, satellite data increase the attractiveness of index insurance for farmers. However, evaluation of farmers' perceptions is necessary (Vroege *et al.*, 2021).

Farmers' preferences for index insurance are of major interest in research (e.g. Doherty *et al.*, 2021; Liebe *et al.*, 2012). Surprisingly, studies integrating satellite data in this context are hard to find. Additionally, literature explicitly addressing farmers' perceived usefulness (PU) for satellite-based index insurance is missing. Particularly, until now it is unclear whether or to what extent farmers perceive them as useful. Knowledge of farmers' PU is important since several studies showed a direct relationship to adoption of new technologies (e.g. Rose et al., 2016; Tamirat et al., 2018). Therefore, this study investigates German farmers' PU for satellite-based index insurance in general from the perspective of a new modification of the transtheoretical model of behavior change (TTMC). In this way, preliminary insights regarding influencing factors on different stages of PU are provided.

For our purpose, the TTMC developed by Prochaska and Velicer (1997) was modified and applied as a transtheoretical model of PU (TTMU), which accounts for more than two stages of PU. Although the transtheoretical model is rarely applied to investigate PU compared to Likert scales or binary choices, it is appropriate as it captures the decision-making process gradually at a given point in time. For example, one farmer may perceive the use of satellite data for index insurance as useful while another does not, resulting in them being at different stages of PU. In turn, other farmers might perceive that the use of satellite data could be very useful at the current point of time, which is also another stage of PU. In agricultural research, Lemken et al. (2017) and Michels *et al.* (2020b) modified the TTMC and applied it to the adoption of precision agriculture technologies (PAT). However, the TTMU, as a new specification of the TTMC, has not been applied in an agricultural context.

To the best of our knowledge, this is the first study that investigates the PU of upcoming satellite-based index insurance. Moreover, this is the first study that tests the transtheoretical model in a risk management context by applying a modified TTMU. In doing so, preliminary insights if and to what extent it is perceived as useful by farmers and factors influencing their PU at the current point of time can be derived. Germany is of particular interest because only about 1% of farmers have index insurance despite a dense network of weather stations and a nationwide catastrophic drought in 2018 that caused considerable yield losses (Bundesministerium für Ernährung und Landwirtschaft, 2018; German Insurance Association, 2019). Accordingly, insights into German farmers' PU could be transferred to countries with a sparse network of weather stations. Hence, our results are of interest for insurers who are developing new insurance products. Moreover, this study provides a starting point for researchers interested in ongoing research regarding farmers' perceptions of satellite-based index insurance as well as for further applications of the TTMU.

The remainder of this article is structured as follows. Section 2 presents the hypotheses derived from the literature of possible influencing factors. Section 3 shows the methodology approach of the TTMU and data collection. The results of the TTMU are presented and discussed in section 4, while a conclusion ends up this paper (section 5).

2. Hypotheses

With regard to PAT, the conceptual framework of Pierpaoli *et al.* (2013) was applied to identify influencing factors of adoption. We modified the variables that potentially affect the PU of satellite-based index insurance to the risk management context. Following Pierpaoli *et al.* (2013), we focused on competitive and contingent factors of the farm (H1, H2, H3), socio-demographic factors (H4, H5, H6) and financial resources (H7, H8). Also considered were the attitude of confidence (Lampe and Würtenberger, 2020) (H9) and farmers' general risk attitude (H10).

Although larger farms in terms of hectares (ha) face greater organizational complexity, they can allocate more management resources to risk management to possibly reduce the marginal costs of risk management (Vigani and Kathage, 2019). Indeed, larger farms are more likely to be insured against adverse weather events (e.g. Santeramo *et al.*, 2016; Sherrick *et al.*, 2004). Also, larger farms tend to adopt PAT earlier (Ofori *et al.*, 2020; Tamirat *et al.*, 2018). Accordingly, it can be expected that larger farms perceive satellite-based index insurance more useful, which is shown in the following hypothesis:

H1: Increasing farm size (*FarmSize*) has a statistically significant positive effect on farmers' gradually PU.

Finger and Lehmann (2012) and Sherrick *et al.* (2004) found that more specialized crop producers are more likely to purchase crop insurance. A possible reason might be that livestock farmers perceive risk management tools like crop insurance inappropriate to their farms, resulting in a lower preference (Hall *et al.*, 2003). Additionally, keeping livestock provides income diversification which can reduce demand for crop insurance since it can be classified as self-insurance (Kazianga and Udry, 2006). With regard to the use of satellite data, research focuses mainly on arable crops, fruits and vegetables, which would be of greater importance to arable farmers (e.g. Kölle *et al.*, 2020; Vroege *et al.*, 2021). Therefore, we derive the following hypothesis:

H2: Keeping livestock (*Livestock*) has a statistically significant negative effect on farmers' gradually PU.

Soil is a crucial factor for agricultural production. Crop yields are positively correlated with the factors water content, cation exchange capacity and the content of clay and carbon (Usowicz and Lipiec, 2017). Particularly, poorer soil quality leads to a lower water-holding capacity and is therefore more vulnerable to droughts and heat periods (Lüttger and Feike, 2018). In fact, Liebe *et al.* (2012) found an increasing preference for index insurance with lower soil quality, which Mishra and Goodwin (2003) have shown to be true for crop insurance in general. By using satellite data, the water content of soil is used more frequently as the referring index (e.g. Vroege *et al.*, 2021). Hence, the following hypothesis will be tested:

H3: Higher soil quality (*SoilQuality*) has a statistically significant negative effect on farmers' gradually PU.

Conclusions regarding age and its effect on insurance and technology adoption are ambiguous. Younger farmers are known to show higher adoption rates of crop insurance in general than older farmers (Liesivaara and Myyrä, 2014; Mishra and El-Osta, 2002). However, more recent studies specifically addressing index insurance present different results. While Doherty *et al.* (2021) showed that younger farmers have a higher preference for index insurance, Ghosh *et al.* (2021) found no statistically significant effect. Nevertheless, with regard to new technologies, it is argued that younger farmers have a higher interest in new technologies or willingness to adopt (D'Antoni *et al.*, 2012). For instance, younger farmers are more willing to use satellite imagery for precision management (Larson *et al.*, 2008). Therefore, the following hypothesis is given:

H4: Higher age (*Age*) has a statistically significant negative effect on farmers' gradually PU.

Finger and Lehmann (2012) and Enjolras and Sentis (2011) conclude that higher educated farmers are more likely to buy crop insurance. In contrast, this could not be confirmed for the case of index insurance (Doherty *et al.*, 2021). By using satellite data, the requirements of cognitive ability to guarantee full understanding would be even higher compared to meteorological data as Conradt *et al.* (2015) already mentioned for the use of phenological data. Moreover, farmers with higher education are assumed to understand and apply new technologies, even if they are complex, more quickly than others and exhibit faster learning effects (Cole *et al.*, 2017; Mishra and El-Osta, 2002). Since this was also observed for the application of satellite imagery for precision management (Larson *et al.*, 2008), it can also be expected that the PU is affected by farmers' education as expressed in the following hypothesis:

H5: Higher education (*Education*) has a statistically significant positive effect on farmers' gradually PU.

The role of gender in the adoption of risk management tools depends on the specific context as no differences can be found in general (Hoag *et al.*, 2011). Whereas Mußhoff *et al.* (2014) showed that male farmers are more likely to purchase index insurance, Gaurav and Chaudhary (2020) did not find a statistically significant gender difference. Akter *et al.* (2016) argued that women might be less familiar with index insurance. Beside this, literature identified that male farmers show a higher willingness to adopt new technologies (Michels *et al.*, 2020b). Taking both considerations into account, the following is hypothesized:

H6: Being a male farmer (*Gender*) has a statistically significant positive effect on farmers' gradually PU.

Part-time farmers, who already have a fixed off-farm income, might have a higher tolerance to take agricultural risks (El Benni *et al.* 2016). Likewise, Velandia *et al.* (2009) showed that higher off-farm income reduces incentives to adopt risk management tools in general and crop insurance in particular (Finger and Lehmann, 2012; Mishra and Goodwin, 2003). With regard to new technologies, farmers fully focusing on their farm business tend to be more interested in new technologies (Daberkow and McBride, 2003). Accordingly, it can be expected that full-time farmers are more interested in satellite-based insurance, which is shown in the following hypothesis to be tested:

H7: Being a full-time farmer (*FullTime*) has a statistically significant positive effect on farmers' gradually PU.

Germany was strongly affected by a nationwide drought in 2018. Yields for various crops were up to 30% below the long-term average (Bundesministerium für Ernährung und Landwirtschaft, 2018). Therefore, many of the surveyed farmers were directly affected. The fact that increasing weather risks influence farmers' insurance decisions is clear in literature (e.g. Di Falco *et al.*, 2014). Moreover, Doherty *et al.* (2021) and Enjolras and Sentis (2011) showed that farmers who were previously affected by extreme droughts have a higher preference for crop insurance and index insurance in particular. This relationship is displayed in the following hypothesis:

H8: Higher relative weather-related income losses (*IncomeLoss*) in the past few years have a statistically significant positive effect on farmers' gradually PU.

The attitude of confidence to learn and understand a technology was investigated for the adoption of PAT. For instance, the adoption of drones was influenced by the attitude of confidence in the technology (Michels *et al.*, 2020b). Regarding index insurance, a low understanding and trust in insurance products based on meteorological indices causes a low demand (Cole *et al.*, 2017; Lampe and Würtenberger, 2020). Since satellite-based indices related to chlorophyll production or soil moisture are even more complex than temperature or precipitation, it can also be expected that the level of trust in these indices could influence PU, as presented in the following hypothesis:

H9: Higher attitude of confidence (*Trust*) in index insurance products has a statistically significant positive effect on farmers' gradually PU.

Knowing the general risk attitude of farmers is important to tailor risk management. For instance, risk-averse farmers rate the probability of losses as comparatively higher (Menapace *et al.*, 2013) and are more willing to buy crop insurance (Möllmann *et al.*, 2019; Sherrick *et al.*, 2004; Vigani and Kathage, 2019). However, Liebe *et al.* (2012) and Giné *et al.* (2008) showed the risk attitude does not influence farmers' preferences for index insurance. Nevertheless, risk aversion is related to the introduction of technologies that can reduce farmers' risk exposure (Marra *et al.*, 2003). Therefore, the following is hypothesized:

H10: Higher degree of risk aversion (*RiskAttitude*) has a statistically significant positive effect on farmers' gradually PU.

3. Data and Methods

3.1 Study design and data collection

In June 2021, an online survey addressing German farmers was conducted. Prior to the study, approval was obtained from the ethics committee of the university of Göttingen. Farmers were invited to participate via email if they had already participated in previous surveys, and via social media and agricultural newsletters. Among German farmers, the use of computers and smartphones is over 90% (Michels *et al.*, 2020a), making an online survey suitable for our purpose. Participating farmers were informed that they could end the survey at any time without negative consequences. In the first part of the survey, a hypothetical satellite-based index insurance using a satellite-based soil moisture index as an example was explained to farmers in a learning session (Appendix A). A graph showing the relationship between index and yield over the last few years for an example location in Germany was also shown to make farmers aware of the remaining basis risk. The second part required farmers to answer the TTMU question about their gradually PU of satellite-based index insurance in general. Farmers were also asked to give information on their socio-economic and farm characteristics. Moreover, farmers were asked for their general risk attitude on a 11-point equally spaced Likert scale according to Dohmen *et al.* (2011) (0-4=risk-averse, 5=risk-neutral, 6-10=risk-seeking). Furthermore, their attitude of confidence in index insurance products was quantified on a 5-point equally spaced Likert scale along with the relative effect of weather risks on farm income.

3.2 Transtheoretical model of PU

The TTMC presents a way of taking into account the gradual stages in the process of behavioral change of individuals (Prochaska and Velicer, 1997). Although the TTMC was developed to investigate health behavior issues, Michels *et al.* (2020b) and Lemken *et al.* (2017) applied it successfully in an agricultural context. Table I presents the modification of the TTMC into the TTMU. The first stage is the "pre-contemplation", which does not require any intention or motivation to change. In the second stage, "contemplation", individuals have the general intention to change their behavior but are aware of the advantages and disadvantages of change. Therefore, they can remain at this stage for a long time. The third stage is called "preparation", where individuals have a concrete plan to change their behavior and plan to take an action in the near future. The last stage is "action", which implies that the related behavior has already changed (Prochaska and Velicer, 1997).

Table I: The modified TTMU for the PU of satellite-based index insurance

Stage	TTMC concept	TTMU modification	Coding
Pre-contemplation	No intention or motivation to change	An index insurance based on satellite data is currently of no benefit for me.	1
Contemplation	Intention to change	An index insurance based on satellite data could currently be useful for me.	2
Preparation	Intention to change with a concrete plan	An index insurance based on satellite data could currently be of great benefit for me.	3
Action	Behavior has changed	An index insurance based on satellite data is certainly of great benefit for me at the moment.	4

Note: Translated from German into English.

3.3 Econometric model

The econometric analysis is based on our modified TTMU question. As it is ordinal with four possible categories, an ordered logit model is applied. All variables discussed in section 2 were included as the independent variables. Following Verbeek (2017), the process of PU can be written as:

$$y^* = X\beta + e \tag{1}$$

where y^* describes an unobserved component representing the gradual PU. X includes the independent variables, β represents the estimated coefficients and the parameter e is the error term. However, from the unobservable component y^*, the gradual stages of usefulness can be made visible by considering the following:

$$y = \begin{cases} 0 \; if \; y^* \leq \mu_1 \\ 1 \; if \; \mu_1 < y^* \leq \mu_2, \\ 2 \; if \; \mu_2 < y^* \leq \mu_3, \\ \quad . \\ \quad . \\ \quad . \\ N \; if \; \mu_N < y^* \end{cases} \tag{2}$$

where N denotes the number of gradual stages of usefulness and μ_n indicates the corresponding endpoint of each observable stage. We specify the econometric model by including the independent variables for which we have derived hypotheses to investigate their effect on the dependent variable (TTMU), resulting in the following equation:

$$\begin{aligned} TTMU_i = \beta_0 &+ \beta_1 FarmSize + \beta_2 Livestock + \beta_3 SoilQuality + \beta_4 Age \\ &+ \beta_5 Education + \beta_6 Gender + \beta_7 FullTime + \beta_8 IncomeLoss \\ &+ \beta_9 Trust + \beta_{10} RiskAttitude + \varepsilon_i \end{aligned} \tag{3}$$

where i represents the individual respondent and ε_i represents the error term that is assumed to be logistically distributed. The regression coefficients were estimated as odds ratios (OR). OR's below 1 indicate a negative effect and OR's above 1 indicate a positive effect of the independent variables on the PU. The robustness of the results was checked in advance by excluding possible multicollinearities (Curto and Pinto, 2011). In order to confirm that the parallel regression assumption was met, the Brant test was applied. This assumption states that all coefficients of the dependent variables are equivalent for all ordinal stages. Therefore, according to Guzman-Castillo *et al.* (2015), only one set of coefficients needs to be calculated, since there is a linear relationship between all pairs of stages.

4. Results and discussion

4.1 Descriptive statistics

127 farmers fully answered the questionnaire and were included in the analysis. 19 farmers (15.0%) state that they perceive the use of satellite data in index insurance as not useful at this point of time (pre-contemplation stage) while 57 farmers (44.9%) state that it could be useful (contemplation stage).

Further, 51 farmers (40.1%) indicate that satellite-based index insurance could currently be of great benefit to them (preparation stage). On average, the value for the TTMU is 2.25 which means that the average farmer is in the contemplation stage. As mentioned, farmers in this stage are aware of the advantages as well as the disadvantages, but they are not yet pursuing a concrete plan for adoption (Prochaska and Velicer, 1997).

The descriptive statistics of all integrated variables are shown in Table II. The surveyed farmers farm on average 201 ha, which is more than the average German (63 ha). 53% keep livestock, which does not exactly correspond to the German average (69%). The average farmer in the sample is 42 years old and younger than the German average farmer (53 years). With respect to education, 57% hold a university degree, 27% have an advanced certificate in agriculture, 11% have a certificate in agriculture and 5% have no agricultural education. In Germany, only 14% of all farmers hold a university degree and 36% have an advanced certificate in agriculture. The share of female farmers in our sample matches perfectly with the share of female farmers among all German farmers (10%). Farming is the main occupation for 84% of the farmers, which largely exceeds the German average (48%) (German Farmers Federation, 2021). The average farmer can be classified as slightly risk-averse with an average value of 4.21. Farmers categorized their average income loss from weather risks in recent years at 6-10%. The level of trust in index insurance products reached on average 2.90 points, indicating that farmers rate their trust as medium-high on average. In summary, the surveyed farmers are younger, higher educated, and have larger farms than the average German farmer. However, this group of farmers was identified as the core group of PAT adopters (Michels *et al.*, 2020a).

Table II: Descriptive statistics and the expected effect of the included variables

Hypothesis	Variable	Description	Expected sign	Mean	S.D.	Min	Max	German average[a)]
	TTMU	Transtheoretical model of PU[b)]		2.25	0.70	1	3	n.a.
H1	*FarmSize*	Farm size in ha (arable land + pasture land)	+	200.66	268.95	5	2300	62
H2	*Livestock*	1, if the farmer is engaged in livestock farming; 0 otherwise	-	0.53	-	0	1	0.69
H3	*SoilQuality*	Soil quality in soil points	-	54.57	17.34	25	95	n.a.
H4	*Age*	Famers age in years	-	42.08	13.73	22	75	53
H5	*Education*	1, if the farmer has no agricultural education; 2, if the farmer has a certificate in agriculture; 3, if the farmer has an advanced certificate in agriculture; 4, if the farmer holds a university degree	+	3.38	0.85	1	4	n.a.
H6	*Gender*	1, if the farmer is male; 0 otherwise	+	0.90	-	0	1	0.90
H7	*FullTime*	1, if the farmer is full-time farmer; 0 otherwise	+	0.84	-	0	1	0.48
H8	*IncomeLoss*	"What has been the relative loss of income due to climate risks on your farm during the last 5 years on average?"[c)]	+	3.20	1.25	1	6	n.a.
H9	*Trust*	"How do you rate your confidence in index insurance products in general?"[d)]	+	2.91	0.70	1	4	n.a.
H10	*RiskAttitude*	"Are you a person who is fully willing to take risks or do you try to avoid risks?"[e)]	+	4.21	2.3	0	10	n.a.

Notes: n=127. S.D.=Standard deviation; n.a.=not available. [a)]German Farmers Federation (2021); [b)]1=The use of satellite data in index insurance is currently of no benefit for me. 2=The use of satellite data in index insurance could currently be useful for me. 3=The use of satellite data in index insurance could currently be of great benefit for me. 4=The use of satellite-data in index insurance is certainly of great benefit for me at the moment; [c)]categorical variable (1=0%; 2=1-5%; 3=6-10%; 4=11-15%; 5=16-20%; 6=>20%); [d)]5-point Likert scale (1=very low; 5=very high); [e)]11-point Likert scale (0=strongly risk-averse; 10=strongly risk-seeking)

4.2 Econometric results

Possible multicollinearity was checked by estimating variance inflation factors (VIF). VIF's must be less than 5 and the tolerances must be higher than 0.1 (Curto and Pinto, 2011). For our model, VIF's between 1.05 and 1.27 (mean of 1.14) and tolerances from 0.79 to 0.95 were obtained. Hence, multicollinearity cannot impair the robustness of the results. Additionally, the Brant test was conducted to ensure that the parallel regression assumption was not violated (Guzman-Castillo *et al.*, 2015). The statistical insignificance of the Brant test (chi2=6.542, p=0.768) demonstrates reliable results.

The results of the ordered logit model are shown in Table III[1]. Coefficients are expressed as OR's with their corresponding standard error. Moreover, p-values and 95%-confidence intervals are presented. Given a statistically significant result of the likelihood-ratio test (LR chi2=21.910, p=0.016), at least one coefficient is statistically different from zero. For a deeper insight into each stage of the TTMU, marginal effects and predicted probabilities are given in Table IV. According to the predicted probabilities, the average farmer has a 50% probability of belonging to the contemplation stage (TTMU=2), which is close to the observed choice of farmers (45%). A noteworthy sign change is observed for all variables between the contemplation stage (TTMU=2) and the preparation stage (TTMU=3), indicating that farmers who think that satellite-based insurance could be useful and farmers think that satellite-based insurance could be of great benefit for them differ in the statistically significant variables.

Table III: Results of the ordinal logistic regression for the TTMU

Hypothesis	Variable	Odds ratio	S.E.	p-value	[95%-confidence interval]
H1	*FarmSize*	1.0003	0.0001	0.613	[0.999; 1.002]
H2	*Livestock*	0.714	0.261	0.357	[0.349; 1.462]
H3	*SoilQuality*	1.002	0.011	0.847	[0.982; 1.023]
H4	*Age*	0.998	0.014	0.869	[0.970; 1.026]
H5	*Education*	1.652**	0.374	0.026	[1.061; 2.574]
H6	*Gender*	0.498	0.306	0.257	[0.204; 2.071]
H7	*FullTime*	1.028	0.511	0.956	[0.388; 2.722]
H8	*IncomeLoss*[a)]	1.401**	0.210	0.024	[1.045; 1.880]
H9	*Trust*[b)]	1.749**	0.447	0.029	[1.060; 2.885]
H10	*RiskAttitude*[c)]	1.052	0.083	0.512	[0.902; 1.229]
Log-likelihood-value		-117.335			
McFadden's pseudo-R^2		0.09			

Notes: n=127. S.E.=Standard error. *, **, *** indicate statistical significance at 10%, 5% and 1% level. [a)]Categorical variable (1=0%; 2=1-5%; 3=6-10%; 4=11-15%; 5=16-20%; 6=>20%); [b)]5-point Likert scale (1=very low; 5=very high); [c)]11-point Likert scale (0=strongly risk-averse; 10=strongly risk-seeking).

[1] The results for the statistically significant variables are robust when all of the statistically nonsignificant variables are removed from the model.

Table IV: Predicted probabilities and marginal effects

		TTMU=1	*TTMU=2*	*TTMU=3*
	Predicted probability	0.12	0.50	0.38
Hypothesis	Variable		Marginal effects	
H1	*FarmSize*	-0.00003	-0.00005	0.0001
H2	*Livestock*	0.036	0.043	-0.079
H3	*SoilQuality*	-0.0002	-0.0003	0.0005
H4	*Age*	0.0003	0.0003	-0.001
H5	*Education*	-0.054**	-0.064*	0.118**
H6	*Gender*	0.061	0.110	-0.170
H7	*FullTime*	-0.003	-0.004	0.006
H8	*IncomeLoss*[a)]	-0.036**	-0.043**	0.079**
H9	*Trust*[b)]	-0.060 **	-0.072*	0.132**
H10	*RiskAttitude*[c)]	-0.006	-0.007	0.013

Notes: n=127. *, **, *** indicate statistical significance at 10%, 5% and 1% level. [a)]Categorical variable (1=0%; 2=1-5%; 3=6-10%; 4=11-15%; 5=16-20%; 6=>20%); [b)]5-point Likert scale (1=very low; 5=very high); [c)]11-point Likert scale (0=strongly risk-averse; 10=strongly risk-seeking).

H1: Increasing farm size (*FarmSize*) has a statistically significant positive effect on farmers' gradually PU.

The OR in Table III indicates the expected positive effect on the PU (OR=1.0003; p=0.613). Nonetheless, since no statistical significance was found, no support can be given to H1. A statistically significant positive influence was expected since larger farms are more likely to adopt risk management tools and crop insurance in particular (e.g. Santeramo *et al.*, 2016). Additionally, a higher allocation of management capacity to risk management of larger farms was assumed to influence the PU (Vigani and Kathage, 2019). However, the importance of risk management has grown among farmers in general, as droughts occur more often in Europe and affect larger areas (Grillakis, 2019). Satellite data can depict entire regions as well as high spatial resolution, while weather stations can have a higher distance to smaller farms. This may increase the PU of smaller farms, as the geographical basis risk can be reduced.

H2: Keeping livestock (*Livestock*) has a statistically significant negative effect on farmers' gradually PU.

According to the model, keeping livestock has a negative influence on the PU (OR=0.714; p=0.357). Nevertheless, given no statistical significance, H2 is not supported. Livestock farming is discussed as self-insurance because it diversifies farm income, protects against crop loss due to extreme weather, and reduces crop insurance demand (e.g. Finger and Lehmann, 2012; Kazianga and Udry, 2006). Hence, livestock farming was assumed to have a negative effect. However, previous findings could not be confirmed. Unlike weather station data, satellite data can also focus on grass and its health (Vrieling *et al.*, 2014; Vroege *et al.*, 2019). This may also make them more attractive to livestock producers and explain this finding.

H3: Higher soil quality (*SoilQuality*) has a statistically significant negative effect on farmers' gradually PU.

The soil quality has no statistically significant effect on the PU and, contrary to expectations, the OR is higher than 1 (OR=1.002; p=0.847). Thus, no support can be given to H3. A negative effect of increasing soil quality was expected as soils of higher quality are less prone to droughts because of their higher water-holding capacity, which is directly linked to crop yields (Lüttger and Feike, 2018; Usowicz and Lipiec, 2017). Yet, systematic droughts and heatwaves occur more often in Europe by affecting larger areas and longer periods, causing yield losses also on better soils (Grillakis, 2019). Indeed, the relative increase in frequency of adverse weather events is found to be higher on better soils (Trnka *et al.*, 2014). Moreover, Germany was affected by a catastrophic drought in 2018, which led to high yields losses nationwide. Therefore, satellite-based insurance could be of interest for many farmers regardless of their soil conditions.

H4: Higher age (*Age*) has a statistically significant negative effect on farmers' gradually PU.

A higher age has a negative effect on the PU (OR=0.998; p=0.869). However, given the lack of statistical significance, H4 is not supported. Regarding the effect of age in the context of insurance demand, mixed results exist. While age was identified to influence the willingness to pay for crop insurance in general and index insurance in particular (Doherty *et al.*, 2021; Liesivaara and Myyrä, 2014), Ghosh *et al.* (2021) could not confirm this. Nevertheless, we expected a statistically significant effect of age on the PU, as younger farmers are more likely to adopt new technologies (D'Antoni *et al.*, 2012; Tamirat *et al.*, 2018). However, the statistical significance could not be confirmed by our results.

H5: Higher education (*Education*) has a statistically significant positive effect on farmers' gradually PU.

Farmers' education has a statistically significant positive effect on the PU (OR=1.652; p=0.026). Accordingly, our model supports H5. Therefore, the higher the educational level, the more likely they are on a higher stage of PU. Beside this, the marginal effects in Table IV indicate that the educational level has a statistically significant effect on whether a farmer perceives satellite-based insurance as useful or very useful. Our results are in line with relevant studies on insurance demand and technology adoption (e.g. Cole *et al.*, 2017; Enjolras and Sentis, 2011; Larson *et al.*, 2008). Higher educated farmers might understand that of basis risk can be addressed by the application of e.g. satellite-retrieved soil moisture. However, a higher level of intellect may be necessary to understand the benefit, as Conradt *et al.* (2015) state for the application of phenological data. This should be considered by insurers.

H6: Being a male farmer (*Gender*) has a statistically significant positive effect on farmers' gradually PU.

The model does not support H6 since the effect of gender on the PU is negative and has no statistically significance (OR=0.498; p=0.257). We expected a positive influence of being a male farmer as Akter *et* *al*. (2016) suggested that men are more familiar with the concept of index insurance. Notwithstanding, Hoag *et al*. (2011) mentioned that in general no gender difference in the adoption of risk management tools can be found. Further, this finding is in line with Gaurav and Chaudhary (2020) who could also not find a statistically significant effect of gender on the willingness to buy index insurance.

H7: Being a full-time farmer (*FullTime*) has a statistically significant positive effect on farmers' gradually PU.

Full-time farming has a positive, however, not statistically significant effect (OR=1.028; p=0.956). Due to this, H7 can be given no support. Part-time farmers are assumed to have a higher tolerance to take agricultural risks given their fixed off-farm income, which can lead to reduced incentives to adopt risk management tools like crop insurance. (El Benni *et al.*, 2016; Mishra and Goodwin, 2003; Velandia *et al.*, 2009). Nevertheless, a statistically significant effect on farmers' PU was not found. One possible explanation might be that farms owned by part-time owners, which are smaller in terms of ha on average, could benefit more from the high spatial resolution of satellite data. If index insurance can thus be improved in terms of basis risk, this could increase their PU. Although part-time farmers have a certain share of fixed off-farm income, they are also affected by the increasing risk of drought and have an interest in avoiding financial distress.

H8: Higher relative weather-related income losses (*IncomeLoss*) in the past few years have a statistically significant positive effect on farmers' gradually PU.

H8 is supported by the model. A higher income loss over the past five years has a statistically significant positive effect on the PU (OR=1.401; p=0.024). Further, the marginal effects indicate that farmers who perceive satellite-based insurance as very useful significantly differ regarding their relative income losses from farmers who think that they could be useful. Therefore, our results confirm existing literature (e.g. Di Falco *et al.*, 2014). This is not surprising, given the catastrophic drought in 2018 that affected nearly the entire study region. Moreover, risk managers tend to be more interested into new risk management measures after a loss in order to avoid further damage (Weinstein, 1988). Given the more frequent and intense droughts causing yield losses (Schmitt *et al.*, 2022), the PU could further increase for more farmers.

H9: Higher attitude of confidence (*Trust*) in index insurance products has a statistically significant positive effect on farmers' gradually PU.

A higher level of trust in index insurance products has a statistically significant positive effect on the PU (OR=1.749; p=0.029). Hence, H9 can be given support. Marginal effects show that farmers who perceive satellite-based index insurance as potentially useful differ significantly in their attitude of trust compared to farmers who think that they can be very useful. Our results confirm previous studies like Cole *et al*. (2017) who found that low understanding and trust is an inhibiting factor for willingness to buy index insurance. Since satellite-based indices may require a high degree of trust in the product, insurers can be advised to explain their potential customers about the functionality and reliability of satellite indices at an early stage.

H10: Higher degree of risk aversion (*RiskAttitude*) has a statistically significant positive effect on farmers' gradually PU.

Since the general risk attitude was measured on a scale from 0 to 10 based on Dohmen *et al.* (2011), an OR below 1 indicates a positive effect of a higher risk aversion on the PU. According to the results, a higher risk aversion of farmers has a negative but not statistically significant effect on the PU (OR=1.053; p=0.512). Therefore, H10 is not supported. A positive effect was expected because risk-averse farmers show a higher willingness to adjust their risk management by purchasing crop insurance or adopt new technologies (Marra *et al.*, 2003; Möllmann *et al.*, 2019; Vigani and Kathage, 2019). Yet, our study is in line with literature that could not identify an effect of general risk attitude on insurance demand (e.g. Giné *et al.*, 2008). One possible explanation may be that our measurement of farmers' risk attitude is too general. Given the huge increase in weather risks over the last decade, the measurement of risk attitude could focus more specific to contextualize farmers' risk attitude.

5. Conclusion

The availability of index insurance has grown to deal with increasing weather risks. To address basis risk as a main inhibiting factor of farmers' demand, the integration of satellite data is promising. As no literature deals with farmers' perceptions for satellite-based index insurance, this study obtains preliminary insights on farmers' PU for satellite-based index insurance by applying a modified TTMU for the first time. Thereby, influencing factors on different stages of PU are identified. To do so, an ordered logit model was estimated based on a survey dataset of 127 young, highly educated German farmers with larger farms.

Our results indicate that a higher level of agricultural education has a statistically significant positive effect on the PU. Furthermore, a higher trust in index insurance products and higher relative losses of farm income over the past years show a statistically significant positive effect on the PU, providing first insights into potential early adopters. Therefore, index insurance in general and satellite-based products in particular should be more widely addressed in agricultural training programs to ensure understanding and increase trust in the concept. Moreover, given a higher frequency of droughts, more farmers will be adversely affected in the future, which can further increase their PU. Insurers can therefore be advised to accelerate research and development of satellite-based policies because a large proportion of farmers perceive them at least potentially useful.

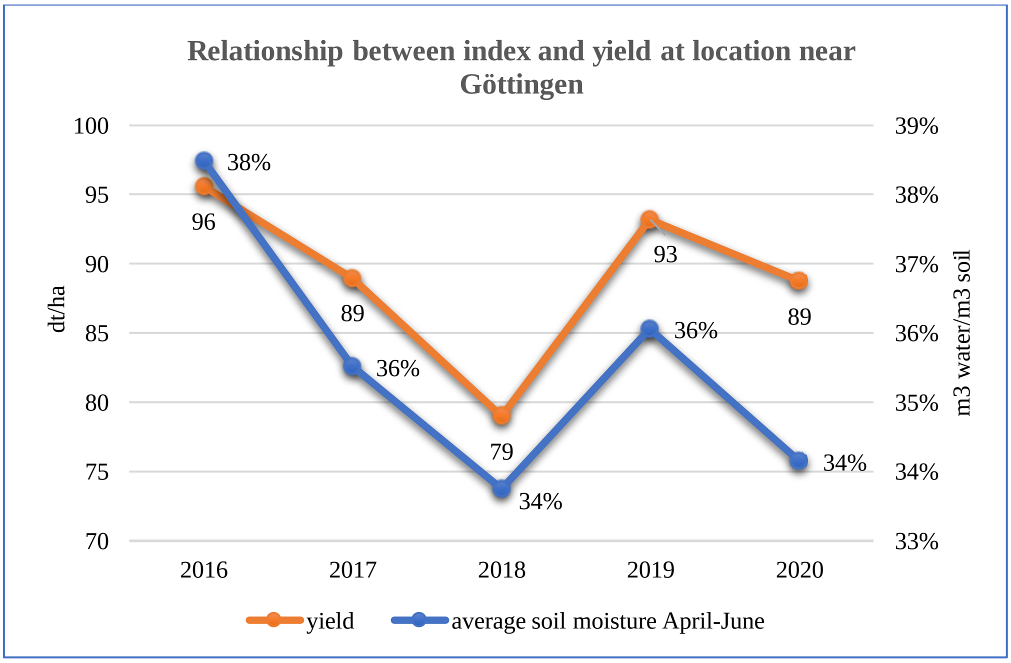
However, our study is limited with respect to the sample size. To corroborate the results, a larger sample with greater consideration given to smaller farms and less educated farmers is recommended. In addition, our identified statistically significant factors need to be complemented by other factors to better understand the PU as possible influencing factors like farm size, livestock farming, soil quality, age, gender, full-time farming and risk attitude show no statistically significant effect on the PU. For example, the effect of latent factors such as social influence or communication on insurance demand has not received sufficient research attention so far (Brown *et al.*, 2016; Jaspersen and Aseervatham, 2017). Moreover, since we asked the farmers for satellite-based index insurance in general, the PU for a specific type of satellite data could be addressed by ongoing research.

While this study focused on a developed country, our results can be applied to a certain extent to developing countries, which also suffer from climate change. Given that many of these countries do not have a comparable network of weather stations, satellite-based index insurance could reduce basis risk considerably, which could increase the PU. Furthermore, farmers' education and the level of trust in, for instance, insurance agents, are also discussed as inhibiting factors in the developing context. Although not all drivers of PU would be the same, similar tendencies could provide guidance to insurers in identifying pioneers to implement satellite-based insurance. Therefore, further research is needed to confirm our findings in other countries.

Appendix A Relevant questions of the questionnaire (translated from German into English)

Example of satellite-based index insurance:

The satellite-based index insurance is based on satellite-retrieved soil moisture data. For this purpose, satellites use radar radiation to measure the soil moisture at a soil depth of 5-10 cm on your land every day, irrespective of cloud cover, with a spatial resolution of up to 1x1 km. The index is derived from the relative volumetric soil moisture (m3 of water/m3 of soil). If the soil moisture index on your fields is below a defined damage threshold on average during the insurance period, you would receive a payout. [….]. The damage threshold, which leads to e.g. 20% yield loss, is calculated on the basis of the historical observations of the index and yields. [….]. The following graph shows how the index and the winter wheat yield have developed over the last 5 years at a location near Göttingen."



References

Akter, S., Krupnik, T.J., Rossi, F. and Khanam, F. (2016), "The influence of gender and product design on farmers' preferences for weather-indexed crop insurance", *Global Environmental Change*, Vol. 38, pp. 217–229, doi: 10.1016/j.gloenvcha.2016.03.010.

Barnett, B.J. and Mahul, O. (2007), "Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries", *American Journal of Agricultural Economics*, Vol. 89 No. 5, pp. 1241–1247, doi: 10.1111/j.1467-8276.2007.01091.x.

Brown, J.R., Kapteyn, A. and Mitchell, O.S. (2016), "Framing and claiming: How information-framing affects expected social security claiming behavior", *Journal of Risk and Insurance*, Vol. 83 No. 1, pp. 139–162, doi: 10.1111/j.1539-6975.2013.12004.x.

Bundesministerium für Ernährung und Landwirtschaft. (2018), "Trockenheit und Dürre 2018 – Überblick über Maßnahmen".

Clarke, D.J. (2016), "A Theory of Rational Demand for Index Insurance", *American Economic Journal: Microeconomics*, Vol. 8 No. 1, pp. 283–306, doi: 10.1257/mic.20140103.

Cole, S., Giné, X. and Vickery, J. (2017), "How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment", *The Review of Financial Studies*, Vol. 30 No. 6, pp. 1935–1970, doi: 10.1093/rfs/hhw080.

Conradt, S., Finger, R. and Spörri, M. (2015), "Flexible weather index-based insurance design", *Climate Risk Management*, Vol. 10, pp. 106–117, doi: 10.1016/j.crm.2015.06.003.

Curto, J.D. and Pinto, J.C. (2011), "The corrected VIF (CVIF)", *Journal of Applied Statistics*, Vol. 38 No. 7, pp. 1499–1507, doi: 10.1080/02664763.2010.505956.

Daberkow, S.G. and McBride, W.D. (2003), "Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the US", *Precision Agriculture*, Vol. 4 No. 2, pp. 163–177, doi: 10.1023/A:1024557205871.

D'Antoni, J.M., Mishra, A.K. and Joo, H. (2012), "Farmers' perception of precision technology: The case of autosteer adoption by cotton farmers", *Computers and Electronics in Agriculture*, Vol. 87, pp. 121–128, doi: 10.1016/j.compag.2012.05.017.

Di Falco, S., Adinolfi, F., Bozzola, M. and Capitanio, F. (2014), "Crop Insurance as a Strategy for Adapting to Climate Change", *Journal of Agricultural Economics*, Vol. 65 No. 2, pp. 485–504, doi: 10.1111/1477-9552.12053.

Doherty, E., Mellett, S., Norton, D., McDermott, T.K.J., Hora, D.O. and Ryan, M. (2021), "A discrete choice experiment exploring farmer preferences for insurance against extreme weather events", *Journal of Environmental Management*, Vol. 290, p. 112607, doi: 10.1016/j.jenvman.2021.112607.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. and Wagner, G.G. (2011), "Individual risk attitudes: measurement, determinants, and behavioral consequences", *Journal of the European Economic Association*, Vol. 9 No. 3, pp. 522–550, doi: 10.1111/j.1542-4774.2011.01015.x.

El Benni, N., Finger, R. and Meuwissen, M.P.M. (2016), "Potential effects of the income stabilisation tool (IST) in Swiss agriculture", *European Review of Agricultural Economics*, Vol. 43 No. 3, pp. 475–502, doi: 10.1093/erae/jbv023.

Enenkel, M., Farah, C., Hain, C., White, A., Anderson, M., You, L., Wagner, W., *et al.* (2018), "What Rainfall Does Not Tell Us—Enhancing Financial Instruments with Satellite-Derived Soil Moisture and Evaporative Stress", *Remote Sensing*, Vol. 10 No. 11, p. 1819, doi: 10.3390/rs10111819.

Enjolras, G. and Sentis, P. (2011), "Crop insurance policies and purchases in France", *Agricultural Economics*, Vol. 42 No. 4, pp. 475–486, doi: 10.1111/j.1574-0862.2011.00535.x.

Finger, R. and El Benni, N. (2021), "Farm income in European agriculture: new perspectives on measurement and implications for policy evaluation", *European Review of Agricultural Economics*, Vol. 48 No. 2, pp. 253–265, doi: 10.1093/erae/jbab011.

Finger, R. and Lehmann, N. (2012), "The influence of direct payments on farmers' hail insurance decisions", *Agricultural Economics*, Vol. 43 No. 3, pp. 343–354, doi: 10.1111/j.1574-0862.2012.00587.x.

Gaurav, S. and Chaudhary, V. (2020), "Do farmers care about basis risk? Evidence from a field experiment in India", *Climate Risk Management*, Vol. 27, p. 100201, doi: 10.1016/j.crm.2019.100201.

German Farmers Federation. (2021), *German Farmers' Federation-Deutscher Bauernverband.*

German Insurance Association. (2019), "Landwirtschaftliche Mehrgefahrenversicherung für Deutschland".

Ghosh, R.K., Gupta, S., Singh, V. and Ward, P.S. (2021), "Demand for Crop Insurance in Developing Countries: New Evidence from India", *Journal of Agricultural Economics*, Vol. 72 No. 1, pp. 293–320, doi: 10.1111/1477-9552.12403.

Giné, X., Townsend, R. and Vickery, J. (2008), "Patterns of Rainfall Insurance Participation in Rural India", *The World Bank Economic Review*, Vol. 22 No. 3, pp. 539–566, doi: 10.1093/wber/lhn015.

Grillakis, M.G. (2019), "Increase in severe and extreme soil moisture droughts for Europe under climate change", *The Science of the Total Environment*, Vol. 660, pp. 1245–1255, doi: 10.1016/j.scitotenv.2019.01.001.

Guzman-Castillo, M., Brailsford, S., Luke, M. and Smith, H. (2015), "A tutorial on selecting and interpreting predictive models for ordinal health-related outcomes", *Health Services and Outcomes Research Methodology*, Vol. 15 No. 3–4, pp. 223–240, doi: 10.1007/s10742-015-0140-6.

Hall, D.C., Knight, T.O., Coble, K.H., Baquet, A.E. and Patrick, G.F. (2003), "Analysis of Beef Producers' Risk Management Perceptions and Desire for Further Risk Management Education", *Review of Agricultural Economics*, Vol. 25 No. 2, pp. 430–448, doi: 10.1111/1467-9353.00148.

Heimfarth, L. and Musshoff, O. (2011), “Weather index-based insurances for farmers in the North China Plain: An analysis of risk reduction potential and basis risk”, *Agricultural Finance Review*, Vol. 71 No. 2, pp. 218–239, doi: 10.1108/00021461111152582.

Hoag, D.L.K., Keske, C. and Goldbach, R. (2011), “Risk Indviduality in Crisis Planning: the Case of Gender in Amercan Agriculture”, *Journal of Risk Analysis and Crisis Response*, Vol. 1 No. 1, p. 21, doi: 10.2991/jracr.2011.1.1.2.

Jaspersen, J.G. and Aseervatham, V. (2017), “The Influence of Affect on Heuristic Thinking in Insurance Demand: The Influence of Affect on Heuristic Thinking in Insurance Demand”, *Journal of Risk and Insurance*, Vol. 84 No. 1, pp. 239–266, doi: 10.1111/jori.12088.

Jensen, N., Stoeffler, Q., Fava, F., Vrieling, A., Atzberger, C., Meroni, M., Mude, A., *et al.* (2019), “Does the design matter? Comparing satellite-based indices for insuring pastoralists against drought”, *Ecological Economics*, Vol. 162, pp. 59–73, doi: 10.1016/j.ecolecon.2019.04.014.

Kazianga, H. and Udry, C. (2006), “Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso”, *Journal of Development Economics*, Vol. 79 No. 2, pp. 413–446, doi: 10.1016/j.jdeveco.2006.01.011.

Kölle, W., Martínez Salgueiro, A., Buchholz, M. and Musshoff, O. (2020), “Can satellite-based weather index insurance improve the hedging of yield risk of perennial non-irrigated olive trees in Spain?”, *Australian Journal of Agricultural and Resource Economics*, Vol. 59, pp. 1–28, doi: 10.1111/1467-8489.12403.

Lampe, I. and Würtenberger, D. (2020), “Loss aversion and the demand for index insurance”, *Journal of Economic Behavior & Organization*, Vol. 180, pp. 678–693, doi: 10.1016/j.jebo.2019.10.019.

Larson, J.A., Roberts, R.K., English, B.C., Larkin, S.L., Marra, M.C., Martin, S.W., Paxton, K.W., *et al.* (2008), “Factors affecting farmer adoption of remotely sensed imagery for precision management in cotton production”, *Precision Agriculture*, Vol. 9 No. 4, pp. 195–208, doi: 10.1007/s11119-008-9065-1.

Leblois, A. and Quirion, P. (2013), “Agricultural insurances based on meteorological indices: realizations, methods and research challenges: Agricultural insurances based on meteorological indices: a survey”, *Meteorological Applications*, Vol. 20 No. 1, pp. 1–9, doi: 10.1002/met.303.

Lemken, D., Spiller, A. and von Meyer-Höfer, M. (2017), “The Case of Legume-Cereal Crop Mixtures in Modern Agriculture and the Transtheoretical Model of Gradual Adoption”, *Ecological Economics*, Vol. 137, pp. 20–28, doi: 10.1016/j.ecolecon.2017.02.021.

Liebe, U., Maart, S.C., Mußhoff, O. and Stubbe, P. (2012), “Risikomanagement in landwirtschaftlichen Betrieben: Eine Analyse der Akzeptanz von Wetterversicherungen mit Hilfe von Discrete-Choice-Experimenten”, *German Journal of Agricultural Economics*, Unknown, Vol. 61 No. 2, pp. 63–79, doi: 10.22004/AG.ECON.199772.

Liesivaara, P. and Myyrä, S. (2014), "Willingness to pay for agricultural crop insurance in the northern EU", *Agricultural Finance Review*, Vol. 74 No. 4, pp. 539–554, doi: 10.1108/AFR-06-2014-0018.

Lüttger, A.B. and Feike, T. (2018), "Development of heat and drought related extreme weather events and their effect on winter wheat yields in Germany", *Theoretical and Applied Climatology*, Vol. 132 No. 1–2, pp. 15–29, doi: 10.1007/s00704-017-2076-y.

Marra, M., Pannell, D.J. and Abadi Ghadim, A. (2003), "The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve?", *Agricultural Systems*, Vol. 75 No. 2–3, pp. 215–234, doi: 10.1016/S0308-521X(02)00066-5.

Menapace, L., Colson, G. and Raffaelli, R. (2013), "Risk Aversion, Subjective Beliefs, and Farmer Risk Management Strategies", *American Journal of Agricultural Economics*, Vol. 95 No. 2, pp. 384–389, doi: 10.1093/ajae/aas107.

Michels, M., Fecke, W., Feil, J.-H., Musshoff, O., Pigisch, J. and Krone, S. (2020), "Smartphone adoption and use in agriculture: empirical evidence from Germany", *Precision Agriculture*, Vol. 21 No. 2, pp. 403–425, doi: 10.1007/s11119-019-09675-5.

Michels, M., von Hobe, C.-F. and Musshoff, O. (2020), "A trans-theoretical model for the adoption of drones by large-scale German farmers", *Journal of Rural Studies*, Vol. 75, pp. 80–88, doi: 10.1016/j.jrurstud.2020.01.005.

Mishra, A.K. and El-Osta, H.S. (2002), "Managing risk in agriculture through hedging and crop insurance: what does a national survey reveal?", *Agricultural Finance Review*, Vol. 62 No. 2, pp. 135–148, doi: 10.1108/00214930280001134.

Mishra, A.K. and Goodwin, B.K. (2003), "Adoption of crop versus revenue insurance: a farm-level analysis", *Agricultural Finance Review*, Vol. 63 No. 2, pp. 143–155, doi: 10.1108/00215050380001146.

Möllmann, J., Michels, M. and Musshoff, O. (2019), "German farmers' acceptance of subsidized insurance associated with reduced direct payments", *Agricultural Finance Review*, Vol. 79 No. 3, pp. 408–424, doi: 10.1108/AFR-09-2018-0071.

Mußhoff, O., Grüner, S. and Hirschauer, N. (2014), "Muss man begrenzte Rationalität und heuristisches Entscheiden bei der Erklärung für die Verbreitung von Wetterindexversicherungen in der Landwirtschaft berücksichtigen? – Eine Untersuchung auf der Basis eines Extra-Laboratory-Experiments", *German Journal of Agricultural Economics*, Unknown, Vol. 63 No. 02, pp. 67–80, doi: 10.22004/AG.ECON.253150.

Ofori, E., Griffin, T. and Yeager, E. (2020), "Duration analyses of precision agriculture technology adoption: what's influencing farmers' time-to-adoption decisions?", *Agricultural Finance Review*, Vol. 80 No. 5, pp. 647–664, doi: 10.1108/AFR-11-2019-0121.

Pierpaoli, E., Carli, G., Pignatti, E. and Canavari, M. (2013), "Drivers of Precision Agriculture Technologies Adoption: A Literature Review", *Procedia Technology*, Vol. 8, pp. 61–69, doi: 10.1016/j.protcy.2013.11.010.

Prochaska, J.O. and Velicer, W.F. (1997), "The Transtheoretical Model of Health Behavior Change", *American Journal of Health Promotion*, Vol. 12 No. 1, pp. 38–48, doi: 10.4278/0890-1171-12.1.38.

Quiring, S.M. and Ganesh, S. (2010), "Evaluating the utility of the Vegetation Condition Index (VCI) for monitoring meteorological drought in Texas", *Agricultural and Forest Meteorology*, Vol. 150 No. 3, pp. 330–339, doi: 10.1016/j.agrformet.2009.11.015.

Rose, D.C., Sutherland, W.J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., *et al.* (2016), "Decision support tools for agriculture: Towards effective design and delivery", *Agricultural Systems*, Vol. 149, pp. 165–174, doi: 10.1016/j.agsy.2016.09.009.

Santeramo, F.G., Goodwin, B.K., Adinolfi, F. and Capitanio, F. (2016), "Farmer Participation, Entry and Exit Decisions in the Italian Crop Insurance Programme", *Journal of Agricultural Economics*, Vol. 67 No. 3, pp. 639–657, doi: 10.1111/1477-9552.12155.

Schmitt, J., Offermann, F., Söder, M., Frühauf, C. and Finger, R. (2022), "Extreme weather events cause significant crop yield losses at the farm level in German agriculture", *Food Policy*, Vol. 112, p. 102359, doi: 10.1016/j.foodpol.2022.102359.

Sherrick, B.J., Barry, P.J., Ellinger, P.N. and Schnitkey, G.D. (2004), "Factors Influencing Farmers' Crop Insurance Decisions", *American Journal of Agricultural Economics*, Vol. 86 No. 1, pp. 103–114, doi: 10.1111/j.0092-5853.2004.00565.x.

Tamirat, T.W., Pedersen, S.M. and Lind, K.M. (2018), "Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany", *Acta Agriculturae Scandinavica, Section B — Soil & Plant Science*, Vol. 68 No. 4, pp. 349–357, doi: 10.1080/09064710.2017.1402949.

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z. and Semenov, M.A. (2014), "Adverse weather conditions for European wheat production will become more frequent with climate change", *Nature Climate Change*, Vol. 4 No. 7, pp. 637–643, doi: 10.1038/nclimate2242.

Turvey. (2001), "Weather derivatives for specific event risks in agriculture", *Review of Agricultural Economics*, Vol. 23, pp. 333–351, doi: 10.2307/1349952.

Usowicz, B. and Lipiec, J. (2017), "Spatial variability of soil properties and cereal yield in a cultivated field on sandy soil", *Soil and Tillage Research*, Vol. 174, pp. 241–250, doi: 10.1016/j.still.2017.07.015.

Velandia, M.M., Rejesus, R.M., Knight, T.O. and Sherrick, B.J. (2009), "Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward

Contracting, and Spreading Sales", *Journal of Agricultural and Applied Economics*, Unknown, Vol. 41 No. 1, pp. 107–123, doi: 10.22004/AG.ECON.48751.

Verbeek, M. (2017), *A Guide to Modern Econometrics*, 5th edition., John Wiley & Sons, Inc, Hoboken, NJ.

Vigani, M. and Kathage, J. (2019), "To Risk or Not to Risk? Risk Management and Farm Productivity", *American Journal of Agricultural Economics*, Vol. 101 No. 5, pp. 1432–1454, doi: 10.1093/ajae/aaz020.

Vrieling, A., Meroni, M., Shee, A., Mude, A.G., Woodard, J., de Bie, C.A.J.M. (Kees) and Rembold, F. (2014), "Historical extension of operational NDVI products for livestock insurance in Kenya", *International Journal of Applied Earth Observation and Geoinformation*, Vol. 28, pp. 238–251, doi: 10.1016/j.jag.2013.12.010.

Vroege, W., Bucheli, J., Dalhaus, T., Hirschi, M. and Finger, R. (2021), "Insuring crops from space: the potential of satellite-retrieved soil moisture to reduce farmers' drought risk exposure", *European Review of Agricultural Economics*, Vol. 48 No. 2, pp. 266–314, doi: 10.1093/erae/jbab010.

Vroege, W., Dalhaus, T. and Finger, R. (2019), "Index insurances for grasslands – A review for Europe and North-America", *Agricultural Systems*, Vol. 168, pp. 101–111, doi: 10.1016/j.agsy.2018.10.009.

Weinstein, N.D. (1988), "The precaution adoption process.", *Health Psychology*, Vol. 7 No. 4, pp. 355–386, doi: 10.1037/0278-6133.7.4.355.