SATELLITE-BASED VEGETATION HEALTH INDICES AS A CRITERIA FOR INSURING AGAINST DROUGHT-RELATED YIELD LOSSES

Bokusheva R.[1*], Kogan F.[2], Vitkovskaya I.[3], Conradt, S.[1], Batyrbayeva M.[3]

[1]Swiss Federal Institute of Technology, ETH Zurich
[3]NOAA, National Environmental Satellite Data and Information Services
[2]Space Research Institute of the National Space Agency of the Republic of Kazakhstan
*corresponding author; phone: +41 44 632 5330; fax: +41 44 632 1086;
e-mail: bokushev@ethz.ch

SATELLITE-BASED VEGETATION HEALTH INDICES AS A CRITERIA FOR INSURING AGAINST DROUGHT-RELATED YIELD LOSSES

Abstract

This paper considers the use of indices built on the basis of remote-sensing data for crop insurance purposes. In our analysis, we compare the capacity of two satellite-based vegetation health (VH) indices, the vegetation condition index (VCI) and the temperature condition index (TCI), measured for important periods of the crop vegetation to predict farmers' wheat yields in two main grain producing regions of Kazakhstan. The selected indices are used for the design of index-based insurance contracts. The dependence of wheat yields on vegetation conditions as measured by VCI and TCI, is modeled by applying the copula approach. Our empirical results for 47 grain-producing farms in the Northern Kazakhstan show that insurance contracts built on VH indices can provide substantial risk reductions for a group of farms, though on average for the whole sample, risk reductions were found to be moderate. The study results suggest that the effectiveness of insurance contracts can be improved using satellite data of higher resolutions and measuring indices at more disaggregated levels.

Keywords: satellite-based vegetation health index, drought-related yield losses, wheat, agricultural insurance, copula approach.

1. Introduction

Agricultural production is a risky economic activity. In addition to market, institutional, political and farmers' individual risks, production risk, in the form of adverse weather conditions, presents an important source of risk in agricultural production. Drought, floods, frost, hurricanes etc can partially or completely destroy farmers' harvests and in this way seriously endanger individual farmers' livelihoods. Although farmers generally have many options for reducing their exposure to adverse weather events *on farm*, such as the use of irrigation, drought resistant crop varieties and the cultivation of crops with shorter production cycles, etc., the risk reducing capacity of farm based risk management strategies might be not sufficient to cope with extreme weather events. In this situation, farmers' risks can be more effectively managed by employing crop insurance.

Extreme weather events usually have a systemic occurrence pattern, i.e. they simultaneously affect a number of agricultural producers. This feature of extreme weather events presents an important prerequisite for the introduction of so called index-based insurance. In contrast to the traditional yield insurance, index-based insurance is based not on the actual farm yields, but on an index. Accordingly, an indemnity is paid whenever the realized value of the index exceeds or falls below a threshold index value (Skees et al., 1997). In the case of weather-based insurance, the indemnification (i.e. the insurance payment to compensate the farmer's yield loss) is conditioned on the actual realization of a selected weather index. An aggregate yield index is used in the case of area-based yield insurance to detect crop failure. As in the case of index-based insurance yield losses are assessed on the basis of an index (not on the farmer's actual yield), this type of crop insurance allows a substantial reduction of insurance administrative and other costs (because in this case there is no need to monitor single farm yields). In the last decade, several studies have been conducted to evaluate the potential effectiveness of insurance contracts based on weather and area yield-based indices (e.g. Skees et al., 1997; Turvey, 2001; Vedenov and Barnett, 2004; Breustedt et al., 2008; Kellner and Musshoff, 2011; Bokusheva and Breustedt, 2012).

The effectiveness of index-based insurance products is, however, highly dependent on the availability of reliable and cost-effective information sources. In the case of weather-based insurance, a rather sparse meteorological network is often considered a handicap for the development of this type of crop insurance. Additionally, in contrast to the data from ground weather stations, satellite images can be used to derive independent and in some cases more reliable information about plant growing conditions.

In recent decades, satellite images have been increasingly used for agricultural purposes. The so-called satellite-based vegetation health (VH) indices, which include the vegetation condition index (VCI), the temperature condition index (TCI) and the vegetation health index (VHI) (Kogan, 1998; Unganai and Kogan, 1998; Kogan et al., 2012, Kogan et al., 2015), have been developed and used to predict crop yields in different regions with high variations in climatic and ecosystem conditions since 1982.

Recently, Barrett et al. (2008) discussed the potential for the application of remote-sensing data for the purpose of crop insurance. They suggest that high resolution remote-sensing data can seriously reduce problems of a high basis risk, i.e. the risk that occurs because of an imperfect correlation between an index and farmers' yields (Barrett et al., 2008), which might result in a mismatch between farmers' actual yield losses and insurance payments.

In recent years, several pilot projects have been implemented to evaluate the effectiveness of index-based insurance by employing satellite-based VH indices in such countries as Canada, India, Mali and Kenya (Hazell et al., 2010; Miranda and Farrin, 2012). However, satellite-based VH indices have been used to design insurance primarily for pasture vegetation, which yield is directly related to the quantity of green biomass generated during the vegetation period.

A more recent study by Makaudze and Miranda (2010) developed index-based insurance employing satellite data for maize and cotton. This study focused on Zimbabwe and was based on time series of the Normalized Difference Vegetation Index (NDVI) and maize and cotton yields aggregated at the district level. The authors found that insurance contracts based on the NDVI allowed a higher risk reduction than rainfall-based insurance contracts.

Although the results of some studies have shown that VHI, VCI and TCI show considerable correlation with observed crop yields, the quality of satellite data is not always sufficient and can differ from plot to plot, as well as for different periods of measurement (Kogan et al., 2003). In addition, empirical research has shown that the use of aggregated yields might cause serious undervaluation of the farm yield variability and an underestimation of the farm risk (Claasen and Just, 2010). Therefore, in our view, the applicability of satellite images for the design of insurance products should be evaluated by using long time series of satellite data and farm yields. The novelty of the present study compared to previous analyses on the use of remote-sensing data for insurance purposes is that for the first time it conducts the analysis of the satellite data in combination with *farm* yield data. Moreover, to model the dependence between crop yields and remote sensing indices, our study employs the copula approach, which, compared to linear correlation, presents a more adequate methodological framework for modeling dependence in the tails of multivariate distributions (Embrechts et al., 2002).

In this paper, we analyze the effectiveness of two VH indices for insuring wheat yield losses in grain producing farms in Kazakhstan. Kazakhstan is an important grain producing nation. In the period from 2003 to 2012 the national average wheat production was 13.8 million metric tons (National Agency of Statistics of the Republic of Kazakhstan, 2012). Both the high level of production and a relatively low domestic consumption of 6.2 million metric tons of wheat in 2010 (USDA, 2012) make Kazakhstan a key player in the world grain market and are important factors assuring the country's contribution to global food security. However, the national grain production can vary substantially from year to year subject to weather conditions during the vegetation period. Drought presents the main natural hazard to Kazakhstan's grain producers and is an important source of fluctuation in farm income. For example, in 2010, due to an extensive drought, the national wheat yield dropped to 0.73 tons per ha, while in 2011 – a year with very favorable weather conditions – it rose to 1.66 tons per ha.

The remainder of the paper is structured as follows: Section 2 presents the methodology and empirical procedure employed in the study. Section 3 provides a description of the data. The following section presents and discusses study results. Conclusions are drawn in the final section.

2. Methods

2.1. Satellite-based vegetation health indices

The change in the green biomass of crops within the vegetation period is traditionally described by means of two well known remote sensing indices: the Normalized difference vegetation index (NDVI) and the vegetation conditions index (VCI) (Kogan, 1998; Lui and Kogan, 1996). NDVI quantifies the total amount of green biomass in each pixel of a satellite image during the measurement period; VCI is obtained by normalizing NDVI values by their multi-year absolute minimum and maximum values in the analyzed period. For any given year and pixel in a satellite image, the VCI in week *w* is calculated as follows:

$$VCI_w = 100 \cdot \frac{NDVI_w - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \quad (1)$$

$NDVI_{\max}$ and $NDVI_{\min}$ are the absolute maximum and minimum values of the NDVI over the entire observation period, respectively. The NDVI is derived from visible (VIS) and nearly infrared (NIR) data as (NDVI=(NIR-VIS)/(NIR+VIS)). The principle of this index is based on the fact that moisture stressed vegetation has a higher reflectance in the VIS and lower in the NIR than green healthy vegetation (Spivak et al., 2008). Higher NDVI values indicate well-watered, not moisture stressed vegetation. Dry years are characterized by drought related thermal and moisture vegetation stress, resulting in low levels of green biomass and accordingly low NDVI values. Other factors such as salinity, crop diseases and insects can also contribute to a reduction in green reflectance, but these mostly result in local effects, whereas drought has a large scale spatial effect. This allows the use of satellite-based VH indices to detect and measure the effects of drought.

Additionally, we employed the TCI, which quantifies land surface thermal condition, including the vegetation canopy (Kogan et al., 2012). For any given year and pixel in a satellite image, the TCI in week *w* is calculated using the Brightness Temperature (BT) as follows:

$$TCI_w = 100 \cdot \frac{BT_{\max} - BT_w}{BT_{\max} - BT_{\min}}, \quad (2)$$

where BT_w, $BT_{\max}$ and $BT_{\min}$ are the smoothed brightness temperature, and its multi-year absolute maximum and minimum, respectively (Unganai and Kogan, 1998).

Both the TCI and the VCI have been found to exhibit a high level of correlation with yields for different crops (Kogan, 1995; Kogan et al., 2012). The VCI and the TCI are usually calculated for either a week or a 10-day interval. However, when analyzing long times series of data, more stable and reliable results can be obtained by applying integral values of these indices (Spivak et al., 2008). In our analysis, we calculated the integral value of indices for four consecutive weeks.

2.2. Copula approach

The copula approach has been used extensively for modeling multivariate dependence structures in finance and actuarial mathematics. Recently, several applications of the copula approach have been carried out in the field of agricultural economics (Vedenov, 2008; Zhu et al., 2008; Bokusheva, 2011; Goodwin and Hungerford, 2015).

According to Sklar's theorem (Sklar, 1959), if F is a joint distribution function with marginal distributions $F_1,\ldots,F_d$, then there exists a copula $C\colon [0,1]^d \rightarrow [0,1]$ such that for all $x_1,\ldots,x_d$ in $\overline{R} = [-\infty,\infty]$,

$$F(x_1,\ldots,x_d) = C(F_1(x_1),\ldots,F_d(x_d)), \qquad (3)$$

where $x_1,\ldots,x_d$ is a vector of d random variables forming a joint distribution, and $F_1,\ldots,F_d$ are respective marginal distributions.

Therefore, according to Sklar's theorem, any continuous multivariate distribution can be uniquely described by two parts: the marginal distributions F_i and the multivariate dependence structure captured by the copula C. Sklar's theorem makes the copula approach a powerful instrument for modeling empirical joint distributions. In particular, it allows to reduce an empirical problem of modeling a multivariate dependence structure to the selecting appropriate marginal distributions and fitting an adequate copula.

In general, there are many different copula families. In empirical research, however, the most commonly applied copulas are the Gaussian copula, Student's t copula and three Archimedean copulas: the Clayton, Gumbel and Frank copulas (Nelsen, 1999; McNeil et al., 2005).

To design and rate an index-based insurance contract, we employ the approach as presented in Mainik and Schaanning (2012). In particular, we assume that the dependence between crop yields and VH indices might be stronger in the left tail of the distribution than if measured for entire range of the distribution. Thus, in our analysis we suggest focusing on the expected value of the yield $\tilde{\mu}^*$ given that the satellite-based VH index W falls below its critical level, and in particular, its value at risk VaR at the confidence interval α, $VaR\alpha\,(W)$, i.e.:

$$\tilde{\mu}^* = \tilde{\mu}_{|W \le VaR_{1-\alpha}(W)} = E\left(Y \middle| W \le VaR_{1-\alpha}(W)\right), \tag{4}$$

where E is the expectation operator.

The expression in (4) can be defined in terms of a copula as follows (Mainik and Schaanning, 2012):

$$\mathrm{H}_{\mathrm{Y|W=w}}(y) = c_{G(Y)|F(W=w)}(v)\Big|_{\substack{G(y)=v \\ F(w)=u}} \tag{5}$$

where $F(W)$ and $G(Y)$ are marginal distributions of the index and crop yield, respectively. $\mathrm{H}_{\mathrm{Y|W=w}}(y)$ is the conditional distribution of the yield variable, which can be derived by taking the first derivative of the copula with respect to u, i.e.

$$c_{G(Y)|F(W=w)}(v) = \frac{\partial}{\partial u} C(u,v)\Big|_{F(w)=u} \,, \tag{6}$$

To consider all realizations of the index variable below its VaR, (5) has to be rewritten as:

$$c_{G(Y)|F(W)\leq 1-\alpha}(v) = \frac{1}{P(F(W)\leq 1-\alpha)} \int_{l=0}^{1-\alpha} \frac{\partial}{\partial u} C(u,v)\Bigg|_{\substack{F(w)=l \\ G(y)=v}} \partial l \tag{7}$$

The expression in (7) allows the determination of the conditional distribution of the yield variable in terms of a copula and the marginal distribution of the VH index. By integrating the expression in (7) over the interval [0, 1] of the yield marginal distribution allows to obtain the yield distribution quintile corresponding to $\tilde{\mu}^*$. Thus, $\tilde{\mu}^*$ can be determined and successively applied for the derivation of insurance contract parameters, i.e. potential indemnity payments and fair insurance premium[2] (Bokusheva, 2014).

2.3. *Empirical procedure*

We start our empirical analysis by identifying for each study county the most critical period of the wheat vegetation, i.e. the period that is most important for the grain formation and wheat yield productivity. This period was determined by detecting the weeks with the highest level of

---

[2] Fair insurance premium does not incorporate any loading related to administrative costs of insurance companies etc. and is calculated as the expected indemnity value.

dependency between VH indices and wheat yields using county-level yield data.[3] To estimate dependence between the county average wheat yields and satellite-based VH indices, we employ four different copula models: the Gaussian, Clayton, Frank, and Gumbel survival copulas. While the Clayton and the Gumbel survival copulas assume a strong dependence in the left tail of the joint multivariate distribution, the Gaussian[4] and Frank copulas require radial symmetry of joint distribution, i.e. the same level of dependence in opposite corners of the copula.

In the second part of the analysis, we use the indices selected in the first step to estimate dependence between them and wheat yields at the farm level. Subsequently, we apply the Cramer-von-Mises criterion to select the most appropriate copulas for modeling dependence between selected indices and farm yields. Hypothetical insurance contracts represented by indemnity payments and the insurance premium were specified on the basis of expressions (4) and (7). In the final step, we evaluate the risk-reducing effectiveness of insurance contracts by comparing the risk of wheat yield revenues with and without insurance using the conditional value at risk - a downside risk measure (McNeil et al., 2005). In our empirical application we define downside risk as probability of the index realization below the third decile (p=0.3) of index marginal distribution. Consequently, the conditional value at risk is computed as $ES = \frac{1}{0.3}\int_{p=0}^{0.3} q_p dp$ with q_p being the yield distribution *p*-quantile.

[3] We measure dependence for vegetation indices computed for weeks between the beginning of June to the mid of September. Traditionally, the period around heading has the highest correlation (0.6–0.8) and drops to the minimum prior to this phase and thereafter.

[4] The Gaussian copula corresponds with the linear correlation concept. Accordingly, the Pearson's correlation coefficient is used to model dependence for this copula.

3. Data

Satellite data were extracted from NOAA's Global Vegetation Index (GVI) data set (http://www.noaa.gov/satellites.html). The GVI is produced from the top of the atmosphere reflectance in the VIS (0.58–0.68 µm), NIR (0.725–1.1 µm) and emission in infrared (IR 10-11 µm) spectral bands, obtained from digital counts recorded by the Advanced Very High Resolution Radiometer (AVHRR) onboard NOAA polar-orbiting satellites in the 'afternoon orbit'. The counts were converted to reflectance by applying pre-launch and post-launch calibration coefficients. The daily observations at 1.1 km resolution were aggregated to 16 km and seven day composites to obtain the data in near real time for the entire globe. In our study, VCI and TCI indices were computed for every pixel and week during the period 1982–2010. Furthermore, average values of VCI and TCI were calculated for the grain cultivation areas in each county studied (for more details on this procedure see Spivak et al, 2008).

The location of the study counties is shown in Figure 1. Three of the counties – Zelinograd (C1), Atbasar (C2) and Esil (C3) – are situated in the Akmola oblast[5], and two of them – Denis (C4) and Kamysty (C5) – are located in the Kostanay oblast. As we could not obtain any data for the borders of single farms and small administrative divisions, the VCI and TCI were collected for all AVHRR-based 16 km pixels inside each county. Mean county's values of these indices were obtained averaging all pixels inside rectangular area covering the principal part of each C1-C5 counties. Since wheat is growing everywhere in each county and is planted in a short period of time (USDA 1994), such aggregation is warranted. Table 1 provides the area of aggregation and the number of the aggregated pixels. Spatial variation of VH indices for these pixels (24-31)

[5] *Oblasts* are largest administrative units in Kazakhstan. They consist of several counties.

did not exceed 12%, which corresponds to variation of precipitation over relatively small areas in Kazakhstan (Kogan et al 2003).

INSERT TABLE 1 ABOUT HERE

Wheat is the most representative crop in Akmola and Kostanay. According to the official statistics for the period 2003–2013, it occupied on average 81.6 % and 80.4 % of the sown areas in Akmola and Kostanay, respectively (National Agency of Statistics of the Republic of Kazakhstan, 2012). Other important crops in these regions are also grains, such as spring barley and oats. Since 1988, the prevalent crop rotation in these two grain producing regions has been fallow-wheat-wheat-barley-wheat (Suleimenov and Akshalov, 2011).

Although Kazakhstan is a large country, the spring wheat calendar is quite similar for many main grain-producing regions (variations in the timing of sowing might result in a difference of one or two weeks at maximum) and from year-to-year. Traditionally, wheat is sown in the last 10-days of May, heading takes place predominantly at the end of June/ beginning July, followed by the ear emergence phase in July and finally ripening and harvesting in August, or at the beginning of September. In general, phenological dates show limited variation between the main grain producing regions in Northern Kazakhstan.

INSERT FIGURE 1 ABOUT HERE

The county and farm yield data for the same time span were obtained from regional statistical offices. The wheat yield time series were tested for structural breaks and adjusted for a time trend using linear, and second- and third-degree polynomial functions. Figure 2 shows the development of average wheat yields in the study counties. It exemplifies that severe droughts in

1984, 1989, 1991, 1995, 1997, 1998 and 2010 caused dramatic yield declines in all five of the study counties.

The marginal distributions of wheat yields and both VH indices were modeled using one of the following distribution families: Normal, Log-normal, Logistic, Log-logistic, Gamma and Weibull distributions. The most appropriate distribution was determined employing the Kolmogorov-Smirnov test.

INSERT FIGURE 2 ABOUT HERE

Summary statistics of index and farm yield data can be found in Table A1 of the appendix.

4. Results and discussion

Our empirical results reveal a relatively strong relationship in the joint distributions of wheat yields and each of two VH indices. The magnitudes of the Pearson's correlation coefficients between wheat yields at the county level and the VH indices range between 0.63 and 0.77 for VCI, and 0.64 and 0.79 for TCI (Table 2). The estimates of dependency between VH indices and county wheat yields are very consistent across all three copula models employed in the study with critical periods coinciding across all four copula models for each county[6]. According to our estimates, the periods with the highest dependence differ only marginally across single counties in the case of VCI. They span the period between weeks 26th (end of June) and 31st (end of July) , which correspond to the phenological phases of "ear emergence" and "grain formation", i.e. the

[6] Dependence parameters for Clayton, Frank, and survival Gumbel copulas have other measurement scales than the Gaussian copula. In the case of the Clayton copula, the dependence parameter is defined in the interval $[-1,\infty)\setminus\{0\}$, for the Frank copula the feasible interval is $[-\infty,\infty)\setminus\{0\}$, and for the Gumbel copula it takes values $[1,\infty)$ (Nelsen, 1998). Higher values of dependence parameters indicate a stronger dependence.

two most influential phases in formation of spring wheat yield. However, we have found more divergent results for TCI. In three of the study counties, Zelinograd, Atbasar and Esil, TCI seems to be mostly influential in weeks 29 (mid July) - 34 (mid August), while for the other two study counties, which are situated in the Northwest of the country, soil surface temperature seems to be decisive for the wheat formation several weeks earlier, namely in weeks 25-29.

INSERT TABLE 2 ABOUT HERE

Using the Cramer-von-Mises criterion we found that the survival Gumbel copula provided best statistical fits for most study farms when modeling the dependence between VCI and farm yields, whereas the Frank copula was more adequate in most cases when estimating dependence of farm yields on TCI. These findings suggest that the sensitivity of wheat yields on VCI can be modeled more adequately by a copula allowing for an asymmetric dependence, namely with a stronger dependence in the left tail of the joint distribution; while the relationship between wheat yields and TCI seems to demonstrate a radial symmetry suggesting the same extent of dependence in the left and right tails of the joint distribution. Considering the above-mentioned results, in the following we reduce the scope of our analysis to results obtained using these two copula models.

Our estimates of relative risk reduction presented in the upper part of table 3 show that the study farms could benefit only to a limited extent from VCI- and TCI-based insurance contracts when selecting relevant indices/periods based on the county average yields. On average, VCI-based insurance could reduce the downside risk of farm wheat yields by 25% when designing insurance contracts on the survival Gumbel copula estimates. The corresponding estimate obtained employing Frank copulas is 22%. TCI-based insurance contracts seem to provide slightly higher relative risk reductions, 29 and 26 % on average for survival Gumbel and Frank copulas, respectively (Table 3). However, the performance of both VCI- and TCI-based insurance contracts vary substantially across single counties and farms. According to our estimates the average risk reduction were the highest in Kamysty county in the case of the VCI-based insurance, while for TCI-based contracts the highest average risk reductions were found for Denis and Kamysty counties.

INSERT TABLE 3 ABOUT HERE

Considering relatively low risk reduction estimates obtained when detecting relevant vegetation weeks based on the county yields, in the next step we examine whether the risk-reducing effectiveness of satellite index-based insurance can be improved when selecting indices on the basis of farm yields. The later procedure caused practically no shift in the relevant periods for most farms from Atbasar county, but for majority of farms from other four counties. For the later, the critical periods moved from one to two weeks later in the case of VCI, spanning overall the period from the 30th to 35th weeks. As for TCI, no considerable changes in critical periods were found for most farms from Atbasar, Esil and Kamysty counties; yet the critical period shifted to an earlier period (weeks 27-30) for most farms from Zelinograd county and to a later period (by one week) for farms from Denis county. Results presented in the lower part of Table 3 show that the farm-yield-based index selection procedure attained substantially higher risk reductions than the county-yield-based procedure for farms from Zelinograd, Kamysty and Denis counties in the case of VCI-based contracts. A small increase in the average risk reduction due to VCI-based insurance contracts is also observable for farms from Esil county. However, the average risk reduction hardly changed for the study farms from Atbasar county, since, as mentioned above, the period for measuring VCI did not change between county-based and farm based procedures for most farms in this county. The risk reducing performance of the TCI-based contracts did not show considerable differences between two procedures employed for index selection.

For the VCI insurance, the highest risk reductions were found for farms from Zelinograd and Kamysty counties with the average estimates of 0.57 and 0.52, respectively. A group of farms from Denis county would also benefit from VCI-based insurance. However, most farms in this county would achieve higher risk reductions using TCI-based contracts. The average risk reduction estimates for farms in Atbasar and Esil were found to be very low for both VCI- and TCI-based insurance contracts. We believe that a low risk reduction for these two counties could be explained by quality of yield or satellite data rather the lack of dependence between yield and VH indices in these two counties in general.

Furthermore, our estimates for both types of contracts suggest that a higher effectiveness of insurance contracts is attained using the survival Gumbel copula. This finding might be surprising taking into account that Frank copulas showed a better fit for most farms when modeling the dependence of farm yields on TCI. It can be explained by the fact that the goodness-of-fit test evaluates copula models considering the entire interval of the distribution. Accordingly, it selects a copula model that shows a good fit in both tails of the joint distribution. Given that the survival Gumbel copula shows a strong left tail dependence and a relatively week right tail dependence, it might be tested as showing a worse fit than a copula with radial symmetry in the case of joint distributions with a considerable magnitude of dependence in the right tail. However, the later would not assure that the radial copula provides the best fit in the left tail of the distribution. In the context of our empirical analysis, this implies that the Frank copula might show best fits when evaluating the entire interval of joint distributions of TCI and farm yields, but the survival Gumbel copula might be better suited to model left tail dependence between TCI and farms yields. Actually, our empirical results support the conclusion that the relationship between TCI and study farm yields in the left tail can be better captured by survival Gumbel copulas.

INSERT FIGURE 3 ABOUT HERE

Our study results show that the performance of both index-based insurance schemes varies substantially not only among study counties (Table 3) but also among single farms within counties (Figure 4). While a number of farms could achieve considerable risk reductions (for a group of 16 farms risk reduction estimates are found to be above 50%), there is a number of farms (12 farms primarily in Atbasar and Esil counties) for which risk reduction was estimated to be below 25%. For remaining 19 farms, we have found only moderate magnitudes of risk reduction, between 25 and 50%. The later finding implies that the indices used in our analysis do not sufficiently represent vegetation conditions for some study farms. This might happen because we used relatively low resolution AVHRR data. Additionally, our indices were measured at the county level, not for single farm parcels. This procedure could negatively affect the performance of the VCI- and TCI-based insurance contracts.

If comparing VCI- and TCI-based insurance contracts for single farms (Figure 4), one can see that there is an only small group of farms that would attain higher or comparable risk reductions using TCI-based contracts instead of VCI-based contracts. These later farms are situated in Denis county. This finding suggests that there are some local effects that cause TCI slightly outperform VCI in this county.

Finally, we want draw attention to a high variation in risk reduction estimates within single counties. These differences might be related to both geographical location and soil specifics, and technological aspects of production. During the Soviet time farms used relatively similar technologies, whereas since the mid-1990s there have been considerable differences in technologies applied and intensities of input use among single farms. These later differences may explain considerable deviations in productivity and risk exposure at the farm level.

5. Conclusions

This paper analyses the applicability of two satellite-based VH indices–VCI and TCI–to insure yield losses of wheat-producing farms in Kazakhstan. The methodological contribution of the study consists in applying the copula approach for estimating dependence between VH indices and crop yields, and designing and rating insurance contract. The empirical relevance of the study relies on the use of the farm yield time series and the application of satellite data for the development of index-based insurance for grain crops.

Different copula models were employed and tested for their adequacy to represent the dependence structure in the tails of joint distributions of two VH indices and wheat yields. Our empirical results for wheat-producing farms in Kazakhstan showed that survival Gumbel copula provided a better fit when modeling joint distributions of farm wheat yields and VCI, while Frank copulas showed a better performance in describing dependence of farm yield on TCI.

Furthermore, our analysis revealed that the performance of the satellite-based VH index insurance varies substantially among farms: while for one third of sample farms yield risk could be reduced by 70% on average, for a quarter of sample farms risk reduction was estimated to be

16%. These findings suggest that in general VH indices can provide a solid basis for detecting drought-related yield losses. However, their performance strongly depends on quality of yield and satellite data, as well as regional and local specifics. The effectiveness of the satellite-based VH index insurance can be improved by employing satellite data of a higher resolution, using more sophisticated way of time aggregation of VH indices, and constructing VH indices for single farms. Multi-year weekly indices at 4 km resolution are currently available from NOAA web (http://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/index.php). Another options to increase risk-reducing effectiveness of satellite index-based insurance would be to (a) complement it with information on crop sowing dates for more accurate selection of critical periods in plants' response to weather; (b) use VHI (combined VCI and TCI), which often correlates stronger with crop yield than individual indices (Kogan et all 20115, Kogan et all 2012).

Finally, differences in the risk reduction estimates between two index selection procedures based on county yields and farm yield suggest that index-based insurance, designed by using aggregate index and yield data, could involve a relatively high basis risk, that might affect the demand for this kind of insurance. This puts a premium on the development of insurance products based on more precise data, i.e. farm-level yields and higher resolution satellite data.

Acknowledgement

The authors thank financial support of the Swiss National Science Foundation within its Program of Scientific Co-operation between Eastern Europe and Switzerland (SCOPES).

References

Barnett, B. J., Barrett, C. B., Skees, J. R. 2008. Poverty traps and index-based risk transfer products. *World Development*, 36(10), 2045-2102.

Bokusheva, R., Breustedt, G. 2012. The effectiveness of weather-based index insurance and area-yield crop insurance: How reliable are ex post predictions for yield risk reduction? *Quarterly Journal of International Agriculture*, 51(2), 135-156.

Bokusheva, R. 2014. Improving the effectiveness of weather-based insurance: An application of copula approach. Working paper, MPRA (Munich Personal RePEc Archive).

Bokusheva, R. 2011. Measuring dependence in joint distributions of yield and weather variables. *Agricultural Finance Review* 71(1), 120-141.

Breustedt, G., Bokusheva, R., Heidelbach, O. 2008. The potential of index insurance schemes to reduce farmers' yield risk in an arid region. *Journal of Agricultural Economics*, 59(2), 312-328.

Claassen, R., Just, R.E. 2010. Heterogeneity and distributional form of farm-level yields. *American Journal of Agricultural Economics* 93, 144-160.

Coles, S. 2001. An introduction to statistical modeling of extreme values. Springer London..

Embrechts, P., McNeil, A., Straumann, D. 2002. Correlation and dependence in risk management: properties and pitfalls In: Risk Management: Value at Risk and Beyond, ed. M.A.H. Dempster, Cambridge University Press, Cambridge, 176-223.

Goodwin, B.K., Hungerford, A. 2015. Copula-based models of systemic risk in U.S. agriculture: Implications for crop insurance and reinsurance contracts. *American Journal of Agricultural Economics* (in press).

Hazell, P, Anderson, J., Balzer, N., Hastrup Clemmensen, A., Hess, U., Rispoli, F. 2010. Potential for scale and sustainability in weather index insurance for agriculture and rural livelihoods. International Fund for Agricultural Development and World Food Programme.

Lui, W.T. and F.N. Kogan. 1996. Monitoring regional drought using the vegetation condition index. *International Journal of Remote Sensing* 17, 2761-2782.

Kellner, U., Musshoff, O. 2012. Precipitation or water capacity indices? An analysis of the benefits of alternative underlyings for index insurance. *Agricultural Systems* 104, 645-653

Kogan, F., Guo, W., Strashnaia, A., Kleshenko, A., Chub, O., Virchenko, O. 2015. Modelling and prediction of crop losses from NOAA polar-orbiting operational satellites. *Geomatics, Natural Hazards and Risk* (in press).

Kogan, F., Salazar, L., Roytman., L. 2012. Estimation of crop production using satellite-based vegetation health indices in Kansas. *International Journal of Remote Sensing* 33(9), 2798-2814.

Kogan, F., Gitelson, A., Zakarin, E., Spivak, L., Lebed, L. 2003. AVHRR-based spectral vegetation index for quantitative assessment of vegetation state and productivity: Calibration and validation. *Photogrammetric engineering and remote sensing*, 69(8), 899-906.

Kogan, F.N. 1998. A typical pattern of vegetation conditions in southern Africa during El-Nino years detected from AVHRR data using three-channel numerical index. *International Journal of Remote Sensing*, 19(18), 3689-95.

Kogan, F. N. 1995. Drought of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. *Bulletin of the American Meteorological Society* 76, 655-668.

Mainik, G., Schaanning, E. 2012. On dependence consistency of CoVaR and some other systemic risk measures. RiskLab, Department of Mathematics, ETH Zurich (http://arxiv.org/pdf/1207.3464v3.pdf).

Makaudze, E.M., Miranda, M.J. 2010. Catastrophic drought insurance based on remotely Sensed normalized difference vegetation index for smallholder farmers in Zimbabwe. Agrekon 49(1), 418-432.

McNeil A, Frey R, Embrechts P. 2005. Quantitative Risk Management, Princeton University Press, Princeton.

Miranda, M.J., Farrin, K. 2012. A index insurance for developing countries. *Applied Economic Perspectives and Policy*, 34 (3), 391-427.

National Agency of Statistics of the Republic of Kazakhstan. http://www.stat.kz/digital/selskoe_hoz/Pages/default.aspx, accessed on January 11, 2012.

Nelsen, R. B. 1999. An Introduction to Copulas. Springer, New York.

Skees, J. R., Black, J. R., Barnett, B. J. 1997. Designing and rating an area yield crop insurance contract. *American Journal of Agricultural Economics* 79, 430-438.

Sklar A. 1959. Fonctions de répartition à n dimension et leurs marges, *Publ. Inst. Stat. Univ. Paris*, 8, 299-231.

Spivak, L., Vitkovskaya, I., Batyrbaeva, M. 2008. Analysis of intra-seasonal variations in the productivity of vegetation in Kazakhstan, using time series remote sensing. *Bulletin of National Academy of Sciences of the Republic of Kazakhstan: Series in Physics and Mathematics* 4, 29-32.

Suleimenov, M.K., Akshalov, K.A. 2011. Productivity and quality of spring wheat grain subject to cultivation technology, crop rotation and weather. Bulletin of Agricultural Sciences of Kazakhstan 630, 17-21.

Turvey, C. G. 2001. Weather derivatives for specific event risks in agriculture. *Review of Agricultural Economic*s 23, 333-351.

Unganai, L.S., Kogan, F.N. 1998. Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. *Remote sensing of environment*, 63(3), 219-232

USDA Foreign Agricultural Service. Kazakhstan - 2011 Grain and Feed Annual Report. http://gain.fas.usda.gov/, accessed on January 11, 2012.

USDA 1994. USDA Agricultural Handbook, Handbook No 664. *Major World Crop Areas and Climate Profile*, 157-170.

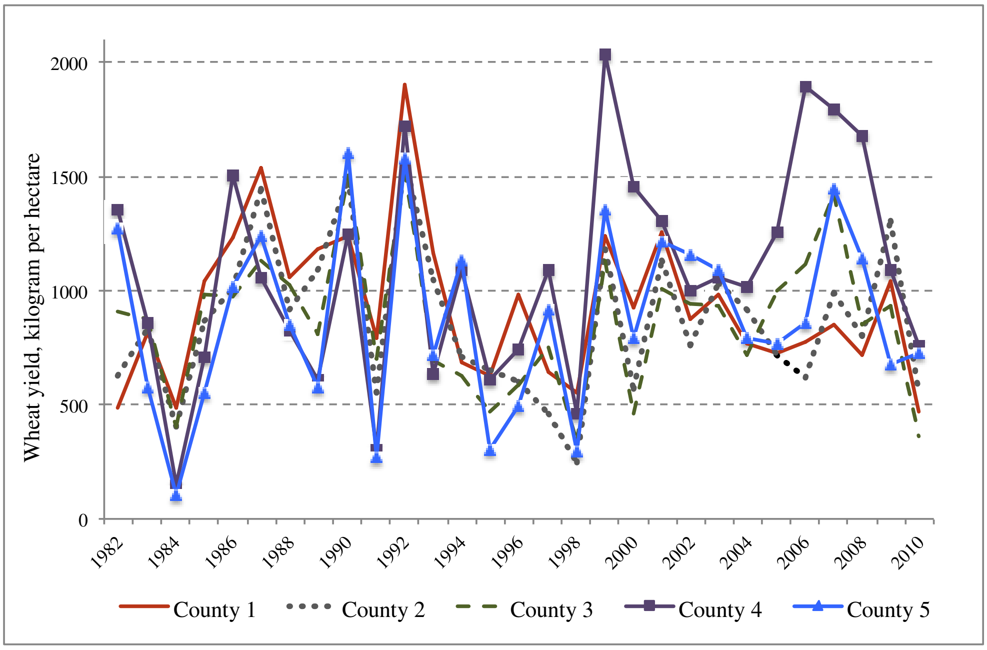
Vedenov, D.V. 2008. Application of copulas to estimation of joint crop yield distributions. Contributed paper at the Annual Meeting of the AAEA 2008, Orlando, USA, July 27-29.

Vedenov, D. V., Barnett, B. J. 2004. Efficiency of weather derivatives as primary crop insurance instruments. *Journal of Agricultural and Resource Economics* 29, 387-403.

FIGURES

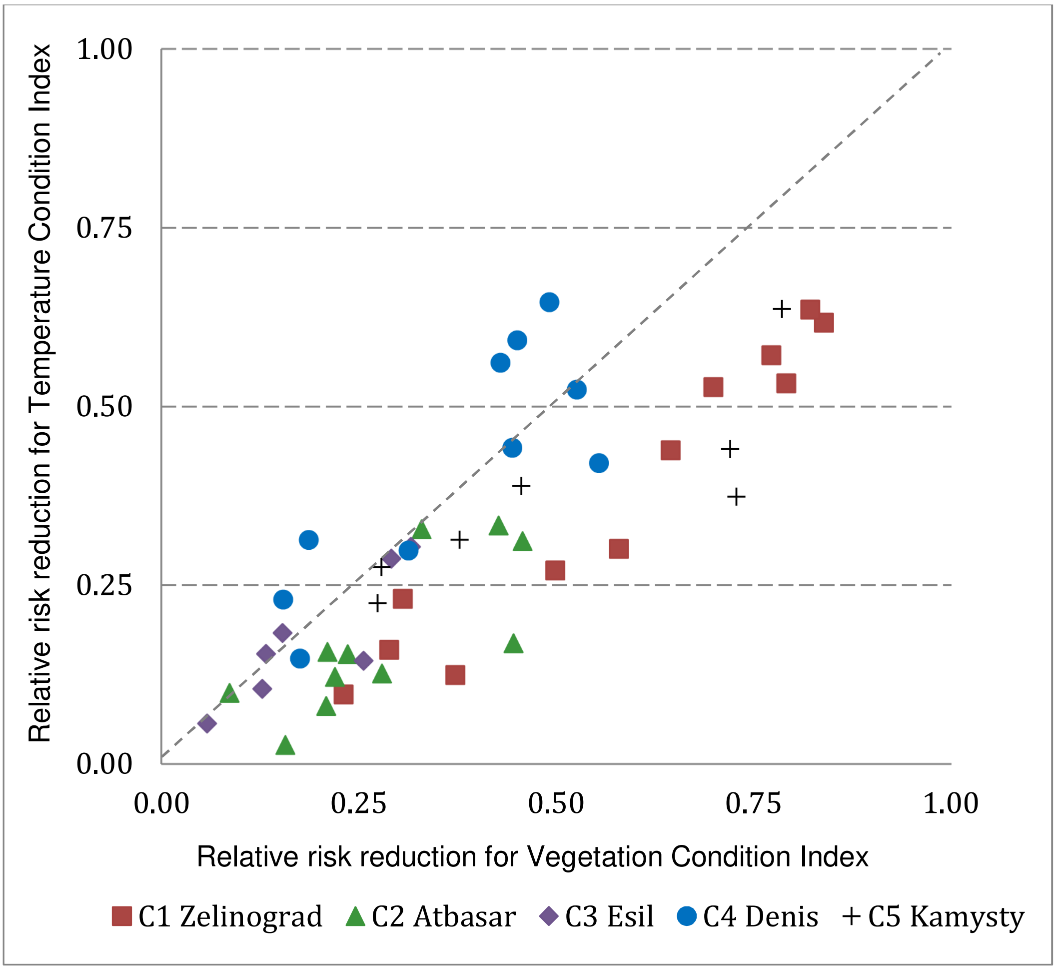
Note: 1 – Zelinograd county, 2 – Atbasar county, 3 – Esil county, 4 – Denis county, 5 – Kamysty county.

Figure 1. Location of the study counties



Source: Regional offices of statistics

Figure 2. Wheat yield time series for 5 study counties from 1982 to 2010



Note: each point corresponds with a sample farm and shows relative risk reduction due to insurance based on Vegetation Condition Index (x-axis) and Temperature Condition Index (y-axis).

Figure 3. Relative risk reduction estimates for two satellite-based vegetation health indices, Vegetation Condition Index and Temperature Condition Index, using survival Gumbel copula model

TABLES

Table 1. Aggregation of VH pixels within each county

Oblast	Region	Number on the Fig 1 map	Latitude range, °N	Longitude range, ° E	Number of pixels
Akmola	Zelinograd	1	50.4-51.2	71.2-72.0	30
	Atbasar	2	50.7-51.7	68.2-68.9	24
	Ezil	3	51.4-51.8	66.0-67.3	25
Kostanay	Denis	4	52.0-52.5	61.3-62.4	27
	Kamysty	5	50.8-51.4	61.5-62.6	31

Source: https://ru.wikipedia.org/wiki/

Table 2. Copula dependence parameter estimates at the county level

County	week	Gaussian	Clayton	Frank	surv. Gumbel
VCI					
C1 Zelinograd	28-31	0.69	1.86	5.42	1.93
C2 Atbasar	29-32	0.78	2.10	5.95	2.05
C3 Esil	29-32	0.64	1.94	2.67	1.79
C4 Denis	28-31	0.64	1.59	4.79	1.80
C5 Kamysty	26-29	0.70	1.97	5.60	1.97
TCI					
C1 Zelinograd	31-34	0.72	1.41	4.34	1.70
C2 Atbasar	31-34	0.75	0.89	4.07	1.45
C3 Esil	29-32	0.64	1.76	2.80	1.79
C4 Denis	25-28	0.71	1.90	5.52	1.95
C5 Kamysty	26-29	0.79	1.94	5.26	1.97

Note: the estimates for the Gaussian copula correspond with the respective values of the Pearson correlation coefficient.

Table 3. Downside risk reduction estimates for VCI and TCI (two index selection alternatives)

County	VCI		TCI	
	surv Gumbel	Frank	surv Gumbel	Frank
County-yield based index selection				
C1 Zelinograd	0.28	0.25	0.34	0.32
C2 Atbasar	0.28	0.24	0.17	0.14
C3 Esil	0.12	0.10	0.15	0.12
C4 Denis	0.14	0.12	0.39	0.37
C5 Kamysty	0.44	0.40	0.38	0.34
Whole sample	0.25	0.22	0.29	0.26
Farm-yield based index selection				
C1 Zelinograd	0.57	0.52	0.38	0.34
C2 Atbasar	0.26	0.22	0.17	0.15
C3 Esil	0.18	0.14	0.16	0.12
C4 Denis	0.37	0.35	0.42	0.39
C5 Kamysty	0.52	0.48	0.38	0.34
Whole sample	0.39	0.35	0.30	0.27

APPENDIX

Table A1. Summary statistics of index and farm yield data, 1982-2010

	Mean	SD	Min	Max
Farm yields				
C1 Zelinograd: 12 farms	8.9	3.8	0.2	24
C2 Atbasar: 11 farms	8.8	3. 8	0.8	21
C3 Esil: 7 farms	8.3	3.4	1.2	19.3
C4 Denis: 10 farms	10.7	5.1	0.9	25.6
C5 Kamysty: 7 farms	9.2	3.9	0.3	22.1
VCI (weeks 22-36)				
C1 Zelinograd	42.2	21.8	1.4	96.1
C2 Atbasar	42.2	22.2	0.1	98.1
C3 Esil	43.1	24.2	4.0	98.4
C4 Denis	41.0	23.8	2.1	100.0
C5 Kamysty	38.4	21.5	1.4	99.9
TCI (weeks 22-36)				
C1 Zelinograd	51.0	23.7	3.1	98.1
C2 Atbasar	51.4	22.7	1.9	97.4
C3 Esil	51.8	24.3	1.0	99.0
C4 Denis	54.5	26.2	1.3	100.0
C5 Kamysty	49.5	24.5	1.8	99.1