RISK METHODS AND THEIR APPLICATIONS IN AGRICULTURE

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Abstract. In agriculture we face several decision problems in which, among proficiency and sustainability, the risk aspects have to be investigated more and more seriously. In Hungary the risk of production is especially meaningful as it has considerably been increased in the last few decades. In this paper we review those risk analysis methods which are very useful in climate change impact research. We give a case study of the application of the described methods in which we prove that the risk of corn and wheat production has increased between 1951 and 1990 in four Hungarian regions (Hajdú-Bihar, Bács-Kiskun, Fejér and Győr-Moson-Sopron), independently to the rate of absolute risk aversion. In some regions the rate of increase became even quicker.
Keywords: *risk of production, Phillips-method, efficiency criteria, climate change, decision analysis*

Introduction

Considering risk in agriculture is nowadays more necessary than ever. With climate change the consequences of all decisions are becoming more and more serious, especially in agricultural production. In this paper we review some results and give a case study.

Review of literature

Risk analysis is quite a young discipline, the base of which was established by Knight, in 1933. After some decades the structure of risk analysis was very similar in the books of Raiffa (1968) and Schlaifer (1959, 1969). Risk analysis started to improve dinamically in the end of the 70s which can be noticed in the books of the 80s with the main principles of the field (Barry (1984), Lindley (1985), Robison and Barry (1987), illetve Gregory (1988)). In some works the risk of agriculture is considered with high relevance (Halter and Dean (1971), Dillon (1971)).

Risk analysis is surveyed with deep mathematical tools in Spetzler and von Holstein (1975), Smith (1988), Smith and Mandac (1995) and Pratt et al. (1995).

The book of Anderson et al. (1977) is mighty comprehensive with several agricultural applications and the operation research aspects are considered as well.

In Clemen (1996) a general description of modern risk analysis with data management and decision analysis can be found.

Just (2003) gives an outlook to the possible improvements in the following 25 years, especially with respect of agricultural risk.

The book of Hardaker et al. (2004) is an excellent monography in which there is a special emphasis on agricultural risk.

Notations

Let us denote one of the decisions, between which the decision maker (DM) must choose by a_j ($a_j \in A$, the set of possible choices), the uncertain states of nature by S_i ($i \in I$, $j \in J$, I and J are sets of indexes) and their (subjective) probability with $P(S_i)$. The consequencies of the jth act supposed the state S_i are denoted by X_{ij}.

The axioms of decision analysis

Let us accept the following version of the axioms of decision analysis as the base of our survey (Anderson et al., 1977):

There is an ordering $<$ on the set A, namely if $a_1, a_2 \in A$ then exactly one of the following holds:

$a_1 < a_2$ $\qquad$ $a_2 < a_1$ $\qquad$ $a_1 = a_2$

where $a_1 < a_2$ means that the DM prefers a_2, $a_1 = a_2$ means that the DM is indifferent between the two decisions.

The relation $<$ is transitive.

The relation $<$ is continuous. If $a_1 < a_2 < a_3$, then there exists $0 < P(a_1) < 1$ and $P(a_3) = 1 - P(a_1)$ such that $a_1 = a_2 = a_3$ with these subjective probabilities.

The relation $<$ is independent. If $a_1 < a_2$ with $P(a_1) = P(a_2)$, then for any other $a_3 \in A$: $(a_1 \text{ AND } a_3) < (a_2 \text{ AND } a_3)$.

With the help of the above axioms the Bernoulli's principles (1738) can be formulated. (Also called by the subjective expected utility – SEU – hypothesis.)

Under the conditions of the above axioms there exists a utility function $U : A \to \mathbf{R}$ for which

If $a_1, a_2 \in A$ $a_1 < a_2$ holds, then $U(a_1) < U(a_2)$.

The DM's utility function can be expressed as the function of the decisions:

$U(a_j) = \sum_i U(a_j \mid S_i) \cdot P(S_i)$ for discrete probability;

$U(a_j) = \int U(a_j \mid S) \cdot P(S) dS$ for continuous probability);

or as the function of the certainty equivalent of the decisions (CE_j):

$U(a_j) = U(CE_j)$.

Certainty equivalent is the value "for sure" that would make the DM indifferent to facing the risky prospect or to accept the value "for sure" with $\min_i(X_{ij}) < CE_j < \max_i(X_{ij})$ (Hardaker et al., 2004).

The function U is invariant to a positive linear transformation.

Based on the above axioms and principles risk analysis can be structured in an exact way (Savage, 1954, Edwards, 1992, Quiggin, 1993).

General problems of data management

In several cases one of the main problems in agricultural surveys that there is no available data of necessary quality and/or quantity. The problem has its objective reasons: detailed and unique monitoring and data management do not have a long history.

In case of sparse data we need to think over thoroughly how we can get the most information from the few data. One of the most evident ways of gaining more information is to take experts' opinion into consideration.

Relative frequency contra subjective probability

In classical probability it is mostly assumed that abundant and relevant data are available (theoretically an infinite number of possible experiments). In these cases the use of relative frequency to estimate probability is quite evident. It occurs several times in agricultural surveys, however, that probability estimations for such kinds of events are needed that

- happen quite rarely (e.g. catastrophes) or
- are changing in time not accidentally (prices).

In these occasions relative frequency estimations are not suitable.

In the recent past a new school of thought has developed. According to this, a probability can be defined as the 'degree of belief' (called subjective probability) which is mainly based on experts' estimations. This kind of estimation is, of course, subjective, though experience has proved its relevancy (Wright and Ayton, 1994, Phillips, 1971).

Subjective probability and the way of defining the distribution function from it have both widely applied literatures (Raiffa, 1968, Anderson, Dillon and Hardaker, 1977, Lindley, 1985, Clemen, 1996).

Elicitation of the distribution function in case of sparse data

The judgemental fractile method is based on subjective experts' estimations (Hardaker et al., 2004). First, we ask our respondent to estimate the range of the distribution (x_0, x_{n+1}). Further on it is supposed that $F(x) = 0$, if $x \le x_0$ and $F(x) = 1$, if $x > x_{n+1}$. Next the interval (0 , 1) should be divided into $n+1$ parts:

$$y_i := \frac{i}{n+1} \qquad (i = 0, 1, ..., n+1)$$

and the following values of the distribution functions are asked to be estimated: $F(x_i) = y_i$ $(i = 0, 1, ..., n+1)$. The estimated points of the distribution function can be approximated and smoothed with other known methods.

Phillips-method

If historical data are available it is reasonable to use them combined with subjective judgements. Phillips (1971) has given a smart method for the case when the data are obsolete and thus not relevant for future conclusions any more. The method involves the following steps:

First, the subjective mean and standard deviation of the subjective distribution have to be elicited. To this several known estimations can be used, e.g. the triangular distribution method: $E_s = \dfrac{a+b+m}{3}$, $D_s = \dfrac{(b-a)^2 + (m-a)(m-b)}{18}$.

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where a, b and m are the highest, the lowest and the most likely values of the distribution, respectively.

Next, the historical data have to be corrected with trend. To this we can apply an appropriate regression function f with residuals $\varepsilon_i = y_i - f(x_i)$. Then the corrected data can be defined as

$$\hat{y}_i = f(x_{\mathrm{curr}}) + \varepsilon_i$$

where $f(x_{\mathrm{curr}})$ denotes the current regression value taken in the most current point x_{curr}.

The values $\hat{y}_i$ should be weighted with appropriate probabilities p_i assessed by considering the current likelihoods of the occurrences of the adequate conditions in the past. If there is no basis for such assignment, all p_i should be chosen equally. Obviously $\sum_i p_i = 1$.

The mean and standard deviation have to be defined with the help of the weighted corrected data: $E = \sum_i p_i \hat{y}_i$, $D = \sqrt{\sum_i p_i (\hat{y}_i - E)^2}$.

The data adequate for the further survey are then: $Y_i = E_{\mathrm{s}} + \frac{\hat{y}_i - E}{D} \cdot D_{\mathrm{s}}$. It is easy to see that $E(Y_i) = E_{\mathrm{s}}$ and $D(Y_i) = D_{\mathrm{s}}$.

Risk aversion

It is evident that most of DMs are risk averse. If they can choose between two decisions with the same expected mean, they would choose the one which is less risky. This aversion to risk has to seriously be taken into account while preparing decisions.

Considering risk aversion we can define the utility ordering amongst decisions much more precisely.

Utility function elicitation

Utility function U can be elicited in several ways. We call for the socalled ELCE (*Equally Likely Certainty Equivalent*) method due to Anderson et al. (1977). Let us use the following notations: $(a_1, a_2, ...)$ are decisions with a set of possible payoffs $(X_1, X_2, ...)$ with probabilities $(p_1, p_2, ...)$, shortly $(X_1, X_2, ...; p_1, p_2, ...)$. We denote by ~ the DM's indifference between the risky decisions $(a_1, a_2, ...)$ and the sure one a_s: $(X_1, X_2, ...; p_1, p_2, ...) \sim (X_s; 1)$.

The sequence of the elicitation is as follows:

- Let us denote by a the lowest and by b the highest payoff of interest. Then we say that $U(a) = 0$ and $U(b) = 1$.
- Estimate c such that $(a, b; 0.5, 0.5) \sim (c; 1)$. Then we get $U(c) = 0.5 \cdot U(a) + 0.5 \cdot U(b) = 0.5$.

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- Estimate d and e such that $(a, c; 0.5, 0.5) \sim (d; 1)$ and $(c, b; 0.5, 0.5) \sim (e; 1)$. Then we get $U(d) = 0.5 \cdot U(a) + 0.5 \cdot U(c) = 0.25$ and
$$U(e) = 0.5 \cdot U(c) + 0.5 \cdot U(b) = 0.75.$$
- Estimate f such that $(d, e; 0.5, 0.5) \sim (f; 1)$. Then we get $U(f) = 0.5 \cdot U(d) + 0.5 \cdot U(e) = 0.5$.

Of course, we can go on with the method as long as we gain so many points that are needed to reach the necessary accuracy. Finally, we plot the points of the utility function (*Fig. 1*). The so called ELRO method (Equally Likely Risky Outcomes) is quite similar to the ELCE one with the difference that in this method those pairs of values c, d are elicited for which $(a, d; 0.5, 0.5) \sim (b, c; 0.5, 0.5)$. For the detailed advantages and disadvantages of these two methods, moreover, for a comparison of ELCE and ELRO methods one can see Hardaker et al. (2004).

$U(a) = 0$ and $U(b) = 1$
$(a, b; 0.5, 0.5) \sim (c; 1)$
$\quad \Rightarrow U(c) = 0.5$
$(a, c; 0.5, 0.5) \sim (d; 1)$
$\quad \Rightarrow U(d) = 0.25$
$\quad (c, b; 0.5, 0.5) \sim (e; 1)$
$\quad \Rightarrow U(e) = 0.75$
$(d, e; 0.5, 0.5) \sim (f; 1)$
$\quad \Rightarrow U(f) = 0.5$

and

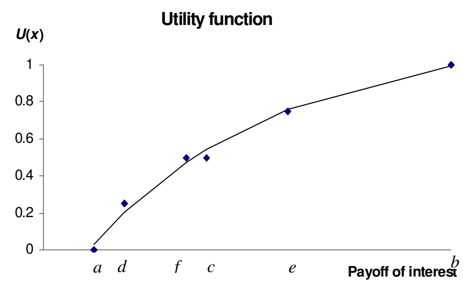

Figure 1. *Utility function elicitation with ELCE method. Decision depends not only on possible payoffs but also on the DM's risk aversion. Considering risk aversion we can define the utility ordering amongst decisions much more precisely.*

Absolute and relative risk aversion

The shape of utility function U gives further information on risk aversion. Generally, the DM is risk averse if the utility function is concave and prefers risk if U is convex. The greater the absolute value of the second derivative of U is the greater the risk averse is.

The absolute risk aversion $r_a(w)$ and the relative risk aversion $r_r(w)$ are defined by

$$r_a : \mathbf{R} \to \mathbf{R} \quad w \mapsto r_a(w) = -\frac{U^{(2)}(w)}{U^{(1)}(w)} \qquad\qquad r_r : \mathbf{R} \to \mathbf{R} \quad w \mapsto r_r(w) = w r_a(w)$$

where w is for wealth (Pratt, 1964, Arrow, 1965).

Anderson and Dillon (1992) provides a classification for relative risk aversion (*Table 1*).

Table 1. *Classification for relative risk aversion due to Anderson and Dillon (1992)*

$r_r(w)$	0.5	**1.0**	2.0	3.0	4.0
The rate of risk aversion	low	**normal**	high	very high	extrem high

Hardaker et al. (2004) reformulate the above classification with using the rate of the maximum percent of the current wealth which is ready to be steaked if there is 50% chance to increase it by 20% (*Table 2*).

Table 2. *Classification for relative risk aversion due to Hardaker et al. (2004)*

Maximum stake percent of wealth	20%	18%	**17%**	14%	12%	11%
$r_r(w)$	0.0	0.5	**1.0**	2.0	3.0	4.0

There are different categories of risk aversion depending on how it is changing with increasing wealth (Eeckhoudt and Gollier, 1966, Hamal and Anderson, 1982) (*Table 3*).

Table 3. *Categories of risk aversion according to how it changes with increasing wealth*

If w wealth is increasing then		
r_a	increasing	IARA (***I****ncreasing* ***A****bsolute* ***R****isk* ***A****version*)
	constant	CARA (***C****onstans* ***A****bsolute* ***R****isk* ***A****version*)
	decreasing	DARA (***D****ecreasing* ***A****bsolute* ***R****isk* ***A****version*)
r_r	increasing	IRRA (***I****ncreasing* ***R****elative* ***R****isk* ***A****version*)
	constant	CRRA (***C****onstans* ***R****elative* ***R****isk* ***A****version*)
	decreasing	DRRA (***D****ecreasing* ***R****elative* ***R****isk* ***A****version*)

Table 4 shows some generally applied utility functions. They are widely used especially when there is no way to consult with the DM, thus his personal utility function can not be elicited.

Table 4. *The mostly applied general utility functions*

CARA/ CRRA	Negative exponential	$U : w \mapsto 1-\exp(-cw)$	$r_a(w)=c$	$r_r(w)=cw$
CRRA/D ARA	Logarithmic	$U : w \mapsto \ln w \quad w>0$	$r_a(w)=1/w$	$r_r(w)=1$
	Power	$U : w \mapsto [1/(1-r)]w^{1-r} \quad w>0$	$r_a(w)=r/w$	$r_r(w)=r$

The mostly used utility function is the logarithmic one which is postulated by D. Bernoulli (1738). For more interesting and useful utility functions see Farquhar and Nakamura (1987), Nakamura (1996), Bell (1988) ands Saha (1993).

Note that risky outcomes can be expressed not only in terms of wealth but also of gains or losses (Hardaker, 2004, Meyer, 2001).

Hardaker et al. (2004) and Pannel et al. (2000) analyse in which cases risk aversion is reasonable to be taken account and in which cases it can be neglected (see also Anderson and Hardaker, 2003 and Hardaker, 2000).

As utility functions are invariant (SEU hypothesis 4), the utility functions due to different persons are not comparable. From this the so called *Impossibility Theorem* was deduced by Arrow (1963): in the case of group decision there no utility function exists without violating some conditions of the individual DMs. For the suitable handling of this problem, see Raiffa (1968) as well as Anderson, Dillon and Hardaker (1977).

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Efficiency criteria

E,V-efficiency criterion

E,V-efficiency criterion is based on a very simple proposition, namely if there are two decisions a_1 and a_2 with $E_1 \geq E_2$ and $V_1 \leq V_2$ (where at least one of the relations is strict), than $a_1 > a_2$, that is to say the DM prefers a_1 to a_2. The criterion is exact if the DM has a normal outcome distribution and a quadratic utility function which is usually not the case. Thus, *E,V*-efficiency criterion should be used as an approximate rule, only. Moreover, in most cases there is no entire ordering between the alternatives. As it is very straightforward and does not need much information, however, it can be applied with success when a great set of decisions should be reduced. That's why the criterion is very popular in practice (Hardaker et al., 2004).

The mean and the variation of the distribution have to be calculated and plotted.

$$E = \sum_i \left(F_{i+1} - F_i\right) \frac{(x_{i+1} + x_i)}{2},$$

$$V = \sum_i \left(F_{i+1} - F_i\right) \frac{x_{i+1}^2 + \left(x_{i+1}x_i\right)^2 + x_i^2}{3} - E^2.$$

$a_1 > a_2$ if the *E,V* point of a_2 lies in the 'north-west' quadrant of the *E,V* point of a_1. If there is no point lying in the 'north-west' quadrant of an *E,V* point, then we say that it belongs to the *E,V* efficient set, that is to say, the point belongs to 'one of the best alternatives'.

A criterion based on the utility function

Let us set out from a negative exponential utility function $U: w \mapsto 1 - \exp(-cw)$. In order to estimate the certainty equivalent CE, we take the Taylor series expansion of the utility function in a region of the mean (Freund, 1956): $CE = E - 0.5cV$. From this we get the approximated functions $U_i : V_i \mapsto E_i - 0.5 r_a V_i$ for each alternative where r_a denotes the absolute risk aversion constant. Illustrate the utility functions for fixed CE values: $U_{i,CE} : V_i \mapsto CE + 0.5 r_a V_i$ that we call indifference curves. According to the criterion based on the utility function, the best alternative for a fixed degree of absolute risk aversion lies on the highest indifference curve (with the greatest value of CE).

Stochastic dominance

a_1 and a_2 are two alternatives with probability distributions F_1 and F_2, respectively. We say that $a_1 > a_2$ (a_1 dominates a_2 in first-degree sense) if $F_1(x) \leq F_2(x)$ ($x \in \mathbf{R}$) and there is a strict inequality at least in one point x. The disadvantage of the first-degree stochastic dominance is that in most cases the distribution functions cross each other which means, that there is no ordering between the alternatives. The rule is, however, suitable for alternative set reducing, again, like *E,V* efficiency criterion.

Having a smaller alternative set we can go on with the second-degree stochastic dominance which can be applied if the conditions for the first and second derivatives of the utility function $U^{(1)} > 0$ and $U^{(2)} < 0$ hold. Then $a_1 > a_2$ (a_1 dominates a_2 in

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second-degree sense), if $\int_{-\infty}^{x} F_1(t)dt \leq \int_{-\infty}^{x} F_2(t)dt$ ($x \in \mathbf{R}$) with a strict inequality at least in one point x.

There are examples in the literature when third-degree dominance is used, nevertheless there is a reasonable doubt whether it is really useful (Anderson et al., 1977).

Stochastic dominance criteria can be extended in the following way: we create a convex combination of the distribution functions such that it dominates an alternative in a certain stochastic dominance sense. Then the dominated alternative can be eliminated from the alternative set, thus in every step the size of the set can be reduced (Drynan, 1986).

Generalized stochastic dominance

The generalized stochastic dominance criterion is a stronger method than the above ones because the risk aversion and the utility function are both taken into account (Goh et al., 1989). First the interval I_r, which contains the value of the risk aversion with great probability, is fixed. Then the utility function has to be estimated with the help of the absolute risk aversion r_a. Based on the approximated utility function first and second order stochastic dominance relations are tried to be found.

This method was simplified by Hardaker et al. (2004) in a very smart way. By the Bernoulli principles the utility function U can be regarded as a function of two variables as it depends on the risk aversion as well:

$$U(x,r) = \int U(t,r) \cdot f(t)dt.$$

From this we get $CE(x,r) = U^{-1}(x,r)$. Supposing a negative exponential utility function both U and U^{-1} can be estimated as:

$$U(x,r_a) = \sum_i \left(F_{i+1} - F_i\right)\left[1 - \frac{\left(\exp(-r_a x_i) - \exp(-r_a x_{i+1})\right)}{r_a\left(x_{i+1} - x_i\right)}\right] \qquad (r_a \in I_r)$$

and

$$CE = \frac{-\ln[1 - U(x,r_a)]}{r_a}.$$

If we illustrate the values CE with respect to the risk aversion, the graph lying the highest points the most preferable alternative. In the case the graphs are crossing each other, we can define the intervals of r_a in which an alternative is better than another.

Materials and methods

Crop and wheat production data (1951-90) in four Hungarian regions (Hajdú, Bács, Fejér and Győr-Moson-Sopron megye) were considered. The data were fitted by logistic regression function of form $f: x \mapsto f(x) = p_1 + \frac{p_2}{1 + \exp[-p_3(x - p_4)]}$ with parameters p_1, p_2, p_3, p_4. (It was quite reasonable to use logistic regression because in Hungary there was a meaningful change in both technology and species at the beginning of the 70s.) Then the *Phillips*-method was applied for making the data comparable.

Based on experts' estimations first the subjective mean and the standard deviation (E_s, D_s) were elicited with triangular distribution estimation.

Secondly, with the residuals of the regression ε_i the data were corrected such as $\hat{y}_i = f(x_{\text{curr}}) + \varepsilon_i$.

Thirdly, with equal weights p_i ($\sum_i p_i = 1$) the mean and standard deviation (E, D) were calculated from which the comparable data Y_i with $E(Y_i) = E_s$ and $D(Y_i) = D_s$ were obtained.

The data of time interval (1951-90) were splitted into three parts: 1951-70, 1961-80, 1971-90. Observing the corn yield we recognized that beside the yield loss caused by the Hungarian political situation at the end of the eighties, the deviation of the yield started to become greater yet at the beginning of the eighties. There was a heavy corn yield loss in 1990, thus we investigated the problem for corn in two ways:

- with tree times twenty years (1951-70, 1961-80, 1971-90) and
- eliminating the year 1990, with a shortened data series (1951-70, 1961-80, 1971-89).

During the survey the most general negative exponential utility function was used.

The *E,V*-efficiency criterion, the criterion based on the utility function and stochastic dominance rules were applied to the three time intervals in order to find out, how the risk of production was changed between 1951 and 1990.

Results

Corn and risk production in four Hungarian regions between 1951-1990

In Hungarian agricultural activity the risk of crop and wheat production has a significant role. With climate change the risk is suspected to be increasing. In what follows we show with the above introduced methods that the risk of corn and wheat production was increasing in four Hungarian regions between 1950 and 1990, partly independently from the risk aversion of the DM. In some regions, moreover, the increase is quite high and became quicker.

Figure 2 shows the corn (left) and wheat (right) production data Y_i of four Hungarian regions obtained by the *Phillips*-method 1951-1990 (kg/ha). As the data are yet comparable, we can deduce that the occurrence of some extreme values at the end of the 80s means that the safety of the corn and wheat yield has explicitly decreased. The deviance at the end of the 80s is generally less for the wheat production, though it is evident, too. This leads us to suspect that the risk has increased for the production of both plants.

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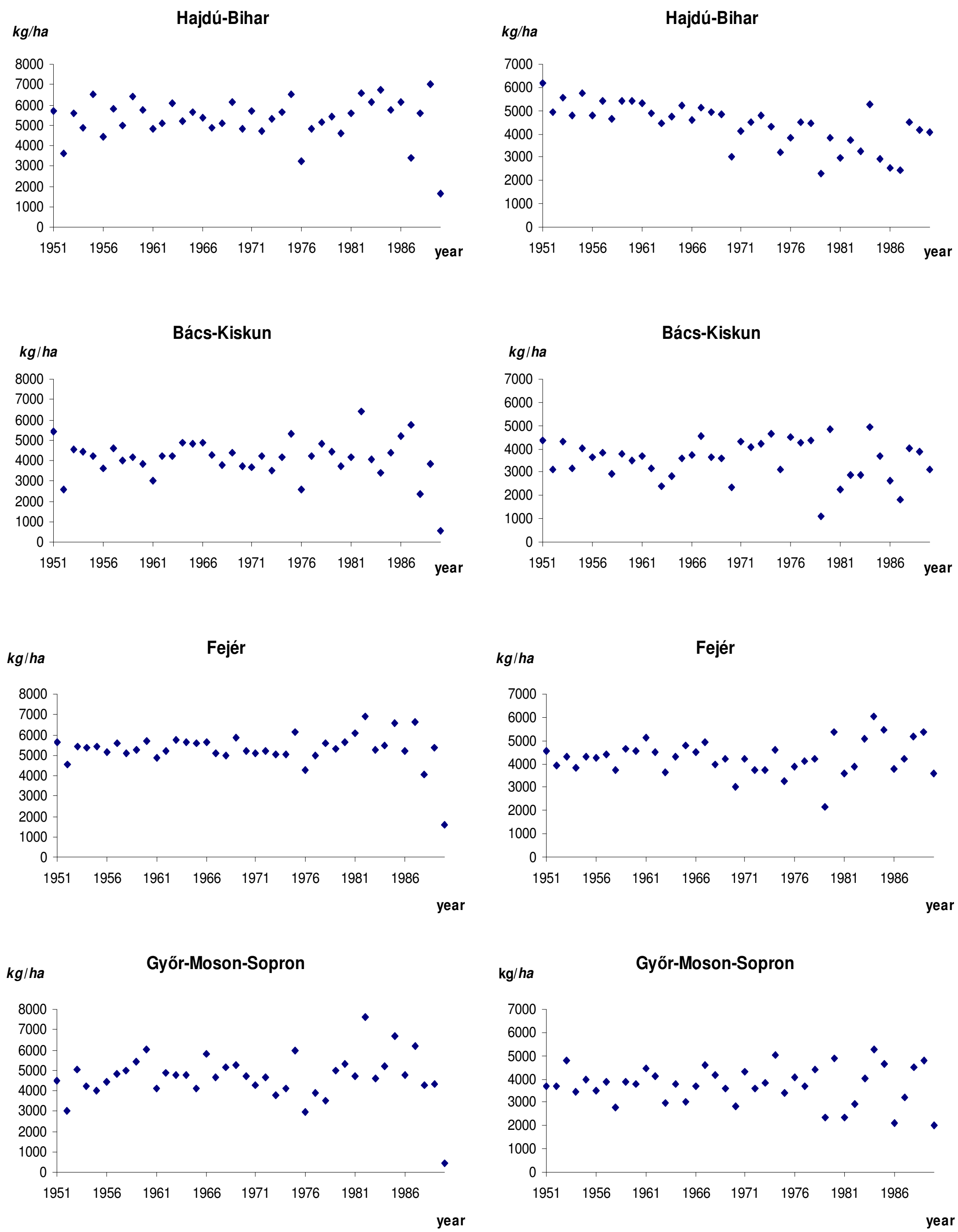

Figure 2. *The corn (left) and wheat (right) production data Y_i of four Hungarian regions obtained by the Phillips-method 1951-1990 (kg/ha)*

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The change of risk of corn production in four Hungarian regions between 1951-1990

Subjective distribution functions

Using the data obtained by the *Phillips*-method on the basis of experts' estimations we defined the subjective distribution functions for the four Hungarian regions and for the time intervals 1951-70, 1961-80, 1971-90 (*Fig. 3*).

In Bács-Kiskun, while the expectation was decreasing in time, the deviation was increasing (the subjective distribution function was shifted left, its slope has increased). For the other regions the change is not so evident.

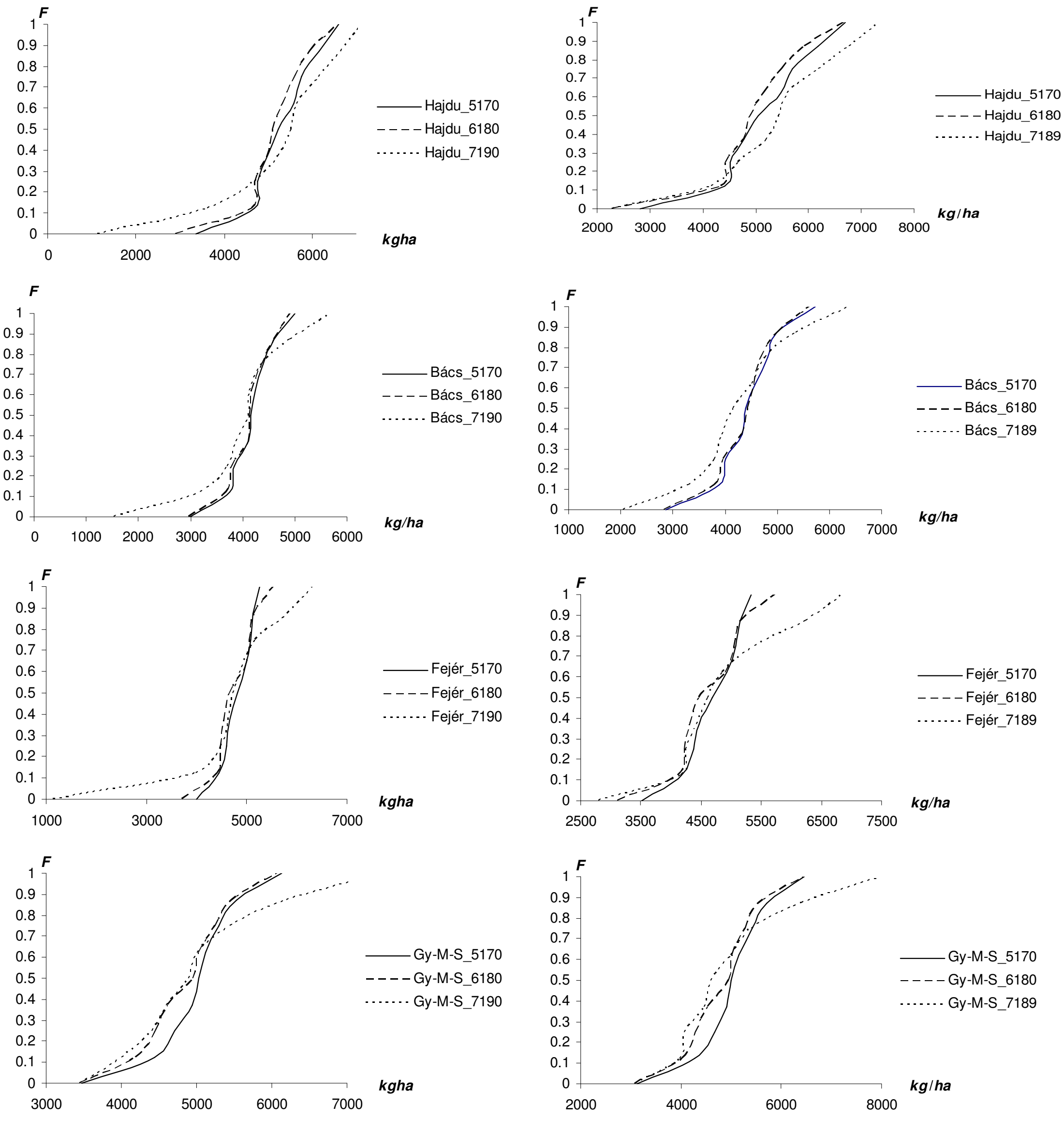

Figure 3. *Subjective distribution functions for corn production in four Hungarian regions and three time intervals 1951-1970, 1961-1980, 1971-1990 (kg/ha) The same is for truncated data where the last time series is 1971-1989 (right).*

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Stochastic dominance, E,V efficiency and the criteria based on the utility function

In Bács-Kiskun and also in Fejér the E,V-efficiency method gives the same result for the whole time intervals. We can see namely, that the points with respect to the last time interval (1971-90) denoted by H7 (*Fig. 4, left*) have both the other points H5 and H6 (with respect to 1951-70 and 1961-80, resp.) in their 'north-west' quadrant. (The last time interval involves the greatest risk.) For the other regions and for Fejér with the truncated data the E,V-efficiency method does not make any ordering. (Truncated data do not contain the very extreme year 1990 and thus H7 is for 1971-1989 instead of 1971-1990.)

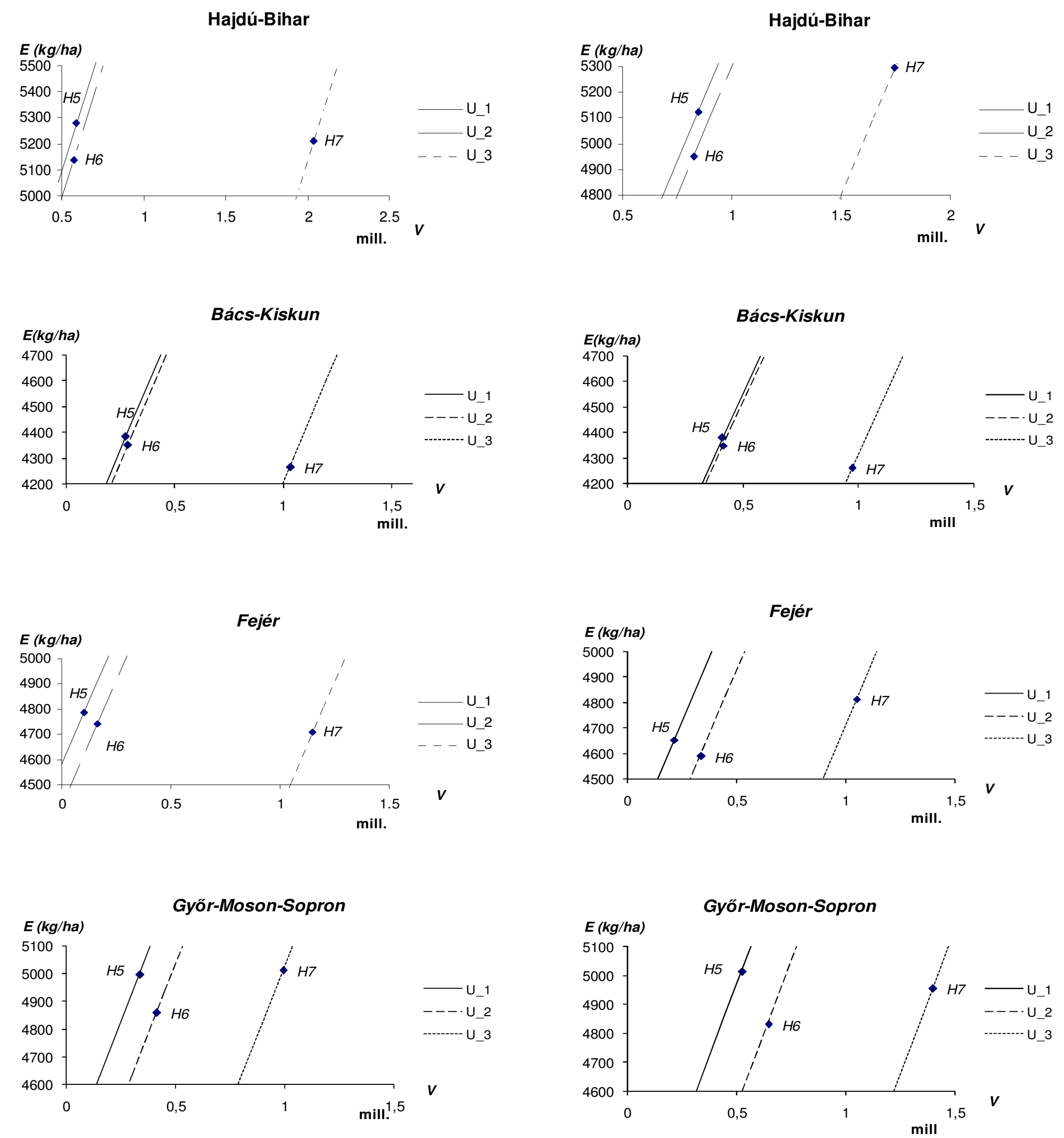

Figure 4. *E,V-efficiency and indifference curves for corn production in four Hungarian regions. H5 is for 1951-1970, H6 is for 1961-1980, H7 is for 1971-1990 (left). The same is for truncated data where H7 is for 1971-1989 (right)*

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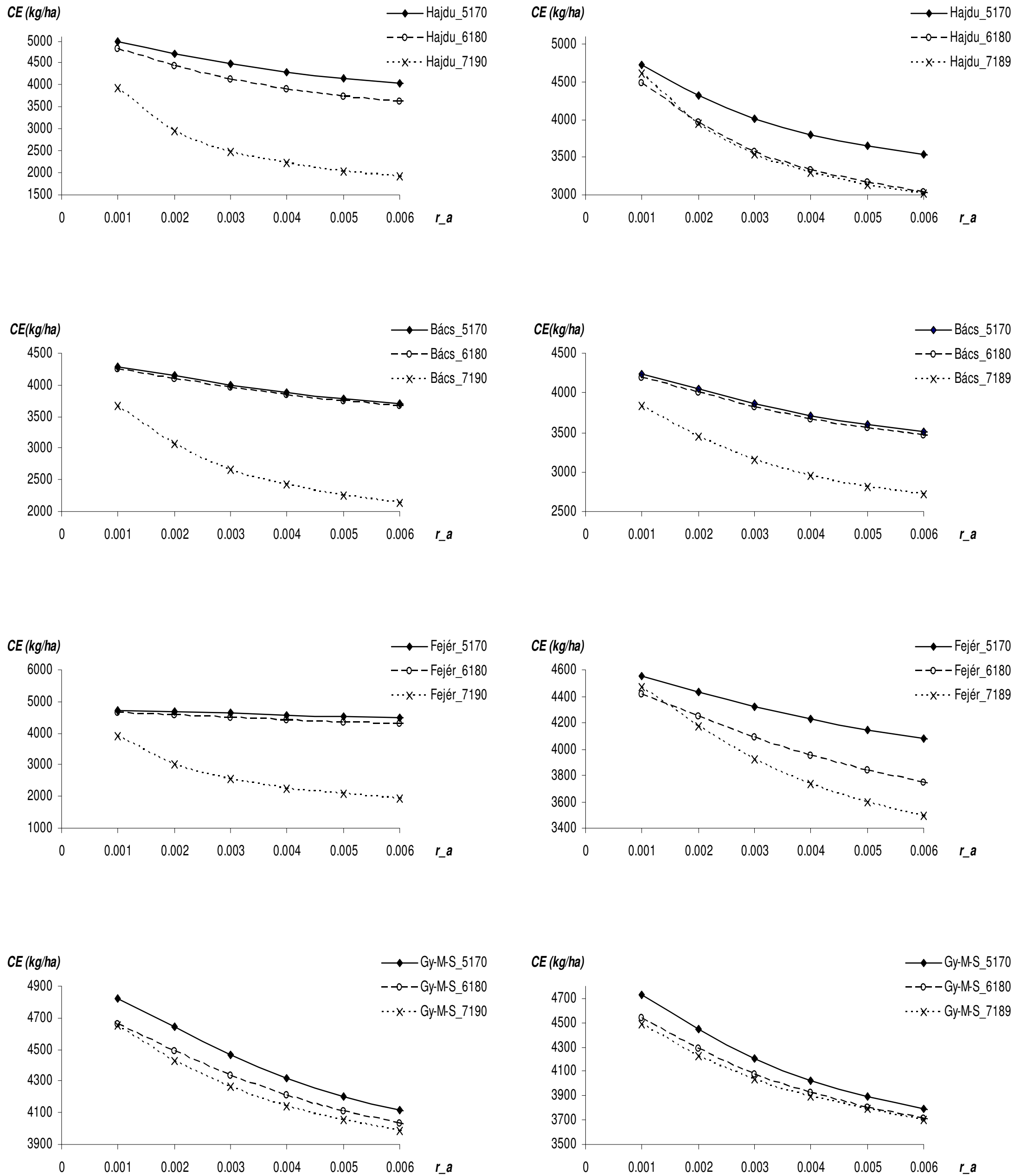

Figure 5. *Stochastic efficiency for corn production in four Hungarian regions with respect to 1951-1970, 1961-1980, 1971-1990 (left). The same is for truncated data when instead of 1971-1990 we have 1971-1989 (right).*

Together with *E,V*-efficiency the linear functions were also defined for absolute risk aversion value $r_a = 0.004$ and for three fixed certainty equivalent (CE) values (*Fig. 4 and 5*). In every case we got that the situations become worse with time. The disadvantage of the method based on utility criterion is, however, that it makes an ordering for fixed absolute risk aversion, only. For more information we should call for the more general stochastic efficiency criterion.

Stochastic efficiency

In *Fig. 5* (left) we consider the graphs of the values CE with respect to the risk aversion. The curves that are lying the higher are the more preferable alternatives with the less risk. Comparing the time intervals 1951-70 and 1961-80, applying the stochastic efficiency criterion we obtained suggestively that the risk of corn production has increased in all the four regions, independently from the rate of absolute risk aversion. (The graphs of the earlier time series are lying higher.) The risk of time interval 1971-90 has increased even more in all regions except Győr-Moson-Sopron, especially for greater r_a values.

We can ask whether this risk increase is caused only by the heavy yield loss of 1990. Using the truncated data we can see that the rate of risk increase is less, but evident, especially for greater r_a values.

For the truncated data we calculated again the CE values depending on the absolute risk aversion r_a *Fig. 5* (right). We got that the time series with the less risk was the earliest (1951-1970). In Hajdú-Bihar and Fejér the risk increase holds only for $r_a > 0.002$. This fact, however, does not make the importance of the objective warning less serious. The risk increase was the greatest in Bács-Kiskun and the less in Győr-Moson-Sopron, but the fact of risk increase is obvious everywhere.

The change of risk of wheat production in four Hungarian regions, 1951-1990

Subjective distribution functions

First the subjective distribution functions were elicited for the four regions and for the three times series 1951-70, 1961-80, 1971-90 with the data obtained by the *Phillips*-method on the basis of experts' estimations (*Fig. 6*). (In the case of wheat the use of truncated data was not reasonable, because the yield loss of the most extreme year 1979) was not as extreme as it was for corn production.) Note that the increase of deviation can be seen in every region which indicates a possible risk increase.

Stochastic dominance, E,V efficiency and the criteria based on the utility function

The most evident risk increase of wheat production was in Hajdú-Bihar. The subjective distribution functions are ordered here pointwise (the earlier time intervals dominate the later ones in first-degree sense). The same can be proved with the *E,V*-efficiency method, though with this method we get no ordering for the time intervals in the other three regions. The criterion based on the utility function gives the same ordering for the three time intervals in all regions except Fejér. This proves the risk increase obviously, though, only for the fixed $r_a = 0.004$ value (*Fig. 7*).

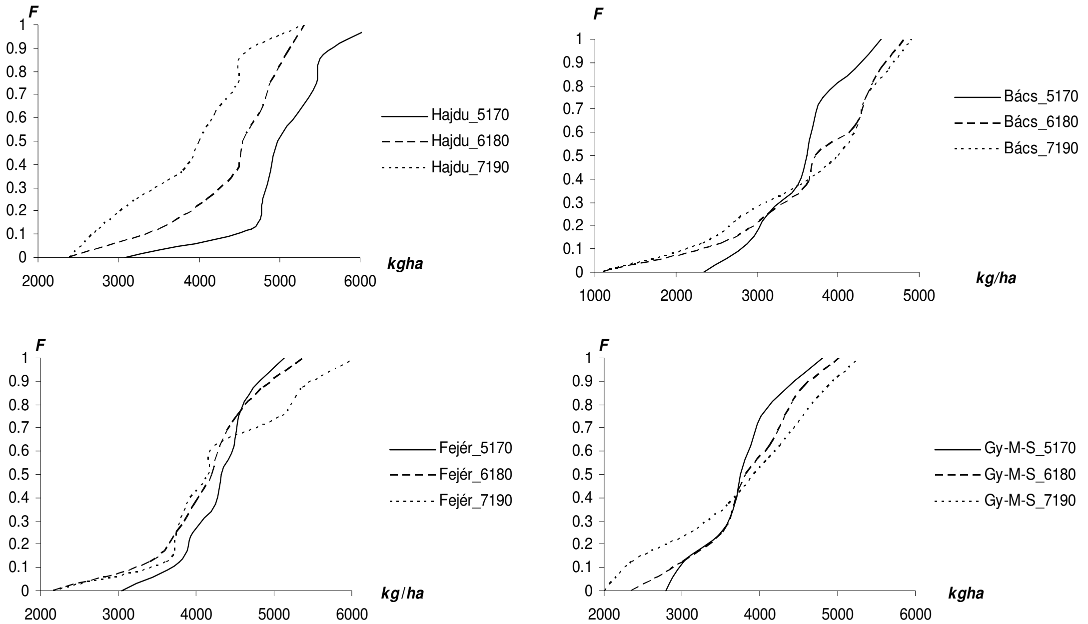

Figure 6. *Subjective distribution functions for wheat production in four Hungarian regions and three time intervals 1951-1970, 1961-1980, 1971-1990 (kg/ha)*

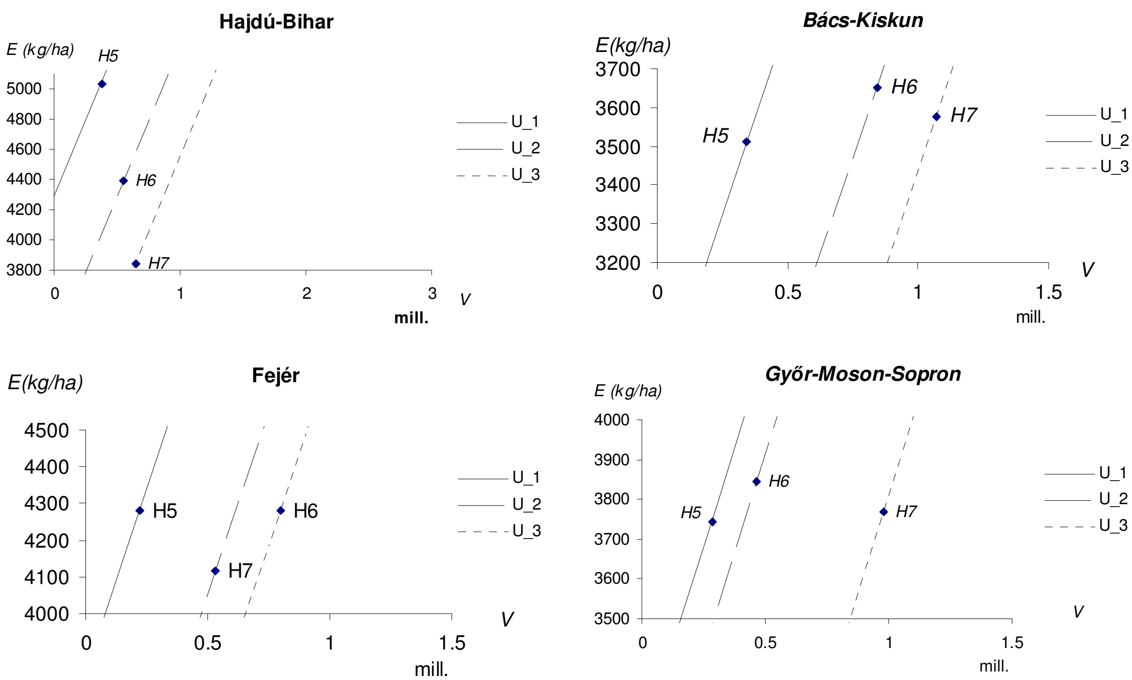

Figure 7. *E,V-efficiency and indifference curves for wheat production in four Hungarian regions. H5 is for 1951-1970, H6 is for 1961-1980, H7 is for 1971-1990.*

Stochastic efficiency

Comparing the time intervals 1951-70 and 1961-80, applying the stochastic efficiency criterion we proved that the risk of wheat production has increased in all the four regions, but Fejér, independently from the rate of absolute risk aversion r_a (*Fig. 8*). In Fejér the less risky interval was 1951-70 and the most risky one was 1961-80 for almost the whole domain of r_a. The risk increase was the greatest for 1971-90 only if $r_a > 0.014$. In contrary to the case of corn production, the rate of increase became greater only in Győr-Moson-Sopron, but independently from r_a.

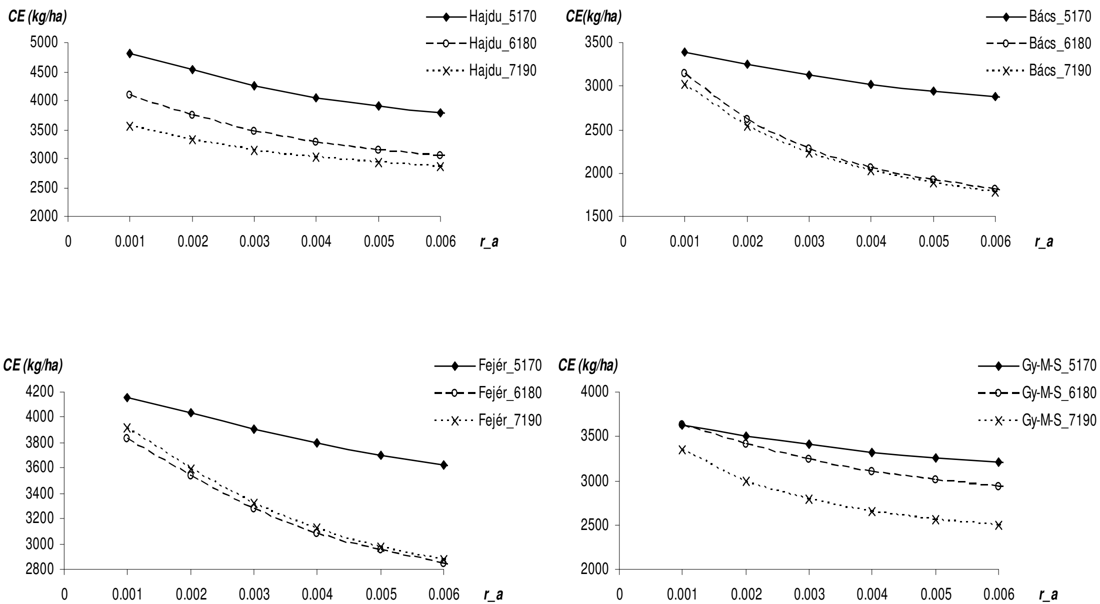

Figure 8. *Stochastic efficiency for wheat production in four Hungarian regions with respect to 1951-1970, 1961-1980, 1971-1990*

Discussion

After having reviewed some recent methods of risk assessment we introduced some case studies. Crop and corn production was investigated between 1951 and 1990. We have cut the long time series into three shorter ones in order to be able to compare them from the production risk's aspect. The risk increase has been proved for all the examined regions in Hungary, the differences were in the rate of them, only. This approach is aimed, above all, to introduce the methodology of risk assessment; nevertheless, the result of it draws our attention to the importance of risk increase in agriculture. Further researches are planned to find the reasons of risk increase based on historical data and to investigate the expected risk caused by climate change based on GCM's.

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