Climate impact on social systems: the risk assessment approach

Yu.M. Svirezhev, W. von Bloh and H.-J. Schellnhuber

Potsdam Institute for Climate Impact Research, P.O. Box 601203, D-14412 Potsdam, Germany

A novel approach to the problem of estimating climate impact on social systems is suggested. This approach is based on a risk concept, where the notion of critical events is introduced and the probability of such events is estimated. The estimation considers both the inherent stochasticity of climatic processes and the artificial stochasticity of climate predictions due to scientific uncertainties. The method is worked out in some detail for the regional problem of crop production and the risks associated with global climate change, and illustrated by a case study (Kursk region of the FSU). In order to get local climatic characteristics (weather), a so-called "statistical weather generator" is used. One interesting finding is that the 3% risk level remains constant up to 1.0–1.1°C rise of mean seasonal temperature, if the variance does not change. On the other hand, the risk grows rapidly with increasing variance (even if the mean temperature rises very slowly). The risk approach is able to separate two problems: (i) assessment of global change impact, and (ii) decision making. The main task for the scientific community is to provide the politicians with different options; the choice of admissible (from the social point of view) critical events and the corresponding risk levels is the business of decision makers.

Keywords: risk analysis, global change, agriculture

1. Introduction

There are many reasons why Global Warming (GW) may not be perceived as a crisis in the traditional sense of the term. Although society is continuing to accumulate in the atmosphere "greenhouse gases" inducing global warming, there is a time lag (from decades to a century, i.e., longer than one human generation) before consequences of human action will be obvious. In addition, there are many scientific uncertainties obscuring the problem.

It is quite interesting to trace the evolution of this problem from Arrhenius [1], Kostitzin [11] and Callendar [2] up to present investigations. In fact, the social perception of global warming remains, essentially, the same as it was in the Kostitzin's and Callendar's time in spite of modelling and paleoclimatic reconstruction.

There is a tragic mismatch between social, economic and political time horizons on the one hand, and environmental horizons, on the other hand. While political leaders are elected every 4–6 years, the time scale of global warming consequences is around $\approx 10^2$ years.

There is another reason for inadequate political response connected to scientific uncertainties: GCMs (General Circulation Models) have a poor record in producing scenarios (especially for precipitation) for the regions of the Earth, while national, regional and local decision makers need to know what global values will mean at their local scale of action [6].

It is obvious that the choice of any particular strategy depends on the particular social perception of GW. It seems to us (and as mentioned above), GW is not (yet) perceived as a global crisis or a global disaster. First of all, any climatic extreme event is perceived at regional and local levels, even if it has a global origin. The event is considered as an extreme one if it is accompanied by serious social perturbations. For instance, the hot summer of 1988 in the USA was an extreme event since:

(1) navigation on large rivers broke down so that water transport had to be replaced by trains and trucks;

(2) big losses took place at hydropower plants;

(3) disturbances in industrial and urban water supply, agricultural losses, etc. were triggered.

The most serious problems were connected to navigation, though from a common sense viewpoint it would seem that agricultural losses should be the most important [8]. However, a long drought would be a disaster for any rural region with agriculture as the main sector of economy.

2. Concept of critical levels

Many of the crucial values for society are being changed under climatic variations more or less smoothly: crop yield, water storage, water level of rivers, sea level, etc. (Note that their "smoothness" is determined, in the first place, by their measurability.) Therefore, these values can be considered, generally, as continuous functions of climate change, which is a consequence of the emission of "greenhouse gases". This process is determined mainly by the structure and organisation of the world energy system. However, a social perception transforms the continuous range of those values to a discrete set, namely "good–medium–bad–disaster". For instance, the difference between a bad crop yield and a catastrophic one may be less than the difference between medium and bad yields, but the social consequences of "bad" and "catastrophic" yields are not comparable. The impossibility of navigation is a result of the fact that the water levels sink below some critical threshold. A local agricultural disaster may certainly be compensated at the regional scale (with the help of market mechanisms), but there may exist a critical level for total crop production which destroys the market as a whole. For many social systems such critical thresholds (either scalars or vectors or surfaces in the space of basic variables) exist. If a system crosses such boundaries then the system's homeostasis is destroyed.

Therefore, we define *a critical event as a crossing of the homeostasis boundary for some social system* (see below) *after which this system cannot be reconstructed* (*or will not reconstruct itself*).

Note that in numerous works the "CO_2 doubling" is considered as a crucial point for climate, biota, etc. So, this is not a critical event, and what is more, the state of the biosphere corresponding to CO_2 doubling is not unique, because it depends substantially on the path of transition from the present state to the state where CO_2 concentration will be doubled. The concentration of carbon dioxide in the atmosphere is simply one of many strategic variables of the whole system.

Suppose there is a social system, the state of which is described by the vector x (in general case x may depend on time, that is, to be a dynamic variable). We suppose also that the state depends on climate which is described by the vector λ, so that $x = x(\lambda)$.

Let $F(x) \geqslant 0$ be a homeostasis domain for this system. It is obvious that the critical level, x_{crit}, is defined by the equation $F(x_{\text{crit}}) = 0$. In turn, the inequality $F(x) \geqslant 0$ induces the set $\Omega(x)$ of admissible x with the boundary $\Gamma(x = x_{\text{crit}})$.

Suppose that the inverse mapping $\lambda = \lambda(x)$ does exist. Then we can calculate the set $\omega(\lambda)$ of admissible climates with the boundary $\gamma(\lambda = \lambda_{\text{crit}})$, where $\lambda_{\text{crit}} = \lambda(x_{\text{crit}})$. Note that the mappings $x = x(\lambda)$ and $\lambda = \lambda(x)$ may be non-unique.

The solution of this criticality problem is trivial: *if the predicted climate does not belong to the set* $\omega(\lambda)$, *then the state of the system is catastrophic*.

We illustrate these abstract considerations by the following concrete example. Let our social system be the agriculture system producing cereals. The state of the system is described only by the crop yield, that is, by the scalar x. If $x < x_{\text{crit}}$, then we have an "agricultural disaster", the value x_{crit} is determined by economic and social arguments. The homeostasis domain for this system is defined by the inequality $F(x) = x - x_{\text{crit}} \geqslant 0$. Then Ω: $x \geqslant x_{\text{crit}}$, Γ: $x = x_{\text{crit}}$ (see figure 1). If we assume that the crop yield depends only on the annual temperature t^0, then the climate is described by the scalar $\lambda = t^0$ and $x = x(\lambda)$. As a rule, the dependence is uni-modal, and, as we can see in figure 1, the mapping $\lambda = \lambda(x)$ is non-unique. Therefore the set $\omega(\lambda)$ of admissible temperatures is the interval $\lambda^1_{\text{crit}} \leqslant \lambda \leqslant \lambda^2_{\text{crit}}$ with the boundary γ: $\lambda^2_{\text{crit}}, \lambda^2_{\text{crit}}$. These two boundary points correspond to two solutions of the equation $x_{\text{crit}} = x(\lambda)$.

Revenons à nos moutons, we can say that the solution of our criticality problem is trivial if we have:

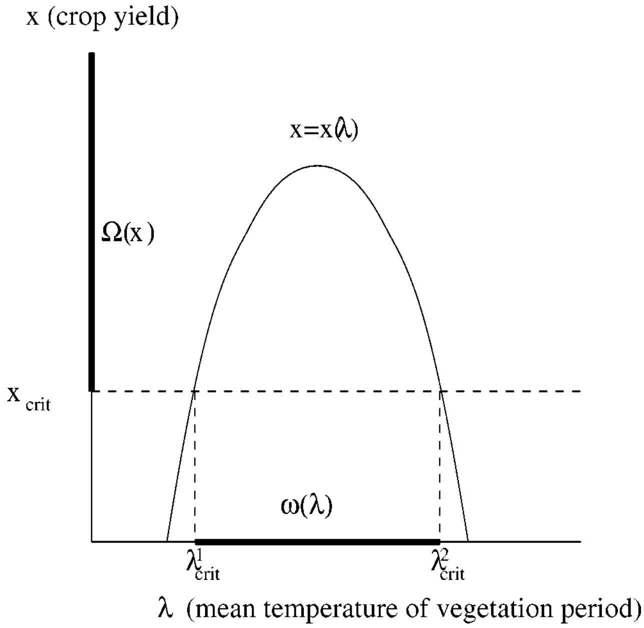

Figure 1. To the definition of the sets $\Omega(x)$ and $\omega(\lambda)$: $F(x)$: $x - x_{\text{crit}}$; Γ: x_{crit}; $\Omega(x)$: $x \geqslant x_{\text{crit}}$; γ: $\lambda^1_{\text{crit}}, \lambda^2_{\text{crit}}$; $\omega(\lambda)$: $\lambda^1_{\text{crit}} \leqslant \lambda \leqslant \lambda^2_{\text{crit}}$.

(1) an ideal model for the system, that is, for each λ there is a finite number of separated x (and vice versa). (If, for instance, the dependence of crop yield on the temperature is a probability function, then this assumption is not true. The ideal model is a deterministic one, which predicts the state x corresponding to climate λ with unit probability, possibly apart from hysteresis.)

(2) an ideal climatic prediction (again with the unit probability).

In actuality, we neither have an ideal model nor an ideal forecast.

Let us suppose that there are different deterministic models $x^i = x^i(\lambda)$ and that each of them possesses a different "predictive power" depending on its structure, complexity, scientific uncertainties, etc. The simple way to describe this power is to associate some specific probability $p^i(x; \lambda)$ to each predicted value x^i. Thus, some probability measure can be constructed on the basis of the set of models $x^i(\lambda)$. Another way is to use some stochastic model with a probability measure. In these cases we can formulate the following probabilistic statement: *the inequality* $x < x_{\text{crit}}$ *takes place for any* λ *with the specific probability* $P_{\text{crit}}(x_{\text{crit}}; \lambda)$.

Next we have to take into account that there is no ideal prediction for λ. Scientific uncertainties in climate prediction will allow us to predict the value λ only with some probability $\pi(\lambda)$, so that instead of unique prediction for λ we have a set of values for λ, and each of them can be realised with a specific probability. Certainly, the suggested method of uncertainty analysis is not unique in a problem of GW, there are other approaches (see, for instance, [6]), which can also be used in calculation of corresponding probabilities.

And, finally, for the given x_{crit} the probability of the event $x < x_{\text{crit}}$ is equal to

$$R(x_{\text{crit}}) = \int P_{\text{crit}}(x_{\text{crit}}; \lambda)\pi(\lambda)\,\mathrm{d}\lambda \qquad (2.1)$$

under the normalisation condition

$$\int \pi(\lambda)\,\mathrm{d}\lambda = 1. \qquad (2.2)$$

There is not a problem in generalising this approach to the case when $x(\lambda)$ is a functional and the critical event is also a functional, etc.

The probability R can be considered as a measure of the risk for the catastrophic event $x < x_{\text{crit}}$. But we also have to keep in mind the following facts:

1. The value x_{crit} is defined by social factors only. This means that the event $x < x_{\text{crit}}$ could be either admissible or inadmissible depending on the social consequences.
2. The risk level is defined by politicians, who have to compare two sets: x_{crit} and the corresponding $R(x_{\text{crit}})$. The choice of the risk level depends on many factors: the state of society, economy, social stress, etc.
3. The main task of the scientific community is to provide the politicians with options: to present them the values for x_{crit} and R_{crit}, and illustrate the events $x < x_{\text{crit}}$ with facts and pictures.

Let us now consider the following situation: We have determined the value x_{crit}, the probability predictions for climate change, that is, $\pi(\lambda)$, and by calculation of $R(x_{\text{crit}})$ we have found out that $R > R^*$, where R^* is an admissible level of risk. What kind of action can be started in such a case?

1. We can take steps in order to lower the critical level x_{crit} to x'_{crit} such that $R(x'_{\text{crit}}) = R^*$. In the case of crop production we can, for instance, import an additional amount of grain (adaptive strategy).
2. We can select and cultivate a new variety of plants in the region (that is, we change $x = x(\lambda)$).
3. At the global level we can reduce the greenhouse gases emissions in order to change $\pi(\lambda)$ and, by the same token, $R(x_{\text{crit}})$ until it becomes equal R^*.
4. Finally, we can take the risk and do nothing.

The algorithm for risk assessment consists of the following sequence of steps:

1. By using a model for the social system which is driven by the climatic input λ, we construct the Ω-domain with the boundary Γ.
2. On the set of possible $x = x(\lambda)$, we construct the probability measure $\Pr\{x(\lambda)\}$.
3. Using $\Pr\{x(\lambda)\}$ we calculate the probability $P(\Gamma; \lambda) = P_{\text{crit}}(\lambda)$ for the event $x \notin \Omega \cup \Gamma$ (for any λ).
4. We determine the probability distribution $\pi(\lambda)$, i.e., the probability of the realisation of the given climate scenario λ.
5. Calculating the risk level $R(\Gamma) = \int P(\Gamma; \lambda)\pi(\lambda)\,\mathrm{d}\lambda$ we construct the table $\{\Gamma; R(\Gamma)\}$.
6. Politicians choose the pair $\{\Gamma^*; R(\Gamma^*)\}$.
7. For the chosen pair we have to find either the appropriate structure of the system $x = x(\lambda)$, or the appropriate climate $\pi(\lambda)$.

Certainly, it is easier said than done (especially this is true for the first two points), but for relatively simple systems it is possible. We have shown above how to do this, for instance, for such a system as an agricultural one.

3. Case-study: Barley crop production in the center of European Russia (Kursk region)

The method has been applied to the risk analysis of crop production at the regional level (Kursk region of the FSU).

Crop production model. We use a specific crop production model [3,15], calibrated by data which have been collected by Denisenko in the course of two periods: 1978 and 1983. A model structure is shown in figure 2.

The basic state variables are the phytomasses of leaves, stems, roots and generative organs (ears), $x_i(\tau)$, $i = 1, \ldots, 4$, correspondingly. All these values are functions of time, τ, measured in days. The general equations of the model are

$$x_i(\tau + 1) = x_i(\tau) + e_i Y\left[x_j(\tau), \lambda_k(\tau)\right], \quad i, j, k = 1, \ldots, 4, \qquad (3.1)$$

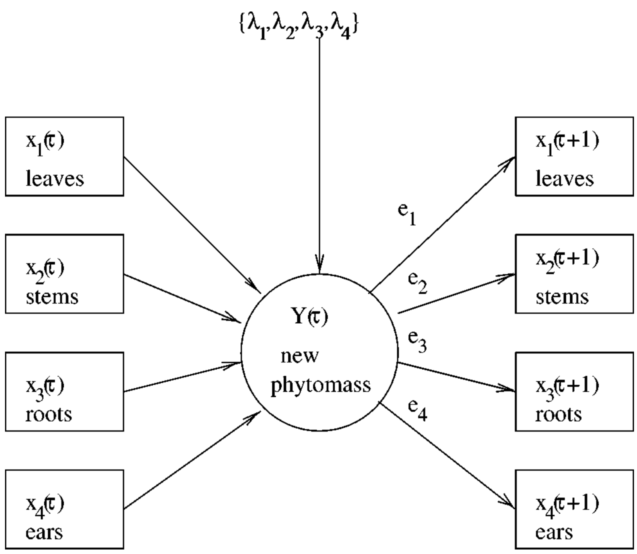

Figure 2. Conceptual diagram of the crop model. Environmental (weather) parameters: λ_1 is the daily PAR, λ_2 is a parameter of water regime, λ_3 is the CO_2 concentration in the atmosphere, λ_4 is the daily temperature.

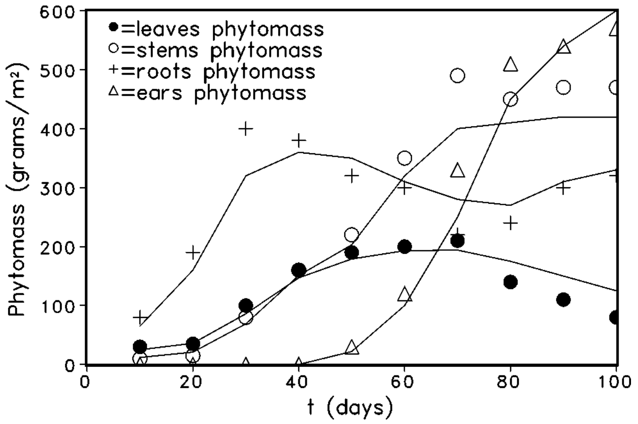

Figure 3. Comparison of the observed (markers) and model (lines) data of the Kursk region for the year 1983.

where the daily net production, Y, depends both on the state variables x_i and the weather parameters λ_k. Here λ_1 is a daily amount of the Photosynthetically Active Radiation (PAR). The latter is presented in the form of the so-called *solar hours*. λ_2 is the parameter determining the water regime of barley crops. In fact, this value depends on precipitation dynamics, in particular on alteration and lengths of the so-called "dry" and "wet" series, that is, series of days with no precipitation and days with significant precipitation without dry period between them. The parameters λ_3 and λ_4 are the concentration of atmospheric CO_2 and the daily temperature.

The function Y is defined by standard dependencies taken from plant physiology and ecology (see, for instance, [7]). The coefficients $e_i,\ i = 1, \ldots, 4$ ($\sum_{i=1}^{4} e_i = 1$), describe some *allocation principle*, that is, they show how the new phytomass is allocated among the different organs of plant. In order to calculate them we postulate the following local variational principle which reflects the process of plant adaptation to variations of environment.

All the vegetation period is divided into two parts: *before* and *after* the appearance of generative organs.

Before: the new phytomass is allocated among leaves, stems and roots in this way that to maximise the growth rate of total phytomass in the next time, under the condition that the state of environment does not change.

After: the new phytomass is allocated among leaves, stems, roots and generative organs in this way that to maximise the growth rate of generative organs in the next time, under the condition that the state of environment does not change.

The comparison of the model results and observed data for 1983 is shown in figure 3.

It is obvious that the crop yield $y = kx(\tau_f)$, where k is an empirical coefficient and τ_f is the end of the vegetation period. In this model the crop yield is a functional that depends on the trajectories of the daily temperature, precipitation and PAR during the vegetation period. It is obvious that the Λ-set, that is, the set of climatic parameters (climates) λ is a functional space, the elements of which are trajectories of the values mentioned above. In order to estimate the dependence of crop production on this type of trajectories for the future changed climate we have to know how to generate them. For this we have used a so-called

Statistical weather generator which generates time-series for daily average temperature, precipitation and solar hours [17]. This generator was fitted to the meteorological observations carried out in the Kursk Biosphere Station from 1970 up to 1984. The generator was constructed in the following way.

Let $P_{\mathrm{w}}(\tau, n_{\mathrm{w}})$ and $P_{\mathrm{d}}(\tau, n_{\mathrm{d}})$ be the probabilities of occurrence for wet and dry series of length n_{w} and n_{d}, associated with day τ. The distribution $P_{\mathrm{w}}(\tau, n_{\mathrm{w}})$ may be approximated by the geometric distribution with the parameter obtained from observation data by the maximum likelihood method. The distribution $P_{\mathrm{d}}(\tau, n_{\mathrm{d}})$ is approximated by mixing of two geometric distributions with the probability p for short series (shorter than one week) and the probability $1 - p$ for long series.

The distribution of precipitation (in mm) is a mixing of three distributions:

$$P_p = \begin{cases} \mathrm{UNI}(0, 0.5) & \text{with probability } p_{\mathrm{s}}(\tau), \\ \mathrm{EXP}(\mu(\tau)) & \text{with probability } p_{\mathrm{m}}(\tau), \\ \widehat{P}(\tau) & \text{with probability } p_{\mathrm{l}}(\tau). \end{cases} \tag{3.2}$$

Here $p_{\mathrm{s}}(\tau)$, $p_{\mathrm{m}}(\tau)$ and $p_{\mathrm{l}}(\tau)$ are the probabilities of "small" (less than 0.5 mm), "medium" (0.5–20 mm) and "large" (more than 20 mm) precipitation for each τ ($p_{\mathrm{s}}(\tau)+p_{\mathrm{m}}(\tau)+p_{\mathrm{l}}(\tau) = 1$). UNI is the uniform distribution for small precipitation, EXP is the exponential distribution for medium precipitation and $\widehat{P}$ is the mean large precipitation.

The temperature is described by a normal distribution with different parameters for wet and dry series, so that

$$P_t(\tau) = E_t^k(\tau, l) + \sigma_t^k(\tau, l) \cdot R_t(\tau), \tag{3.3}$$

where $R_t(\tau) = aR_t(\tau - 1) + bN(0, 1)$ is the correlation coefficient between two consecutive days, $N(0, 1)$ is the Gauss function with parameters 0 and 1, a and b ($a^2 + b^2 = 1$) are the parameters providing the standard normal distribution for R_t. The index l points the position of day τ within the series, the index k stands for w (wet) and d (dry) series. In this way the daily temperature is defined for each τ by its arithmetic mean, E_t^k, and its variance, σ_t^k.

Solar hours are also described as a normal stochastic variable with the parameters depending on the number of day, τ, and its position within either wet or dry series, l.

As an illustration, one result of calculation with the help of our generator is shown in figure 4.

Since the functional dependence is very unwieldy for descriptive presentation of calculation results, we shall try to compress these distributions to a few moments of them. Thus, each trajectory will be described by two values: mean and variance calculated for the vegetation period, and then the crop yield will be a function of six variables. At the beginning we suppose that crop production depends on two

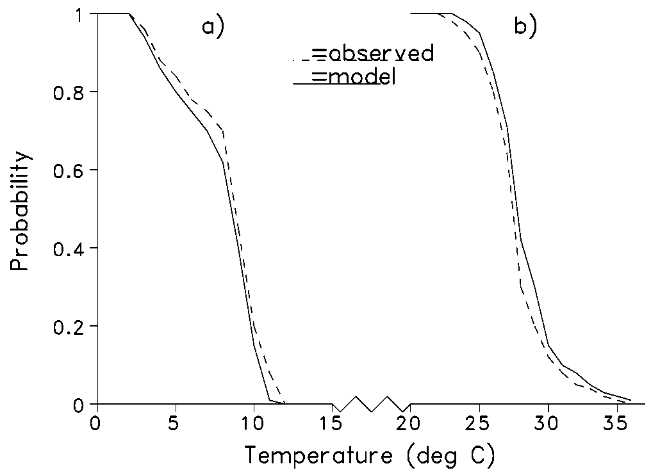

Figure 4. Probabilities of the following events: (a) minimal temperature exceeds a given value within the period from day 120 to 240; (b) maximal temperature exceeds a given value within the period from day 20 to 240.

variables only: annual (more correct, vegetation period) mean temperature and temperature variance.

4. Construction of the set of climatic parameters for different climate scenarios

The next problem is: how to construct the Λ-set, that is, the set of climatic parameters (climates) λ prescribing a climate scenario?

Let us assume that the local climate is not changing (at least during the last two decades covered our observation interval from 1970 up to 1984 during 15 years). Thus, despite annual variation of crop yield as a consequence of weather variation, the local climate is fixed, and there is only one point (corresponding to this climate) in Λ-space. Suppose we have the model of this climate, the "statistical weather generator", which is a stochastic parametric process. Its parameters are, in turn, *characteristics of the mesoclimate at the given site*. One realisation of this stochastic process (a trajectory) is considered as the weather at a given site and in a given year.

The simplest hypothesis is the following:

Hypothesis 1. The pertinent stochastic parameters are the mean values of "vegetation" temperatures, precipitation, etc., as well as their variances.

Let us take 15 (for each vegetation period) time-series $t_i^0(\tau)$, $i = 1, \ldots, 15$, for the temperature, where τ is any point of time within the vegetation period.

$$E_t(\tau) = \frac{1}{15}\sum_{i=1}^{15} t_i^0(\tau) \tag{4.1}$$

is the mean temperature in the course of a vegetation period for this site, that is, a characteristic trait of the local climate. The average current variance of the temperature is also calculated as

$$\sigma_t(\tau) = \frac{1}{15}\sum_{i=1}^{15} \sigma_i(\tau). \tag{4.2}$$

Using these values we calculate (by formula (3.3)) a statistical consequence describing some standard daily temperature dynamics, which is typical for the given site. As generalised characteristics for the local climate we use the temporal averaging of the functions $E_t(\tau)$ and $\sigma_t(\tau)$ over the interval $[\tau_0, \tau_f]$ which is the vegetation period, so that

$$t^0 = \frac{1}{\tau_f - \tau_0}\int_{\tau_0}^{\tau_f} E_i(\tau)\,\mathrm{d}\tau \tag{4.3}$$

and

$$\sigma = \frac{1}{\tau_f - \tau_0}\int_{\tau_0}^{\tau_f} \sigma_i(\tau)\,\mathrm{d}\tau \tag{4.4}$$

are the "vegetation" temperature and variance. If the first value is the mean temperature of the vegetation period, then the latter is a variance of a seasonal temperature during a vegetation period.

In the same way, the mean precipitation for the vegetation period and its variance are calculated. The "weather generator" is constructed in such a way that the generated stochastic series do not differ statistically from the real climatic time-series, that is, the statistical characteristics (means and variances) of the generated series are equal to those of the local climate. Thus, the next hypothesis may be formulated:

Hypothesis 2. The change of local climate is, in effect, the change of the parameters (statistical characteristics) for the local climate.

At the first stage we assume that as a result of climate change the mean temperature t^0 and its variance σ are changed. For instance, $t^0 = 13.8$ and $\sigma = 7.2$ for the Kursk region. The values of t^0 and σ make up the set of climatic parameters (climates), that is, the Λ-set.

In accordance with different climate models (GCMs, paleoclimatic and extrapolation models), the increase of mean summer temperature in the Kursk region would be 1–3°C for the doubling of CO_2 scenario. The methods of "optimal filtration" (in case some marginal predictions are rejected) give us the interval equal to 1.5–2°C. Concerning the change of variance, there are only some qualitative estimations available. For instance, the estimations of variance by GCMs show that, in general, the variance of summer temperatures decreases [9]. It seems that this statement could be valid for the polar and tropic regions, but it is doubtful for such a temperate region as the Central Russia. On the other hand, statistical extrapolation of the observed data shows the increase of variance. We prefer the latter.

In our calculation we shall use an old empirical rule of statistics [10], which suggests that $4|\Delta\sigma| \cong \Delta t^0_{\max} - \Delta t^0_{\min}$.

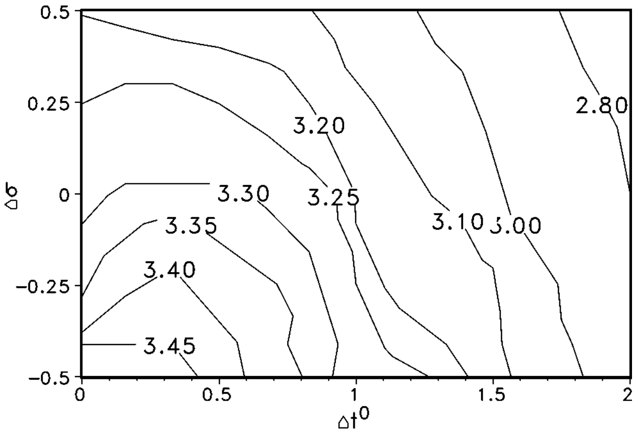

Figure 5. Isolines of the mean crop production (in tons per hectare).

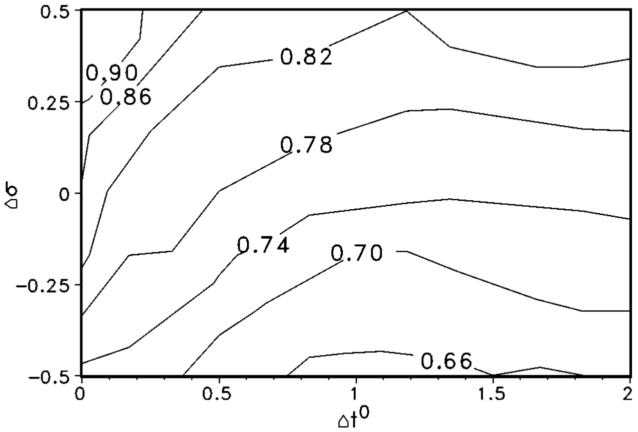

Figure 6. Isolines of the crop production variance (in tons per hectare).

Thereby, we obtain the following biased estimation: $\Delta\sigma = 0.25$°C. Assuming that the variance either does not change or rise, we obtain that the interval of possible values for $\Delta\sigma$ is equal to 0–0.25°C.

5. Risk assessment: results and discussion

The base for visualisation of results of the numerical experiments is the plane $\{\Delta t^0, \Delta\sigma\}$, each point of which can be considered as a climatic scenario (see figures 5, 6 and 8). For instance, the point ($\Delta t^0 = 1$°C$, \Delta\sigma = 0.25$°C) means that the mean temperature of the vegetation period and its variance increase by 1 and 0.25°C, respectively (in comparison with their contemporary values). Using the crop production model and the statistical weather generator (the mean temperature and its variance are the parameters of generated stochastic process) 300 Monte Carlo experiments were carried out for each point of the plane. In fact, using these experiments we construct an empirical distribution for the crop yield y. Then the distribution is tested as a normal one and the sample mean of the crop production $\widehat{y}$ and its sample variance s are calculated. The procedure is repeated again for the next Δt^0 and $\Delta\sigma$. As a result, we obtain the functions $\widehat{y} = f(\Delta t^0, \Delta\sigma)$ and $s = \varphi(\Delta t^0, \Delta\sigma)$, the isolines of them are depicted in the plane $\{\Delta t^0, \Delta\sigma\}$ in figures 5 and 6. The origin of co-ordinates in this plane corresponds to the contemporary climate. Since the crop yield unit is t/ha, $\widehat{y}$ and s are measured with the same unit. Note that the increase of number of the experiments does not really change these pictures.

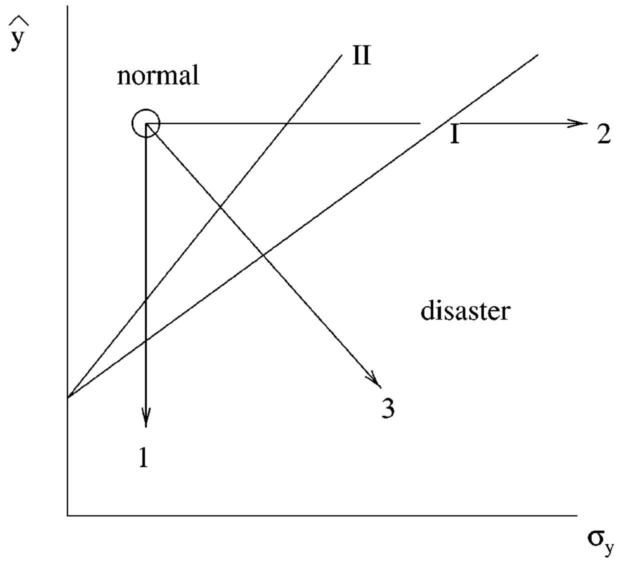

Figure 7. Normal and catastrophic (disaster) domains. Line I: $\widehat{y} = y_{\rm crit} + \alpha_1\sigma_y$, line II: $\widehat{y} = y_{\rm crit} + \alpha_2\sigma_y$, $\alpha_2 > \alpha_1$.

In fact, we use the crop model like some non-linear filter which transforms a set of stochastic climatic time-series into a set of crop yield values. Since suitable probabilistic measures have been defined on both sets, the filter maps one onto the other, and using Monte Carlo experiments we define the functional connection between the moments of corresponding probabilistic distributions.

As mentioned above, if the state of agriculture system is determined by the scalar value of the crop yield y, then the event $y < y_{\rm crit}$ is considered as an "agricultural disaster". The critical value $y_{\rm crit}$ is determined by economic and social arguments laying outside of the considered problem. For instance, $y_{\rm crit} = 1.5$ t/ha for Kursk region. This choice has been made from the social and historical arguments (rural population in the Central Russia was perceiving a crop yield less than 1.5 t/ha as a disaster). The homeostatic domain and its boundary are defined in this case as Ω: $y > y_{\rm crit}$, Γ: $y_{\rm crit}$.

Keeping in mind the risk definition we can formulate the following probabilistic statement: *let* $R(y_{\rm crit})$ *be the probability of the event* $y < y_{\rm crit}$. *Then* $R(y_{\rm crit}) = 1 - \Pr(a)$, *where* $a = \{\langle y\rangle - y_{\rm crit}\}/\sigma_y$ *is the corresponding percentile of the probability distribution* Pr *with the arithmetic mean* $\langle y\rangle$ *and the variance* σ_y. The corresponding statistical test has shown that this distribution is very close to the normal one. If the line $\langle y\rangle = y_{\rm crit} + a\sigma_y$ is drawn in the plane $\{\langle y\rangle, \sigma_y\}$ (figure 7), then it divides the plane on two domains corresponding to normal and catastrophic states.

Let us assume that under some climate change only the mean crop yield was changed (the trajectory $0 \to 1$ in

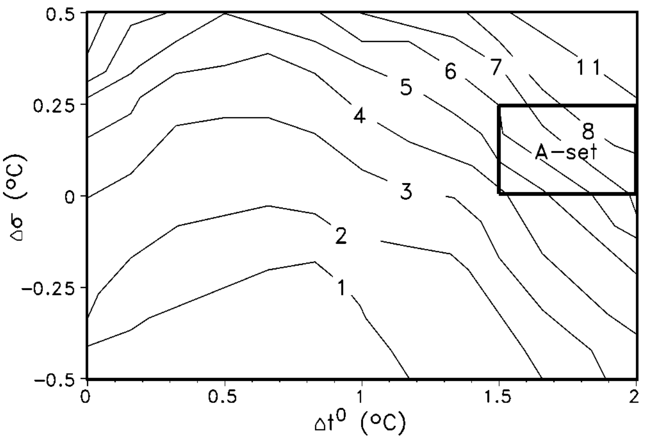

Figure 8. Isolines of the annual risk (in %).

figure 7), and, as a result, that the system was found in the catastrophic domain. On the other hand, the same result is obtained if the mean crop yield is not changed, but only the variance increases (the trajectory $0 \to 2$). In many agricultural forecasts only the first case is considered for the same reason, and the second case is forgotten, which is also possible. In actuality both the mean crop yield and its variance are changed (the trajectory $0 \to 3$). At last, since the increase of the percentile a corresponds to the decrease of risk level, then the catastrophic domain must also increase (line II in figure 7).

By setting $\langle y\rangle$ and $\sigma_y = s$ using the dependencies $\widehat{y} = f(t^0,\sigma)$ and $s = \varphi(t^0,\sigma)$, we have $R(y_{\text{crit}}) = R(y_{\text{crit}}; t^0,\sigma)$. The functions f and φ are known (see figures 5 and 6), therefore $R(y_{\text{crit}}; t^0,\sigma)$ can be calculated. The results are shown in figure 8, where the isolines of R are drawn in the plane $\{\Delta t^0, \Delta\sigma\}$.

We can see that, for instance, the annual 3% risk level remains practically constant when the temperature rises by $\approx$1°C (if the variance is not changed). But the risk rises very fast if the variance increases also (even if the change of mean temperature would be very small)! This is one more argument confirming that a forecast of temperature variance is a very important problem.

Generally speaking, the information contained in figure 8 is sufficient to predict the change of admissible risk for any climatic scenario. We can see that the most dangerous situation would be when both the mean temperature and its variance would be increased in a similar way. In this case the probability of disaster increases very fast. But what is the probability that this case could be realised?

Let us come back to the climate models. Today we cannot decide what kind of model gives the best predictions of the future climate. This is, in particular, true for the prediction of statistical characteristics. Of course, we could combine these models to construct some sort of "optimal predictor", but what kind of criterion do we have to use? We cannot be sure that an average prediction would be the optimal one. A possible approach is to indicate some intervals for probable change of climatic parameters and to suppose that all the changes are equiprobable ("microcanonical ensemble"). This implies that in our case study the Λ-set in the plane $\{\Delta t^0, \Delta\sigma\}$ is a simple rectangular domain A: $1° \leqslant \Delta t^0 \leqslant 1.5°$, $0° \leqslant \Delta\sigma \leqslant 0.25°$ (figure 8), and the distribution $\pi(\lambda)$ is a simple rectangular distribution. In order to calculate the annual risk under climate change, the function $R(y_{\text{crit}}; t^0,\sigma)$ must be integrated over the predicted domain of possible climate change, A, so that

$$R^*(y_{\text{crit}}) = \frac{1}{S_A}\int_A R\big(y_{\text{crit}}, \Delta t^0, \Delta\sigma\big)\,\mathrm{d}\Delta t^0\,\mathrm{d}\Delta\sigma, \qquad (5.1)$$

where S_A is an area of the domain S, $S_A = 0.125$. Here the annual risk $R^*(y_{\text{crit}} = 1.5$ t/ha) turns out to be 7%.

Since the "risk" probability is the result of the convolution of many factors and processes, and of only two moments of the real distribution, we can formulate a plausible hypothesis: *the final result* (*risk assessment*) *depends very weakly on the form of such a distribution*.

Finally, we can say that there are a lot of other works (see, for instance, [4,12–14,16]) dealing with the problem of estimating the impact of climate change on agroecosystems. Their authors are usually using different climatic scenarios and different methods of forecasting. It is no wonder that there is a large inconsistency in their quantitative forecasts (even if they use similar scenarios). On the other hand, there is one common qualitative item among them: they all forecast that the climate change would cause a significant drop of the potential productivity of basic crops (especially spring ones) in many agricultural regions of the world. Note that, as a rule, only the change of mean climatic parameters is taken into account in the forecasts.

6. Crop production: a few remarks on a regional problem

We conclude with several remarks about the problem of agriculture risk when a considered region contains local sub-regions with different local climates. As a consequence, local crop yields will be different. On the other hand, a regional market is a typical averaging operator, which averages local variations of crop production. One of the fundamental (macroscopic) variables (for the market) is the total amount of crop production. If S_k is the area of the ith locality ($k = 1,\dots,K$) and y_k is the specific crop yield (for instance, in tons per hectare), then

$$y = \sum_{k=1}^{K} y_k S_k \qquad (6.1)$$

is the total amount of regional crop production. Let $y_i = \langle y_i\rangle + \xi_i$, where ξ_i is a stochastic component for crop yield. Then, if $K \gg 1$, in accordance with the Central Limit Theorem [5], the total crop production y can be considered as a normally distributed value with the mean $\langle y\rangle$ and the variance $\sigma_y = \sum_{k=1}^{K}\sum_{l=1}^{K}\sigma_y^{kl} S_k S_l$, where $||\sigma_y^{kl}||$ is the covariance matrix for the local crop yields.

The crucial assumption is that there is a minimal critical value of y_{crit}. Note that for the market, overproduction as well as underproduction is dangerous, therefore also the upper critical limit for y may exist. Here we restrict ourselves to the case of the lower limit, so that only the event $y < y_{\rm crit}$ is considered as an agricultural disaster.

In the way sketched above we can scale down our problem to that of local crop production. It is obvious that the matrix $||\sigma_y^{kl}||$ depends on the covariance matrices for climatic parameters, that is, on the statistical traits of the regional climate. Any weakening of the correlation between local climates (as a consequence of the general unsteadiness of the mesoclimate; this is one of the probable consequences of climate change) would reduce the regional risk (?!). Let us recall the well-known probability paradox: *the reliability of a system decreases with the reduction of its diversity* [5]. Certainly, our conclusion is correct if the market scale is close to the scale of the mesoclimate. Scaling up (for markets) tends to further decrease the regional risk, while scaling down results in the rise of risk. Formally, the problem described is similar to the problem of river navigation (the main problem in USA in the course of the "hot summer" of 1988), that is, the problem of critical water levels for large rivers. The water level x is an additive function (functional) of multiple localities which make up the watershed. On the one hand, the river is an averaging operator for the local dynamic elements; on the other hand, the mesoclimate combines all these elements in a statistical way.

7. Conclusion

The main point of this work has been separating two problems from each other: the analysis of consequences of the climate change for different social systems and the decision which is connected to them. In other words, we tried to solve a well-known "business dilemma". By applying the "risk-assessment" approach, we show how the risk probability can be estimated, but the choice of admissible level of the risk is a problem beyond the scope of our work.

Usually only one factor of climate change, namely the shift of mean temperature, was taken into account, when its influence on agriculture was considered. We have shown that another consequence, an increase of the variability of climatic parameters, would be the leading factor influencing on agriculture.

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