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APPROACH TO MULTI-DISASTER VULNERABILITY ANALYSIS BASED ON RISK PERCEPTION MODEL

Podejście oparte na modelu percepcji ryzyka w badaniu podatności w przypadku wielu katastrof

Słowa kluczowe: Pecepcja ryzyka, użytkowanie ziemi, stan rolno-ekologiczny, społeczna podatność, analiza ryzyka
Key words: Risk perception, land-use, agro-ecological conditions, social vulnerability, risk analysis

INTRODUCTION

Human issues are the main components of modern security concept (Lutz, Samir 2011, Kostyuchenko, Movchan 2015). Modern understanding of complex security and complex risk management requires analysis of all natural and social phenomena, the involvement of all available data, the construction of advanced analytical tools, and the transformation of our understanding about vulnerability, perception of the risk and security (Kostyuchenko, Movchan 2015). In some sense the risk management moves from subject of engineering protection to a subject area of social construction (Nelkin 1989, Spink et al. 2007).

Traditionally used deterministic models applied usually for risk analysis are difficult to apply to the analysis of social issues, and also in an analysis of multi-scale multi-drivers phenomena. They are difficult to quantify because the multidimensional distributions of studied parameters generate high uncertainties, and the system is not ergodic in rigorous sense (Ermoliev, Winterfeldt 2012, Kostyuchenko 2014). Therefore, stochastic models of risk analysis are preferable for quantitative analysis of social issues such as human behaviour, social vulnerability and risk perception. The influence of social drivers and factors on disaster damage should be quantitatively estimated in the security and vulnerability analysis.

Therefore, the issues of risk and threat perception should be described in a framework of risk analysis models, using appropriate tools and approaches related to the human dimension of vulnerability (Linnerooth-Bayer, Mechler, Pflug 2005).

RISK PERCEPTION: SOCIO-CULTURAL DIVERSITY AND COGNITIVE HEURISTICS AS A BEHAVIORAL BASIS OF DECISION MAKING UNDER UNCERTAINTIES

To include human dimension into risk analysis we should define risk through social, cultural and behavioral terms. For risk perception studies lets determine a culture as a system of values, dominating in particular group of people at a particular time, and determining a certain social behavior type. Different cultures produce different types of communicative tools, social life, and group division, according to the theory of Douglas (Douglas, Wildavsky 1982). Motivation of every group of people in framework of these cultures is varied, and based on a set of values. According to the Schwartz's theory the motivation goals expressed by values (Schwartz 1992): Interaction of these values determines intension of development, behavior, and perception of threats.

We also will recognize, stable sets of communication tools, inherent to particular group of people at a particular time as key social factors, which influence risk perception. Thus, socio-cultural factors – are the parameters describing the stable type of human relationships, implemented in the form of a specific set of communication tools.

Influence of socio-cultural factors in the perception of risk could be described by a generalized model of risk premium increase as a readiness „to pay for the risk". In this case, an increased willingness to pay for risk, increasing insurance premiums will be expressed in the maximization of the insurance premium by avoiding uncertainty, maximizing returning values, and minimization of damage. Such formalized risk perception in most general case might be presented as (Weber, Hsee 1998):

$$F_t(X_i) \to f(V(\mathbf{X}), R(\mathbf{X})) \tag{1}$$

Where $F_t(X_i)$ - is the "function of willingness to pay for risk" – expected return of interest, risk premium, which can be interpreted as the risk perception rate; V(X) - return of risky values X=(x_1, x_2,... x_i...,x_n), i -assets; R(X) - risk function, t- time. In the simplest case of market behavior the presented equation might be presented in form:

$$F_t(X_i) \propto \sum_{i,t=0}^{T} [V_t(\mathbf{X}_i) - b_i R_t(\mathbf{X}_i)], \tag{2}$$

where b – is coefficient of sensitivity known as "expected asset returns to the excess market returns".

So the role of socio-cultural and cognitive heuristic filters are to maximize expected return of interest (find $Arg \max_{i,t}\{V_t(X_i)\}$), avoid uncertainty, maximize (find $Arg \max_{i}\{V_t(X_i)\}$), and minimize losses (find $Arg \min_{i}\{X_i^t\}$).

This task was formally proposed and solved for separated cases by (Gritsevsky, Ermoliev 2012) as ”increasing returns” model.

Surveys and calculations show that for majority of communities some important hypotheses are true, such as: (i) social equity and, in particular, equitable distribution of income increases stability of society (Hofstede 1995); (ii) individualistic groups are more stable and have higher risk premiums because of overconfidence and self-attribution biases (Glaser, Weber 2009); (iii) higher masculinity leads to increase of vulnerability (Borghans et al. 2009); (iv) uncertainty avoidance usually, but not always lead to sustainability increasing, because seeks for safe investment (De Mooji 2000).

Both component of right side of equation (2) has a significant behaviorist load. “Market” component *V*(X) is more dependent on culture, social behavior and communications, “Risk” component – on cognitive heuristics and personal behavior during a disaster. Structure of influences to our decision making is complex and complicated, and might be presented a distribution of personal and collective biases (Fig. 1).

In this study we focused on formalization of cognitive heuristic component (“Risk” component on Fig. 1 and Eq. 2) of risk perception, considering socio-cultural component (“Market” component on Fig. 1 and Eq. 2) as the perception filter (Alexander 2014) – complex of stable communicative tools, which are attributes of certain social group (Kostyuchenko, Movchan 2015, Douglas, Wildavsky 1982).

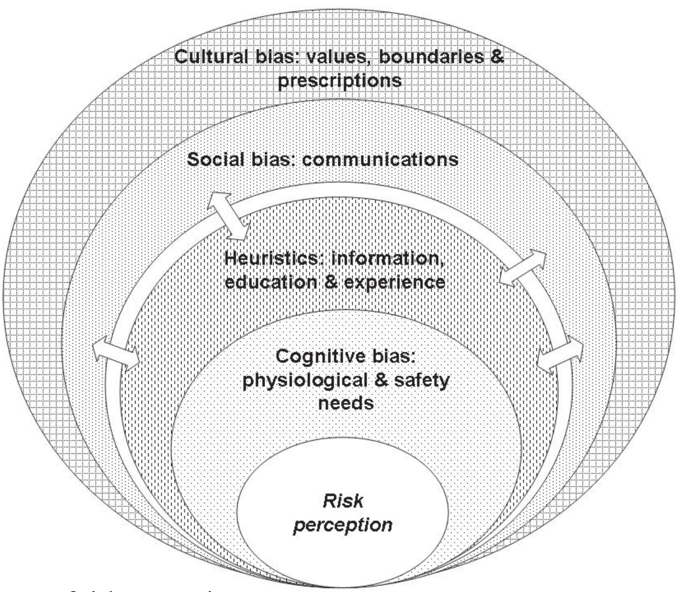

Fig.1. Component of risk perception
Source: Own elaboration

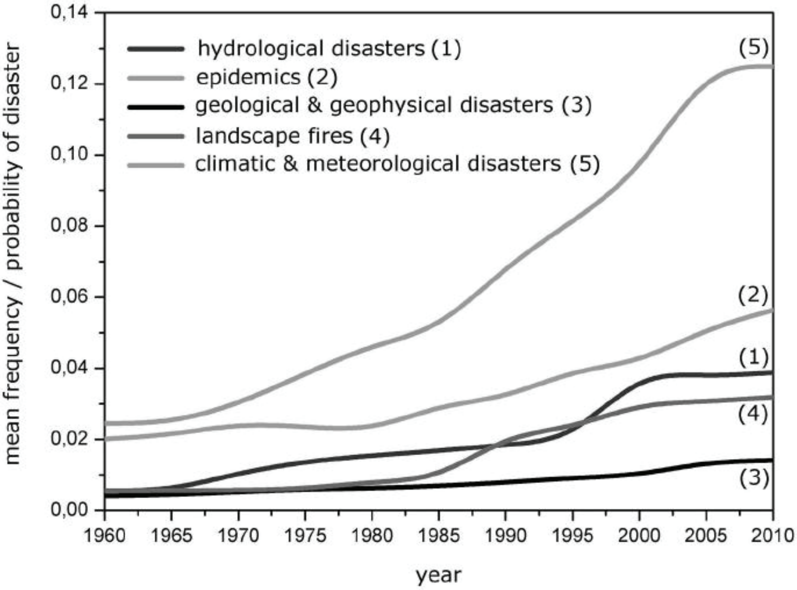

Fig. 2. Distribution of frequency of disasters in Ukraine 1960-2010 (Source: Kostyuchenko et al. 2013, Kostyuchenko, Movchan 2015)

In a situation where the data of sociological surveys of values in Ukrainian society is substantially scattered, and only selectively processed in the framework of techniques, oriented to risk assessment, we will focus on the separate components of the perception of threats.

The construction of proposed approaches to assessment of risk perception is based on the cognitive heuristics theory (Kahneman, Tversky (eds.) 2000, Tversky, Kahneman 1974).

METHODOLOGICAL NOTES: MULTI-SOURCE DATA ANALYSIS TOOL FOR RISK AND VULNERABILITY ASSESSMENT

A problem of correct statistics is the usual problem of risk and vulnerability analysis. In framework of most common and most comprehensive case the risk can be presented as the superposition of interrelated distribution function ($f(x,y)$) and damage function ($p(x,y)$):

$$R \propto \sum_{x,y} f(x,y)\,p(x,y) \tag{3}$$

Distribution function $f(x,y)$ describes an impact of expanded disaster; damage function $p(x,y)$ describes distribution of damaged assets: infrastructure, people, natural features, etc. To analyse a role of social factors in risk measure variation a huge number of disasters were studied.

For the risk analysis 894 natural disasters in Ukraine in the interval 1960–2012 were selected and analysed. General trends have been detected; the period 1991–2010 was selected for detailed analysis, as it is the time interval with the most reliable statistics (*National report...* 2010) validated by satellite observations (Kostyuchenko et al. 2013). Socio-economical data has been analysed on the sample of 42 disasters, including 11 most affecting events. List of major disasters includes 6 floods, 3 storms, 1 cold wave, and 1 epidemic. Total losses of major disasters is about 1,67 billions EUR, 2 721 918 persons were affected, and 1 173 people were killed (Table 1). Analysis of most affecting events (Table 2) was aimed to evaluate the influence of risk perception on the damage function.

Analysis and mapping of spatial and temporal distributions of heterogeneous disasters and its parameters are very complicated problem, as well as the direct

Table 1. Major disasters in Ukraine in 1991–2010

Disaster type	Disaster	N of events	N of killed	N of affected	Estimated losses (USD, 2001)
Epidemics	Infectious diseases	3	275	6,771	n/a
	Average per event		*97.1*	*2,257*	*n/a*
Temperature extremes	Cold waves	1	--	21	850,000
	Hot waves	2	--	34	1,860,000
	Average per event		--	*18.3*	*903,333.3*
	Winter temperature extremes	1	801	59,600	78,750
	Summer temperature extremes	3	11	416	120,500,000
	Average per event		*203*	*15,004*	*30,144,687.5*
Floods	River flood	12	76	2,589,895	1,296,114,000
	Average per event		*6.3*	*215,824.58*	*108,009,500*
Storms	Indeterminate type	5	10	64.184	120,000,000
	Average per event		*2*	*12,836.4*	*24,000,000*
	Extra-tropical cyclone	2	--	--	190,000,000
	Average per event		--	--	*95,000,000*
	Tropical cyclone	2	11	1,000	35,600,000
	Average per event		*5.5*	*500*	*17,800,000*
	All types	9	21	65,184	345,600,000
	Average per event		*2.3*	*7242.7*	*38,400,000*
All disasters		31	1,173	2,721,918	1,675,002,750
	Average per event		*37.52*	*87,803.8*	*54,032,346.78*

Table 2. Most affecting events in Ukraine in 1990-2010 – major disasters included in the analysis

Disaster	Date	N of killed	N of affected
Cold wave	January 2006	801	59,600
Epidemic	January 1995	204	1,380
Flood	June 1995	2	1,700,000
Flood	July 2008	38	224,725
Flood	November 1998	18	24,570
Flood	June 1997	11	12,870
Flood	March 2001	9	342,000
Flood	December 1993	5	25,000
Flood	July 1993	4	300,000
Hurricane	July 2000	4	39,010
Hurricane	November 2000	4	7,552

comparison of distributions is not correct way to analyze multi-source catastrophe drivers. First, the different types of disasters have different long-term trend. Second, drivers of different disasters have different spatial and temporal scales and variability.

Problem of construction of correct techniques of complex regional risk assessment requires to estimate all drivers and parameters of all disasters in the area studied. It requires the determination of measure of statistical distributions of observations, which would be invariant toward data properties.

The problem of data analysis in the context of disaster induced socio-ecological risks, is often connected with the lack of reliable long-term series of observations of catastrophic events, reliable socio-economic and ecological data. According to the general estimations (Kostyuchenko et al. 2015) based on satellite observations and statistical assessment, the official data reliability in separate fields is about 65-88% (on the sub-regional and local scale 88-92%). These levels, and especially the variations of reliability are not sufficient for correct integrated security assessment. Therefore, correct and regular statistics is important for a construction of adequate risk function and also for risk management strategies development (Kostyuchenko et al. 2015).

To estimate a regional risk measure we need an approach to understand the complex systemic interrelations between distributions of social parameters and disasters frequency and intensity. Therefore the development of alternative ways of analysis of multivariate distributions is the core element of regional disaster risk analysis and management (Kostyuchenko et al. 2015).

The method proposed is based on non-linear kernel-based principal component algorithm (KPCA) modified according to specificity of data: socio-economic, diment strategies allow decrease vulnerability of society toward natural catastrophes even with increasing of its frequency, intensity and direct losses. Presented disaster distributions for Ukraine demonstrate the necessity of implementation of systemic strategies of risk assessment and management, including huge socio-cultural component.

RISK PERCEPTION FUNCTION AS THE WAY TO ANALYZE THE FACTORS AND DRIVERS OF RISK AND LOSSES DISTRIBUTION

Basing on the prospect theory and decision making under uncertainty on cognitive bias and handling of risk (Kahneman, Tversky (eds.) 2000), we propose to modify a damage function as: $p(x, y \mid \alpha(t))$. Modified damage function includes an awareness function $\alpha(t)$, which is the superposition of risk perception function (r_p) and function of education and log-term experience (c) as: $\alpha(t) \to (c + r_p)$ following to (Tversky, Kahneman 1974).

Education function describes the trend of education and experience. Risk perception function r_p reflects security concept of human behaviour, is the basis for prediction of socio-economic and socio-ecological processes. Also there is an important positive feedback of risk perception function to distribution function. Risk perception depends essentially on recent events.

The awareness function might be presented in a generalized form as follows (Kostyuchenko, Movchan 2015):

$$\alpha(t) = \sum_i (c_i + (r_p)_i) \tag{4}$$

Therefore, two components of this function could be analysed: drivers which form long-term response; and parameters, which form mid- and short-term conditions of risk perception (Figure 4).

INFLUENCE OF COGNITIVE HEURISTICS TO WIDE-SCALE SOCIO-CULTURAL DRIVERS OF RISK DISTRIBUTION: EDUCATION AND AGE STRUCTURE

Using this form (8) we can represent separate parameter distributions. For the assessment of losses related to basic education level of affected people, the regression proposed is (Kostyuchenko, Movchan 2015, Frankenberg et al. 2013):

$$p(\alpha)_c = a_0 + p_o(x, y) \sum_{i,t} (E_{i,t}^{(x,y)} + A_{i,t}^{(x,y)}) + \sum_{i,t} (r_p)_{i,t}^{(x,y)} \tag{5}$$

Here a_0 is constant coefficient; p_0 – basic level of physical losses on the site (x,y); $E_{i,t}$ – education level of people group i in time t on the site (x,y); $A_{i,t}$ – age of people group i in time t on the site (x,y).

saster statistics, climatic, ecological, infrastructure distribution (Kostyuchenko et al. 2015). Using this method the set of long-term regional statistics of disasters distributions and variations of economic activity has been analyzed.

Using the KPCA algorithm it is possible to obtain regularized spatial-temporal distribution of investigated parameters over whole observation period with rectified reliability and controlled uncertainty (Kostyuchenko et al. 2015, Mudelsee et al. 2001), such it presented on the Figures 2, 3.

Quantitative analysis of observations (Kostyuchenko 2014) demonstrates that number of all types of disasters is increasing. Besides, the distribution presented is demonstrates essential increasing of the losses, which is connected with registered increasing of frequency and intensity of disasters, as well as with increasing of the damaged infrastructure cost.

The distribution presented demonstrates that relative natural disasters damage during 1990 is slightly increasing, which is probably connected on impact of climate change. Common trend in the world and the Europe demonstrates decreasing of *IoD*, which connected with economic grows (increasing of economic sustainability toward catastrophic events) and successful implementation of risk management strategies. At the same time on the territory of Ukraine since 1980's and especially since 1990's *IoD* is increasing dramatically. It connected with economical degradation and absence of adequate systemic strategies of risk management.

The distributions presented is more evidently reflect the fact that sustainable economic growth and implementation of adequate risk assessment and manage-

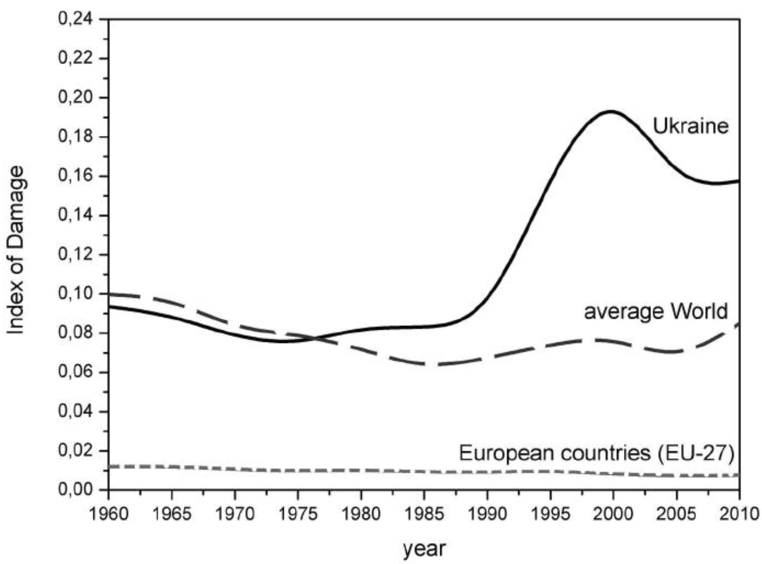

Fig. 3. IoD (The Index of Damage – related disaster losses to annual GDP) distribution in Ukraine 1960-2010 (Kostyuchenko et al 2013, Kostyuchenko, Movchan 2015)

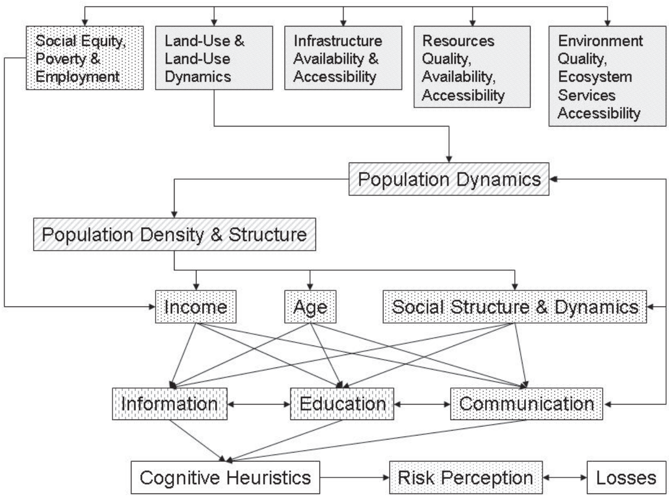

Fig. 4. Risk perception drivers
Source: Own elaboration

Using algorithm (5) with available statistics we have no instruments to measure risk perception function directly. Therefore, we need to apply indirect algorithms to estimate it.

In this form the component $\sum_{i,t}(r_{\ddot{u}})^{\ddot{u}x\ y}_{,}$ might be interpreted as an uncertainty coefficient (Huber 1981). So if few quite reliable intervals τ within the long period t are available for observations of M sites (x,y) from 2 records, we may propose the following uncertainty estimation (Kostyuchenko, Movchan 2015):

$$(r_p)_{i,t}^{(x,y)} = \delta p(\alpha) = \left| p_1(\alpha)_{i,t}^{(x,y)} - p_2(\alpha)_{i,t}^{(x,y)} \right| / \left(\frac{\sigma_\tau \sum_{\tau,m} \left(\frac{| p_1(\alpha)_{m,\tau\in t}^{(x,y)\in M} - p_2(\alpha)_{m,\tau\in t}^{(x,y)\in M} |}{2} - \sum_{\tau} p_1(\alpha)_{m,\tau\in t}^{(x,y)\in M} \right.}{CoVar_m} \right) \qquad (6)$$

This equation can be used (Kostyuchenko, Movchan 2015) as a simple form for estimation of risk perception function of a group of population i with education level E and age range A on site (x,y) during time interval τ within the geographic region M and an observation period t.

Combination of equations (5) and (6) describes the education function distribution among the studied groups of population during time interval τ within the geographic region M and an observation period t (Figures 5, 6). The distributions presented are demonstrate that with all types of disaster impacts less educated people suffer more (injuring, missing and killing).

SOCIO-ECONOMIC DRIVERS OF RISK PERCEPTION AND LOSSES DISTRIBUTION ON SHORT AND MIDTERM SCALES

Disaster data (*National report...* 2010) were analysed using modified kernel-based nonlinear principal component analysis (KPCA) algorithm. As the result the spatially and temporally regularized distributions with normalized reliability were obtained.

Figures 5 and 6 present distributions of probability of a proportion of people affected by property damage that depend on education for the most valuable natural disasters in Ukraine 1991-2012 (*National report...* 2010, FAO/ADPC 2006). This

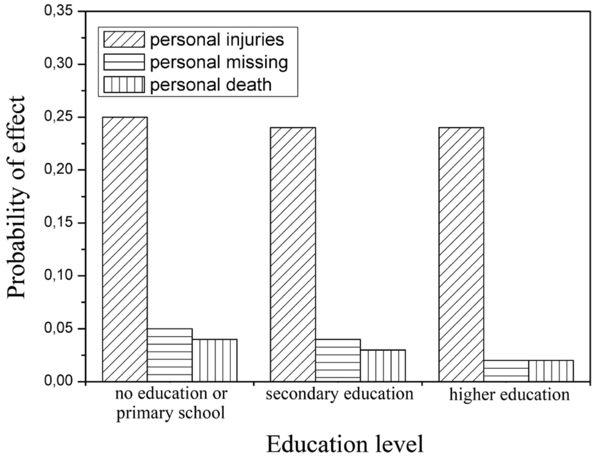

Fig. 5. Distribution of the probability of the effect on the individual (death, injured or missing) depending on education (Kostyuchenko, Movchan 2015)

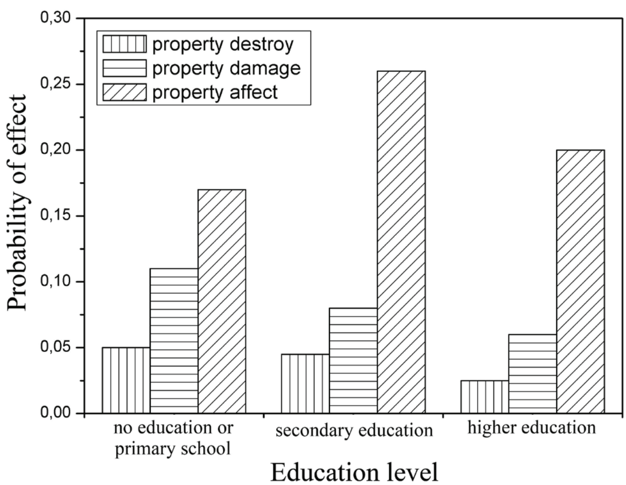

Fig. 6. Distribution of the probability of property damage (homes and business destroyed, damaged and affected) depending on education (Kostyuchenko, Movchan 2015)

corresponds to the average world trends (FAO/ADPC 2006). Moreover, the distribution reflects the disparity on property distribution in Ukraine, and an important connection with social fairness patterns.

Risk component caused by the education (and indirectly by the age) is closely connected with economic parameters, such as per capita income. Surveys show that these interrelations are varied and they are significantly heterogeneous spatially and temporally.

Figures 7 and 8 present the distributions of probability of a proportion of people affected by property damage depending respectively on personal income are presented. These distributions look predictable because correspond to average world trends (FAO/ADPC 2006): in particular, increasing income leads to increase of protection.

Peaks of probability of individual damage and property damage with low income and increasing the probability of affect and destruction of property with high income shown in Figure 8, demonstrates interesting characteristics in Ukrainian society: most poor and most rich people are most vulnerable toward catastrophes. Poorest are vulnerable because of the lack of infrastructure and resources accessibility; and richest because of the neglecting of security regulations. These are the different aspects of social groups behaviour, and could be described as decision making problem under uncertainty (Yudkowsky 2006).

In general case the linearised form might be proposed as follows (Kostyuchenko et al. 2015, Kellenberg, Mobarak 2008):

$$\ln(p_{i,t}(x,y))_r = a_1 P_{i,t} + a_2 F_{i,t}^d + a_3 \ln I_{i,t} + a_4(\ln I_{i,t})^2 + a_5 P_{i,t}^{UR} + a_6(\ln I_{i,t} P_{i,t}^{UR}) + \xi_{i,t}^{(x,y)} \quad (7)$$

Here a_n – regression empirical coefficients; $F^d_{i,t}$ – frequency of disasters on the site (x,y); $I_{i,t}$ – per capita income of people group i in time t on the site (x,y); $P_{i,t}$ –

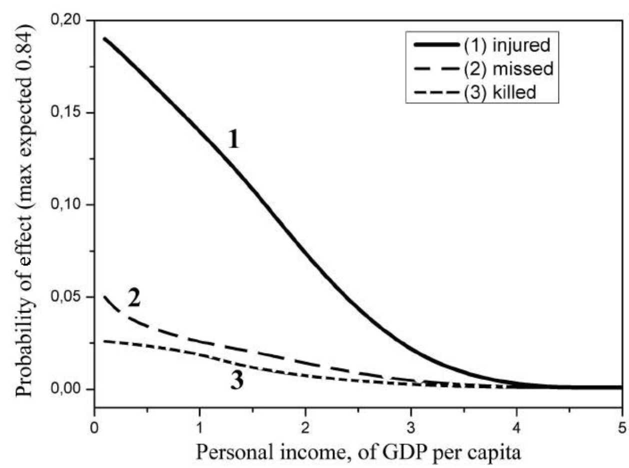

Fig. 7. Distribution of the probability of the effect on the individual depending on personal income. GDP: gross domestic product (Kostyuchenko, Movchan 2015)

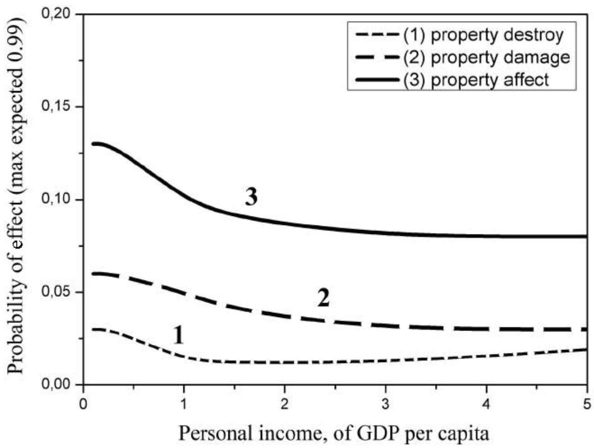

Fig. 8. Distribution of the probability of property damage depending on personal income. GDP: gross domestic product (Kostyuchenko, Movchan 2015)

population in time t on the site (x,y); $P^{UR}{}_{i,t}$ – urban population/social density in time t on the site (x,y); and ξ – uncertainty coefficient.

Proposed equation, which describes natural disasters losses, requires detailed data on used parameter such as distribution of population density or income.

PROBLEM-ORIENTED STOCHASTIC MODEL OF POPULATION DISTRIBUTION

Usually we have not enough accurate data on population distribution and dynamics, so population statistics is an object of statistical estimations. We can evaluate *a* value $P_{i,t}$ – population in time t on the site (x,y) as the stochastic value.

If site (x,y) is the part of mixed area with urbanized and rural districts, population in the site investigated could be presented as:

$$P_{i,t}{}^{(x,y)} = \frac{\mu_i^{RUR} P_i^{RUR}}{\sum\limits_{x,y} \mu_{(x,y)}^{RUR}} + \frac{\mu_i^{UR} P_i^{UR}}{\sum\limits_{x,y} \mu_{(x,y)}^{UR}}, \qquad (8)$$

Where $P_i^{ü}$ is rural population, P_i^{UR} - urban population, $\mu^{ü}$ - rural probability density coefficient, μ^{UR} - urban probability density coefficient for the certain site.

RURAL POPULATION VS. LAND-USE AND CROP PRODUCTIVITY MODEL

So rural population will be determined by the rural population probability density coefficient $\mu_i^{ü}$, which could be defined as:

$$\mu_{i(x,y)}^{RUR} = \sum_{n,(x,y)} u_{n,(x,y)} S_{(x,y)}, \qquad (9)$$

Where $u_{n,(x,y)}$ is agro-ecological zoning coefficient for land-use type n in site (x,y); $S_{(x,y)}$- square of land-use type in site (x,y). Agro-ecological zoning coefficient include number of parameters (Fischer et al. 2002):

$$u_n \to h_n(A_n;\delta)\overline{y}_n(x_n), \qquad (10)$$

Where h_n- land index, calculated for each region taking into account pollutions and soil degradation, A_n - type of land-use, δ - scaling parameter, $\overline{y}_n$ - maximum attainable yield, depends of x_n - agro-ecological condition, which includes parameters of terrain, soil, water: moisture and precipitation, climate and temperature. Maximum attainable yield may be assessed as the functional of annual statistical yield maximum:

$$\overline{y}_n \to y\cdot(1-u)\cdot f(k)\cdot S(T,W,R)+\Delta \qquad (11)$$

Where u – crop degradation index; $f(k)$ – function of crop density; $S(T, W, R)$ – productivity functional depends of distributions of temperature, water load and radiation; Δ – uncertainty coefficient (Gommes et al. 2007).

Rural population vulnerability is determined by natural conditions, quality of lands, effectiveness of land use, intensity of pollutions, crop productivity variations during the period of crop rotation (Kostyuchenko, Bilous et al. 2013, Movchan et al. 2013) and market conjuncture.

Additionally, there is a local parameter, which connects population and income distribution through variations of consumer prices of agricultural production. In the framework of general stochastic socio-economic regional model (Fischer et al. 1996) a production function of "aggregate farmer" should include output index with available provincial prices p_{rc} for yield y_{rc}, the national prices p_c, including weighting coefficient w_i (Albersen et al. 2002):

$$p_r^i = w_l \frac{\sum_c p_{rc} y_{rc}}{\sum_c p_c y_{rc}} \qquad (12)$$

Where w_i is a coefficient of infrastructure availability, reflecting the road quality β, distance l' between the given county and all other cities and county towns, and density of urban population P_i^{UR} as:

$$w_l = \sum_{l'} \frac{P_{l'}^{UR}}{\exp(0.01\cdot\beta_l\cdot distance_{l,l'})}. \qquad (13)$$

This type of stochastic approach with necessary constrains and measurable variables is discussed in (Movchan et al. 2013). The methods of control of current productivity y_{rc} as well as its variations are also proposed (Kostyuchenko, Bilous et al. 2013). Therefore, as it is following from (12) and (13), a rural population vulnerability will depend also on distribution of urban population, in particular, on distance to city centres l, and on national distribution of crops output.

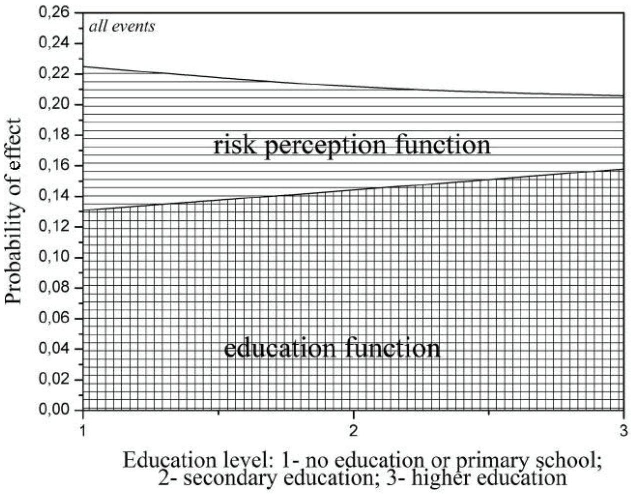

Fig. 9. Estimated distribution of risk perception and the education component of the awareness function for all studied events (Kostyuchenko, Movchan 2015)

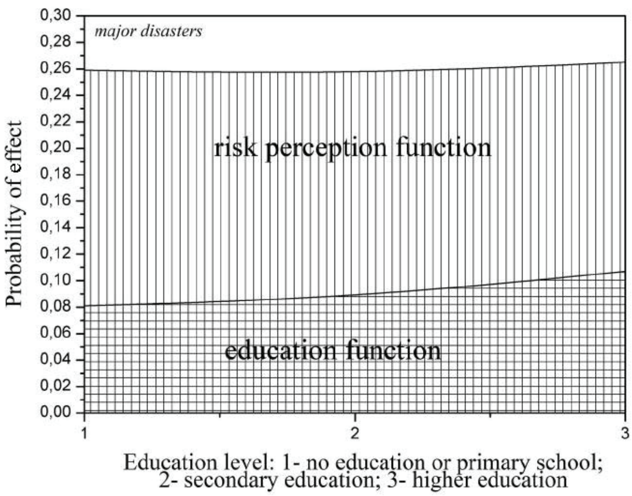

Fig. 10. Estimated distribution of risk perception and the education component of the awareness function for "fast catastrophes" (11 major disasters) (Kostyuchenko, Movchan 2015)

URBAN POPULATION VS. INFRASTRUCTURE AVAILABILITY AND SOCIO-ECONOMIC MODEL

Population on urbanized areas is distributed by other low, and it vulnerability should be described with other relations. General model of urban population density p_n in region n can be presented, according to (Clark 1951, Chen 2008). as:

$$p_n(r) \propto \sum_{n(x,y)} p_{n(o)} \cdot \exp(-\frac{r_n}{r_{n(o)}})^{\sigma} , \qquad (14)$$

Where $P_{n(0)}$ is the population density in the urban centre, r_n - distance of area n with localization (x,y) to centre of urbanized area, $r_{n(0)}$ - functional radius of urbanized area, σ - parameter of stage of town development.

To reduce a difference between land-use types and urban landscapes inside towns and urbanized zones, will use a fracture coefficient, according to (White, Engelen 1994, Chen, Zhou 2008). :

$$\lambda_i = \sum_m (r_{im} - \frac{\sum_i d_{im}}{D_{im}}) . \qquad (15)$$

Where d_{im} is size of land-use type i in district or town m, D_{im} - size of urban fracture or town m, included different types of land-use types d_{im}, r_{im} - distance from town m to the urban centre.

$$\mu^{UR}_{i(x,y)} = \sum_{n,(x,y)} \frac{r_n}{\lambda_i} A_n \ln A_{(x,y)} \exp(-\frac{r_n}{(A_{(x,y)} / \pi)^{1/2}})^{\sigma} \qquad (16)$$

Where A_n is urbanized area, $A_{(x,y)}$ - square of town, r_n - distance to urban centre, σ - parameter of stage of town development. Parameter of stage of urban development could be presented in a form:

$$\sigma_{n(x,y)} = \sum_{n(x,y)} (\frac{A_{b(x,y)} + A^{q_m}_{i(x,y)}}{A_{(x,y)}} + \beta_l \frac{l_{im}}{r_n}) , \qquad (17)$$

Where $A_{b(x,y)}$ is a built-up area of town, $A_{i(x,y)}$ - industrial area, l_{im} - density of roads, β - coefficient of infrastructure availability (reflecting the road quality), q_m- local employment rate.

Therefore, we can conclude that vulnerability of urban population depends of distribution of urban fractures and quality urban environment: density, quality and availability of infrastructure, balance between industrial, residential and recreational zones, effectiveness of urban land use and landscape management, and social policy, particularly and employment.

Proposed equation (7) with additional components from (8) to (17), which describes fatalities from natural disasters corresponds to observed distributions. This regression is good correlating with results of other studies (Kahn M.E. 2005).

Available disaster statistics was analysed using proposed approach from (8) to (10) and KPCA algorithm. Result demonstrates interconnected influence of education function and risk perception function to the damage function as the measure of vulnerability toward disasters (Figure 9 and 10). So we can separately analyse impact of education, long-term experience and short-term information to the losses dynamics as the function of social behaviour.

Data show that no less than 7-11% of direct losses depend of short-term behavior of “information agents”: social activity of experts, scientists, correct discussions in media etc. Other 8-10% of losses are connected with level of public and professional education. Therefore, a cost of systemic education and long-term preparedness work is no less than 10-15 % of total catastrophic losses, and cost of responsible information, social behaviour, and policy making is 8-20% (in case of major disasters) (Kostyuchenko, Movchan 2015).

CONCLUDING REMARKS

Modern world is based on relationships rather than on causalities, so communicative, socio-economic, and socio-cultural issues are important to understand nature of risks and to make correct decisions. Today major part of risk analysts declared new nature of modern risks (Marti, Ermoliev, Makowski 2010). We faced coherent or systemic risks, realization of which leads to domino effect (Kostyuchenko et al. 2012), unexpected growing of losses and fatalities (Ermoliev, Makowski, Marti (eds) 2012). This type of risks originated from complicated nature of heterogeneous environment, close interconnection of engineering networks, and changing structure of society. Heterogeneous multi-agent environment generates systemic risks, which requires analyzing multi-source data with sophisticated tools. Formal basis for analysis of this type of risks is developed during the last 5-7 years (Ermoliev, Makowski, Marti (eds) 2012). But issues of social fairness, ethics, and education require further development. One aspect of analysis of social issues of risk management is studied in this paper.

The result of disaster data analysis demonstrates that about half of direct disaster damage might be induced by social factors: education, experience and social behaviour. Using data presented is possible to estimate quantitative parameters of the losses distributions. Equations (5) and (7) determine a relation between education, age, experience, and losses. Equation (7) with components from (8) to (17) allows estimate vulnerability (in terms of probable damage) toward financial status in current social density depends of environment, land-use and infrastructure state. So on wide-scale range an education determines risk perception and so vulnerability of communities.

But at the local level there are important heterogeneities. Land-use and urbanization structure influence vulnerability at the temporal scale smaller than 3 years (regional crop rotation period) and with spatial size smaller than 20 km (size of landscape diversity).

Model shows that rural community's vulnerability determines by water availability, quality of soils, effectiveness of land use (including climate change adaptation), intensity of pollutions, crop productivity variations during the period of crop rotation, annual national distribution of crops output, and distance to city centres. It should be noted here that "distance to city centres" is not comprehensive indicator of market accessibility in general case: quality and availability of transport infrastructure should be described more detailed on the next stages of analysis.

Urban population vulnerability is determined by distribution of urban fractures and quality urban environment: density, quality and availability of infrastructure, balance between industrial, residential and recreational zones, effectiveness of urban land-use and landscape management, and social policy, particularly, employment.

Basing on the approach proposed, in particular using the equations (5), (7), (8) and (14) it is possible to calculate distribution of vulnerability in terms of most probable losses (risk of personal impact and property damage caused by multi-disaster impact) for different communities, using data of (*National report*... 2010, *Databank*, *Population of Ukraine*... 2015). In Figure 11 such kind of distribution is presented. As we can see, calculated vulnerability corresponds to disaster distribution, population density and socio-economic parameters. Analysis of this data requires more detailed calculations with better grid, as well as interpretation with more comprehensive data is necessary.

Population density is closely connected with social density, with communications and decision making (*Human development in Ukraine*... 2015). Social learning, as the function of social communications is the way to increase sustainability.

It is possible to say that social sustainability is a function of intensity and efficiency of communications between interlinked and interacted networks in the heterogeneous environment.

Therefore, the results of study demonstrated that risk management should include issues of risk and threats perception, which should be described in a framework of appropriate tools and approaches connected with human dimension of vulnerability. For instance, problems of accessibility and availability of resources in view of social fairness and socio-economic dynamics should be included into future studies in the field of risk analysis.

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Summary

This paper is dedicated to the study of community's vulnerability in risk analysis task using multi-source data statistics. Basing on formal algorithm the quantitative approach to analysis of social factors of multi-disaster and varied threat risk is proposed. Modified form of damage function basing on the prospect theory and decision making under uncertainty on cognitive bias and handling of risk is proposed. Formal analysis of relatioships betweeen damage and age, education and income of population is conducted. Way to analyse a distribution of losses relating land-use, ecological conditions ans infractructure state and accesibility is demonstrated. Analysis demonstrates that at least half of disaster damage might be caused by human factors: education, long-term experience and social behaviour. Using algorithm and approach proposed a way was shown to estimate quantitative parameters of the losses distributions in view of dynamics of socio-economical, socio-ecological, and socio-cultural drivers.

Streszczenie

Niniejszy artykuł poświęcony jest badaniu podatności społeczeństwa w analizie ryzyka z wykorzystaniem wieloźródłowych danych statystycznych. Na podstawie zdefiniowanego algorytmu, zaproponowane zostało podejście ilościowe do analizy czynników społecznych dla wielu katastrof oraz do analizy zróżnicowanego

ryzyka zagrożeń. Zaproponowano także zmodyfikowaną formułę funkcji szkód na podstawie teorii perspektywy i podejmowania decyzji w warunkach niepewności względem błędu poznawczego i postępowania wobec ryzyka. Przeprowadzono procedurę analizy zależności pomiędzy zniszczeniami a wiekiem, wykształceniem i dochodami ludności. Zademonstrowano sposób analizowania rozkładu strat związanych z użytkowaniem terenu, warunkami ekologicznymi, stanem infrastruktury i dostępnością terenu. Wyniki analiz wskazują, że co najmniej połowa szkód związanych z katastrofami może być spowodowana przez czynnik ludzki: wykształcenie, wieloletnie doświadczenie i zachowania społeczne. Stosując zaproponowany algorytm i podejście, ukazano sposób estymacji parametrów ilościowych rozkładu strat mając na uwadze dynamikę procesów społeczno-ekonomicznych, społeczno-ekologicznych, jak i społeczno-kulturowych.